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A REVIEW OF MACHINE LEARNING APPLICATIONS IN ADDITIVE MANUFACTURING

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ABSTRACT

Variability in product quality continues to pose a major barrier to the widespread application of additive manufacturing (AM) processes in production environment. Towards addressing this barrier, monitoring AM processes and measuring AM materials and parts has become increasingly commonplace, and increasingly precise, making a new wave of AM-related data available. This newfound data provides a valuable resource for gaining new insight to AM processes and decision making. Machine Learning (ML) provides an avenue to gain this insight by 1) learning fundamental knowledge about AM processes and 2) identifying predictive and actionable recommendations to optimize part quality and process design. This report presents a literature review of ML applications in AM. The review identifies areas in the AM lifecycle, including design, process plan, build, post process, and test and validation, that have been researched using ML. Furthermore, this report discusses the benefits of ML for AM, as well as existing hurdles currently limiting applications.

Keywords: additive manufacturing, machine learning, deep learning, data analytics, algorithm, survey, review

1. INTRODUCTION

Additive Manufacturing (AM) is an advancing and increasingly popular manufacturing technology that embodies the revolutionary progress of the modern manufacturing industry [1]. It is a process in which a part is made by joining material, layer by layer, directly from 3D model data [2]. AM offers competitive advantage over traditional manufacturing techniques by enabling fabrication of low volume, customized products with complex geometries and material properties, in a cost-effective and time-efficient way [3]. The rapid proliferation of AM technologies has resulted in seven well-defined sub-categories of AM, several of which are capable of producing metallic parts [2]. With continuing technological advances, AM has evolved from being limited to fabricating prototypes to producing end-use metallic parts in various applications (e.g., aerospace, defense, biomedical, and automotive) [4].

Despite the growth of and advancements in the AM industry, achieving consistency with part quality and process reliability in AM remains a challenge [3]. The fundamental reason for this situation is that both the shape and material properties of a part are formed during the AM process. Realizing any AM part involves intricate design, material, and process interactions over the course of a complex multi-stage process that includes five major steps: designing, process planning, building, post-processing, and testing and validation [5]. The controlled and precise execution of each of these steps is needed to fabricate a qualified part.

Recent efforts to reduce AM part variability have focused on learning as much as possible about parts and processes through monitoring and inspection [6]. Advancements in sensor technologies, sensor fusion and data acquisition methods [7], have led to an unprecedented increase in AM data, encompassing many of the aspects of "big data" (Table 1). The different types of data generated throughout the design-to-product transformation cycle are creating new opportunities (Figure 1) for knowledge discovery throughout AM processes [8].

Table 1. Characteristics of AM Data

Volume	~0.5 TB of in-situ monitoring data per build [9] ~TBs of CT scan data
Velocity	Up to 600 variables logged per second during the build 75 GB/s of image data [11]
Variety	Numerical (machine logs, process parameters) 2D images (thermal, optical) 3D (CAD models, CT scans) Audio (acoustic signals) and videos (thermal, optical)

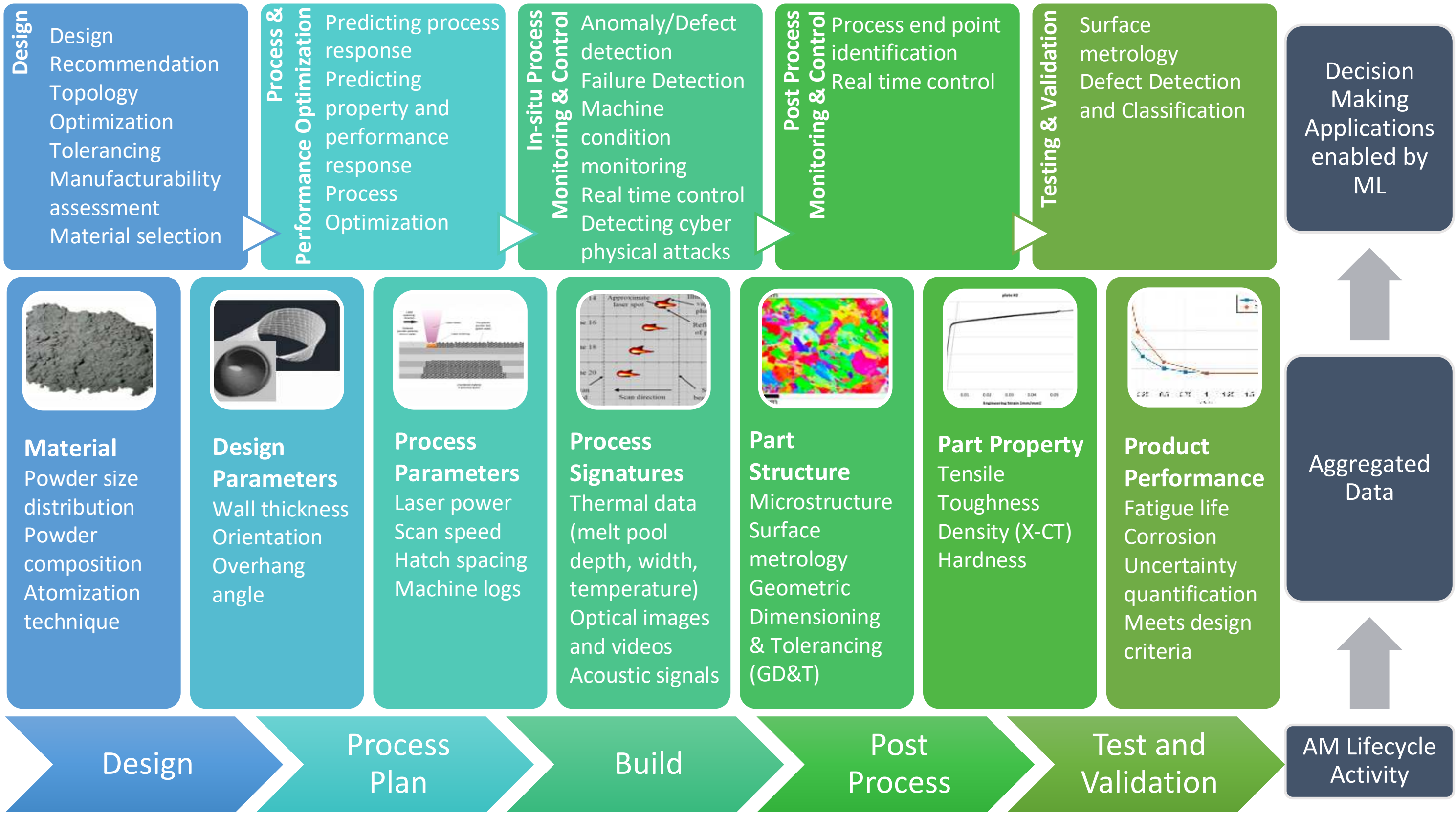

Figure 1. AM Lifecycle, Examples of Associated Data, and Decision Making Applications

In a sense, AM has become a manufacturing domain that is data-rich but knowledge-sparse. Extracting knowledge from the vast amounts of available AM data can be a tedious process. Despite the advances in measurement science and increasing number of datasets from the AM lifecycle, there is limited scientific understanding to characterize AM materials-geometry-process-structure-property-performance relationships. Advanced computational and analytical tools are needed to process the high dimensional and complex data. To this end, new developments in the domain of Machine Learning (ML) offer great potential to transform AM data into insightful knowledge.

ML techniques offer the ability to discover implicit (formerly unknown) knowledge and identify relationships in large manufacturing data sets, transforming unprecedented volumes of data into actionable and insightful information [10,11]. For AM, ML offers new opportunities to optimize and better control AM processes [12]. In this paper, we explore the state-of-the-art literature on the applications of ML techniques throughout the AM lifecycle.

2. MACHINE LEARNING FOR AM

2.1 Overview of Machine Learning Techniques

Machine learning concerns the construction and study of systems that can automatically learn patterns from data. Models built with ML can be used for prediction, performance optimization, defect detection, classification, regression, or forecasting [10]. The largest factor in determining the effectiveness of ML is the data used to train the ML model. ML models are only as good as the training data has prepared them to be.

ML techniques [13] generally fall into two categories: supervised learning and unsupervised learning. In *supervised learning*, a labeled set of training data provides examples of input values and the corresponding correct output. The ML algorithm trains the model using this labeled dataset, inferring the functional relationship between the input and output domains. Supervised learning can be used for both classification and regression. In *unsupervised learning*, there is no labeled training data set available. Instead, the ML algorithm tries to automatically separate the training dataset into different clusters by grouping parameters in the dataset and identifying target classes. Unsupervised learning is useful for applications such as detecting anomalous conditions. The decision between using a supervised or unsupervised ML approach will depend on perceived benefits for a given scenario.

The typing of supervised and unsupervised models provides a high-level classification in which different ML algorithms can be further categorized. Some popular ML models used for both classification and regression are Support Vector Machines (SVMs) and Neural Networks (NNs). An SVM model identifies hyperplanes that separate the data into different classes. A NN is a computational model that consists of a network of nodes ("neurons") and weighted edges between nodes. NNs are very powerful because they can automatically identify features in the raw data that are needed to make good predictions. These capabilities make NNs very suitable for many AM problems where identifying features in the input data may be difficult.

ML algorithms such as deep learning neural networks are especially useful for very complex tasks such as image and audio processing. Deep learning systems employ several hierarchical layers of processing nodes, which help to identify progressively complex features in the input data. Convolutional neural networks (CNNs) are a special type of deep learning model and are particularly useful for processing image data. A CNN is composed of special processing layers that process image pixels represented as matrices. CNNs progressively extract complex features from an image, such as edges, textures, and shapes, which are used to classify the image, for example as a faulty or good layer in an AM process.

The follow sections introduce how some of the approaches described above have been applied to AM.

2.2. Overview of Literature Survey on ML Applications in AM

In this paper we review research related to ML applications throughout the AM lifecycle. Findings have been gathered from an extensive review of literature published over the last ten years using keyword queries such as "additive manufacturing" and its subcategories [2], coupled with the concepts of "ML." After sifting through hundreds of query results, we analyzed over 50 papers, including journal articles and conference papers. The aims of this review are to 1) identify where ML techniques have been successfully applied in the AM lifecycle, and 2) summarize and organize findings from the existing state-of-the-art research in this domain so that new opportunities can be identified.

Figure 1 categorizes the AM design-to-product transformation cycle based on decision support needs and ML opportunities. Here, we have focused on the following four categories: 1) Design, 2) Process and Performance Optimization, 3) In-Situ Process Monitoring and Control, and 4) Inspection, Testing and Validation. In each of these categories, we focused on a few functions that are currently being analyzed using ML by the research community. For example, in the build phase, research on In-situ Process Monitoring and Control has focused on defect detection, machine-condition monitoring, and real time process control. The following sections delve into the main findings of this survey.

3. AM DESIGN

The AM design process can be decomposed into several stages [5]. Several functions within these stages are currently being implemented using a variety of ML techniques: design recommendations, topology and lattice optimization, tolerancing and manufacturability assessment, and material design and selection. Table 2 presents a summary of the ML techniques used to provide Design Decision Support.

3.1. Design Recommendations

Design-recommendation systems using ML have been developed to assist AM designers. Yao et al. [14] developed a hybrid, machine-learning algorithm to provide design feature recommendations and to assist inexperienced designers in the AM conceptual design phase. Their algorithm combines unsupervised learning (hierarchical clustering) with a trained, supervised classifier (support vector machine (SVM)). Furthermore, they indicate a plan to use ontology-based expert systems to represent more complex AM design knowledge.

Table 2. Overview of ML techniques used to provide Design Decision Support

AM Application	ML Technique	Reference
Design feature recommendation	Hierarchical clustering, SVM	Yao et al., 2017 [14]
Part mass, support material and build-time prediction	NN	Murphy et al., 2019 [15]
Build-time prediction	NN	Munguía et al., 2008 [16] Di Angelo and Di Stefano, 2011 [17]
Cost estimation	Dynamic clustering, LASSO, Elastic net regression	Chan et al., 2018 [18]
Topology optimization	Genetic algorithms, NN	Gaynor et al., 2015 [19]
Geometry compensation to counter thermal shrinkage and deformation	Feed-forward NN with back-propagation	Chowdhury and Anand, 2016 [20]
Shape deviation prediction (tolerancing)	Bayesian Inference	Zhu et al., 2018 [21]
Classification of AM powders	CNN, Random Forest Network (RFN) SVM	Ling et al., 2017 [22] DeCost et. Al, 2017 [23]

Researchers are also employing ML techniques to help novice designers predict design for AM (DfAM) attributes such as expected build time and required support structures. Murphy et al. [15] employed 1) an autoencoder NN that was trained to compress and reconstruct voxelized part designs followed by 2) predictive NNs to predict part mass, support material, and build time. Their existing efforts have achieved limited prediction accuracy; consequently, they plan to implement CNNs in the future to improve accuracy by recognizing and representing local geometries such as lattices.

Munguía et al. [16] used an NN to predict build time for Laser Powder Bed Fusion (L-PBF). NN was used for two reasons. First, it can learn and adapt to different cases. Second, it provides accurate estimates regardless of the different types of machine models. These estimates were calculated using only three parameters: Z-height, part volume, and bounding-box volume. Compared to analytical and parametric time estimators, which have prediction errors rates between 20-25 percent, the NN resulted in error rates between 2-15 percent. Similarly, Di Angelo and Di Stefano [17] also implemented a NN-based build-time estimator. However, they used a parametric approach to capture a more complete set of build-time factors that considered both the dimensional and the geometric features of the object. The authors claim that their custom-designed NN, which used eight build-time driving factors, yielded successful results.

Additionally, researchers are using ML techniques to develop cost-estimation frameworks for AM by leveraging the large amounts of available product and production-related data. For example, Chan et al. [18] predicted the cost for a new print job based on historical data from similar parts. They used the similarities in the 3D geometry and printing processes of parts to extract important features from the part geometry. ML algorithms for dynamic clustering, least absolute shrinkage and selection operator (LASSO), and elastic net regression are applied to feature vectors to predict cost based on historical data.

3.2 Topology Optimization

Topology optimization is a more critical problem in AM than traditional, subtractive processes because of the enormous customizability offered by AM processes. Optimization, in this case, usually means selecting the topology that minimizes the total mass of the structure. Gradient-based optimization algorithms, stochastic algorithms such as genetic algorithms, and NNs have all been explored for topology optimization in AM [19].

Chowdhury and Anand [20] developed a geometry-compensation method to counteract thermal deformation in AM parts caused by temperature gradients during AM fabrication. Their methodology uses a back-propagation NN, trained on surface data from the CAD model, to predict the surface of the fabricated part. The trained network can modify the stereolithography (STL) file whenever the CAD surface data for a new part predicts poor surface quality of the final part. The authors successfully demonstrated a reduced error in manufactured parts' conformity to CAD design by using their NN results.

3.3 Tolerancing and Manufacturability Assessment

Zhu et al. [21] proposed a prescriptive, deviation-modelling method coupled with ML techniques to accurately model shape deviations in AM. Bayesian inference is used to estimate geometric deviation patterns by statistical learning from different shape data, thus supporting more accurate tolerancing for AM parts.

In addition to tolerancing, researchers are using ML to assess the manufacturability of AM-designed parts. Balu et al. [24] proposed a deep-learning-based approach for assessing manufacturability. Deep learning is used to learn different Design for Manufacturing (DFM) rules from labeled voxelized CAD models, without additional shape or process information. AM is mentioned as an applicable technology that could benefit from such a deep-learning-based DFM framework.

3.4 Material Classification and Selection

Machine-learning techniques have been explored to uncover knowledge about the fundamental physical, mechanical, electrical, electronic, chemical, biological, and engineering properties of materials [25]. This knowledge is particularly useful for the classification of AM powders. Ling at el. [22] used deep-learning techniques to classify SEM images of AM powders based on the different powder-size distributions. A CNN was used to transform images and extract features. A random forest network (RFN) classifier was used to sort the transformed images into different size distributions.

DeCost et al. [23] developed a feature, detection-and-description algorithm to create micro-structural-scale, image representations of AM powders. The algorithm applied computer-vision techniques to capture the image of the real object. Scale-invariant feature transformations, together with a vector of locally aggregated descriptors, were then used to encode that image into a digital representation. The authors used this encoding approach, over a NN-based representation, due to its strong rotation and scale invariances. This feature is important because AM powder micrographs do not have any natural orientation. After applying the algorithm, the authors used an SVM to classify the various representations into different material systems, with an accuracy greater than 95 percent.

4. AM PROCESS AND PERFORMANCE OPTIMIZATION

A growing field of study is using data-driven analysis to map the complex relationships among process (P) parameters, final material structure (S), properties (P) and performance (P), also known as PSPP, of the AM part [26]. While finite element modeling (FEM) methods have provided some success in mapping complex PSPP relationships, accurately representing AM processes using high fidelity modeling is difficult. Physics-based models are complex, requiring a deep understanding of material properties and the physical laws governing the AM process. Low fidelity models suffer from lack of information about physical properties, specially due to variabilities from machine to machine and material to material [27].

ML techniques have the potential to successfully discover complex PSPP relationships, overcoming many of the limitations associated with the techniques listed above. The gamut of such techniques generally focuses on understanding either process response or performance response [26], by either using data-driven approach, or combining both physics-based and data-driven approaches. Table 3 presents a summary of literature reviewed in this domain.

Table 3. Overview of ML techniques used for AM Process and Performance Optimization

AM Application	ML Technique	Reference
Build precision (deposition height) prediction	Back propagation (BP) NN, LS-SVM	Lu et al., 2010 [28]
Process parameter optimization (melt pool depth and height)	Genetic algorithm, Self-organizing maps	Fathi and Mozaffari, 2014 [29]
Powder spreading prediction	BP NN	Zhang et al., 2017 [30]
Melt pool width prediction	Gaussian Process Regression	Yang et al., 2018 [31]
Material toughness optimization	Self-Consistent Clustering	Yan et al., 2018 [32]
Porosity prediction	RFN	Kappes et al., 2018 [33]
Wear strength prediction	Genetic programming, NN	Garg and Tai, 2014 [34]
Part density prediction	Kriging, Polynomial regression, NN	Yang et al., 2018 [35]

4.1 Data-Driven Approaches to Characterize Process Response

Lu et al. [28] used a variety of ML techniques to monitor responses in a Directed Energy Deposition (DED) process. Specifically, they map the complex, non-linear relationship between DED process parameters - laser power, scanning speed, and feed rate – and one performance response – building precision as measured by deposition height. The authors adapted a back propagation NN (BP NN) with an adaptive, learning rate, and a momentum coefficient algorithm. The modifications accelerated the training time and improved the results.

Similarly, Fathi and Mozaffari [29] developed a data-driven framework for optimizing process parameters in L-PBF. The authors used a bio-inspired, optimization algorithm, called Mutable Smart Bee algorithm, and a fuzzy inference system to relate process parameters to melt-pool depth and layer height. Derived relationships were combined with a non-dominated, sorting, genetic algorithm to optimize process parameters. Additionally, they proposed using an unsupervised, machine-learning approach - known as self-organizing maps - to further post-optimize the process.

4.2 Physics-Based-Simulation Approaches to Characterize Process Response

In lieu of empirical data, another ML approach is creating surrogate models from physics-based simulation data. For example, Zhang et al. [30] used ML to predict powder-spread parameters as a function of spreading speed and surface roughness of the powder bed. They developed a synergistic, multi-step framework combining 1) a Discrete Element Method (DEM) to simulate a powder spreading process with 2) a BP NN to regress between the highly non-linear results obtained from DEM. The result is a powder-spreading process map that can be used by AM operators to manufacture parts with desired surface roughness.

Yang et al. [31] used the results from an L-PBF, single-track, heat-transfer simulation to predict melt-pool width for different combinations of processing conditions. Their prediction approach combines a Dynamic Variance-Covariance Matrix, the kriging method, Gaussian Process Regression, and genetic algorithms to optimize process parameters. Their approach led to a maximum, relative, error magnitude (MREM) less than 0.03 percent and an average, relative, error magnitude (AREM) less than 0.005 percent for the AM case study.

4.3 Combined Approaches to Characterize Performance Response

The process response, together with the raw-material properties and the final-design structure, are critical factors in predicting the performance response of AM-fabricated parts. Yan et al. [32] proposed combining physics-based models, process models, material models, and data-mining techniques to better understand those factors and their relationship to performance. In this case, the performance response was the mechanical toughness of the built part. The authors combined self-consistent clustering analysis with a reduced-order modeling technique to predict the toughness. They did so by mapping the microstructural descriptors to toughness. However, they discovered that ML techniques like Kriging and NN are better suited for evaluating larger databases. They propose to use this discovery in the future for comprehensive modeling of PSP relationships.

Kappes et al. [33] focused on predicting three performance responses for AM-built parts: fraction porosity, median pore-diameter and median pore-spacing. Their goal was to predict responses by combining information/models about the process (L-PBF), the structure (sample position and orientation), and the material (Inconel 718). The authors used an RFN to make those predictions for two reasons. First, RFN is capable of both classification and regression. Second, RFN is insensitive to irrelevant features. These capabilities were important because, in AM, not all processing conditions are consistently important across different processes and materials.

In another approach, Garg and Tai [34] combined genetic programming and NN using the least squares method. This combined model was used to predict the wear strength of aerospace parts produced using Fused Deposition Molding (FDM). The final structure and raw material for each part were known in advance. The process variables were layer thickness, orientation, raster angle, raster width, and air gap. The values of these variables provided the inputs into both the GP and the NN. The authors showed that their combined approach gave better statistical predictions than using a single ML algorithm.

Similarly, Yang et al. proposed a super-metamodeling framework (SMOF) to predict relative density of AM parts as a function of process parameters such as scanning speed, scanning spacing and laser pulse frequency in an L-PBF process [35]. The SMOF was built by aggregating Kriging, polynomial regression, and NN into a weighted composite to improve overall prediction accuracy while being insensitive to dataset variation. The results positively indicated the superiority of SMOF over individual metamodels, with a final AREM of only 5.47 percent.

5. IN-SITU PROCESS MONITORING AND CONTROL

One of the most focused areas of machine-learning applications in AM is in-situ process monitoring and control. In-situ monitoring technologies are rapidly growing; they now include highs-speed optical cameras, thermocouples, pyrometers, and photo-detectors, among other sensors [6]. However, achieving real-time control for AM is still at a nascent stage – despite the streams of "big," multi-modal, sensing data capable of being collected. This is due to a few reasons. First, it is still unclear which sensor data is most meaningful for implementing control strategies. Second, the "data-fusion" techniques needed to understand all that sensor data do not exist. Finally, the ML techniques needed to analyze that fused data do exist; but, they have only recently been applied in AM.

Nevertheless, by using in-situ data to characterize the current "state" of a part, combined with a priori knowledge of part and process, we can predict the "state" of the final part [6]. Using ML to improve real-time control of AM fabrication processes has a significant potential benefit – post-process-inspection tasks might be reduced – possibly significantly. By moving some of that post-process inspection upstream, as part of the fabrication process, potential defects in the final parts could be detected earlier. This saves inspection time; but, it also saves materials and processing [36].

Current efforts towards using ML to realize the vision of real-time control for AM processes are primarily focused on monitoring the state of either the built part, or the AM machine itself. Some elementary work on process control has also been done. Table 4 provides a summary of literature reviewed in this domain.

Table 4. Overview of ML techniques used for in-situ process monitoring and control

AM Application	ML Technique	Reference
Part Defect Detection and Prediction		
Porosity detection	SVM, k-Nearest Neighbors (k-NN), feed forward NN	Imani et al., 2018 [37]
Quality of fusion and defect detection	Bayesian classifier	Aminzadeh and Kurfess, 2018 [38]
Anomaly detection and classification	Bag-of-keypoints (words), K-means unsupervised clustering, CNN	Scime and Beuth, 2018 [39,40]
Melt pool features and spatter detection	SVM, CNN	Zhang et al., 2018 [41]
Defect detection and classification with acoustic emissions	Spectral CNN	Shevchik et al., 2018 [42]
	Probabilistic graph-based deep belief networks	Ye et al., 2018 [43]
Fault detection from multi-sensor data	Support Vector Data Description (SVDD)	Grasso et al., 2018 [44]
Quality monitoring using heterogeneous sensors in FDM	Bayesian Dirichlet process, Evidence Theory, NN, Naïve Bayes clustering, SVM, Quadratic discriminant analysis	Rao et al., 2015 [45]
Defect detection for L-PBF using in-situ images coupled with ex-situ CT scans	SVM, NN SVM ensemble classifier	Petrich et al., 2017 [46] Gobert et al., 2018 [47]
Machine-Condition Monitoring		
Machine-condition monitoring	k-NN, Bayes Classifier, NN, SVM	Uhlmann et al., 2017 [48]
FDM machine-condition monitoring using acoustic emissions	SVM, K-means clustering, Hidden semi-Markov model	Wu et al., 2015 [49][50][51]
Process Control		
PID process control for FDM	SVM	Liu et al., 2017 [52]
Image-guided process control for L-PBF	Markov Decision Process	Yao et al., 2018 [53]

5.1. Part Defect Detection and Prediction

AM parts can have several different types of defects including porosity, poor surface finish, layer delamination, cracking, and geometric distortion, to name a few [54]. Detecting defects is important to identifying failed builds and predicting the final properties of the part.

5.1.1 Defect Detection with Visual Data

Imani et al. [37,55] presented a qualify-as-you-build model where ML techniques use real-time sensor data to identify process conditions that are likely to cause porosity. The authors analyzed the relationship between laser power, hatch spacing, and velocity, on the size, frequency and location of pores in parts produced through L-PBF. Statistical features are extracted from layer-by-layer in-situ images. These features are subsequently classified by ML techniques like SVM, k-NN, and feed forward NN to identify process conditions most likely to produce pores.

Aminzadeh and Kurfess [38] developed an online monitoring system, using computer vision and Bayesian inference, to inspect both the porosity and the quality of parts in metal L-PBF. They created a labeled dataset of defective and non-defective features from in-situ camera images of each layer. They extracted frequency-domain features from those images and used a Bayesian classifier to identify of defective vs non-defective parts.

Instead of using layer wise images of the powder after laser interaction, Scime and Beuth [39] used computer vision and ML techniques to detect and classify anomalies and flaws in the powder prior to fusion. They investigated six different types of powder bed anomalies captured in labeled images from an L-BPF machine. The bag-of-keypoints ML technique used to detect and classify anomalies was able to detect the presence of an anomaly in 89 percent of cases, with 95 percent accuracy in correctly identifying the type of anomaly. Separately, the authors showed that accuracy can be further improved by implementing a multi-scale CNN for autonomous anomaly detection and classification [40].

Zhang et al. [41] used Principal Component Analysis (PCA) with SVM to enable using CNN to recognize features in the laser melting process. Features include melt pool, spatter, plume, and anomalies. The accuracy is reported to be 92.7 percent.

5.1.2 Defect Detection with Acoustic Data

Acoustic emissions (AE) have also been used for defect detection. AE sensors are non-intrusive to the build process and provide high throughput for real-time monitoring. Ye et al. [43] developed a method of analyzing acoustic signals with deep belief networks (DBN) to detect defects in the L-PBF process. Temperature changes from melting to solidification create variations in the acoustic signals. The authors trained a DBN to recognize defects based on the categorizations of balling, keyholing, and cracking, using the sparking sound spectrum in the time domain and the signal power spectral density in the frequency domain.

Shevchik et al. [42] investigated the use of AE combined with CNN to detect various defects due to lack of fusion. The authors used a fiber Bragg grating acoustic sensor to detect the airborne AE signals, generated from the melting, sparking, spattering, and solidification processes. The signals collected in the time domain are transformed to the frequency domain using the wavelet packet transform, an extension of the traditional wavelet transform. The Spectral CNN, an extension of CNN with improved efficiency in classification and regression, is used to recognize features in the frequency domain that correspond to defects in the L-PBF process. The confidence level in SCNN is between 83 to 89 percent, according to the authors.

5.1.3 Defect Detection with Multi-Sensor Data

As aforementioned, data gathered from in-situ monitoring of AM processes is highly varied. Registering and fusing together data from multiple sensors provides a rich context for fault detection. Therefore, a growing area of research involves multi-sensor data fusion for process monitoring and control.

Grasso et al. [44] explored data fusion methodologies to combine in-situ data from multiple sensors embedded in Electron Beam PBF systems. The Support Vector Data Description (SVDD) ML technique is used to classify in-control vs. out-of-control process signals. The SVDD automatically detects faults and process errors that can be related to the stability of embedded signals from multiple sensor data streams. The limitation of their approach is that it applies only to serial production of the same product.

Rao et al. [45] fused data from a heterogeneous sensor suite as part of an online-monitoring system for FDM. The suite comprises of thermocouples, accelerometers, an infrared temperature sensor, and a real-time, miniature, video borescope. Process failures (such as nozzle clog) are detected from the fused sensor data using the non-parametric Bayesian Dirichlet process mixture model and evidence theory, achieving a prediction accuracy of up to 85 percent. In comparison, existing approaches, such as probabilistic NN, Naïve Bayes clustering, and SVM had poorer performance.

Petrich et al. [46] and Gobert et al. [47] used multi-sensor data fusion to detect discontinuity defects – such as pores, overheating areas, and unmolten powders – in L-PBF. They merged together homogenous sensor data (eight sets of layer-wise images of the powder bed under varying lighting conditions, pre- and post-sintering) with heterogenous sensor data (post build CT scans). Ground-truth labels (anomalous or normal) extracted from the CT scans were used to train NN and SVM [46], as well as SVM ensemble classifiers [47] to detect defects directly from images. Ensemble classifiers can analyze multiple images under different lighting conditions with a high classification accuracy (85 percent) as compared to classification using images from only a single lighting condition (65 percent accuracy).

5.2. Machine-Condition Monitoring

Another approach to in-situ monitoring is observing the machine logs or build condition instead of monitoring the part. Clustering techniques can classify features extracted from machine logs and identify normal or problematic build states [48]. In a series of papers, Wu et al. [49–51] developed an approach for FDM machine condition monitoring using AE data to identify normal and abnormal machine states. They extracted time- and frequency-domain features from the data and used a variety of ML algorithms (SVM with radial bias function kernel [49], K-means clustering [50], and hidden semi-Markov model [51]) to classify normal vs. abnormal machine-condition states. Their monitoring method can be used as a diagnostic tool to identify failure states such as material runout or filament breakage.

5.3. Process Control

Liu et al. [52] developed an online closed-loop controller for FDM. Their control architecture consists of 1) real-time image acquisition, 2) a tool for image analysis, and 3) a Proportional-Integral-Derivative (PID) controller for closed-loop control. They identified two types of defects, overfill and underfill, at different severities. After extracting textural features from the image data collected from a microscope, they used SVM to differentiate those features into two groups: normal and defective. Then they used another SVM to identify the severity of defects. The PID controller used the results of that analysis to modify the feed rate to mitigate each type of defect.

Yao et al. [53] developed a smart, closed-loop optimal control system for L-PBF. They used multifractal analysis to estimate the defect condition of each layer, and then predicted the future evolution of defects in following layers. Finally, they modeled the stochastic dynamics of layer-to-layer defect conditions as a Markov decision process for deriving an optimal control policy.

6. INSPECTION, TESTING AND VALIDATION

ML techniques are used for final AM part inspection and validation. The focus is primarily on surface metrology, and defect detection and classification using ex-situ measurements, such as X-CT data. Table 5 presents an overview of the literature reviewed in this domain (excluding X-CT).

Table 5. Overview of ML techniques used for post-process inspection and validation

AM Application	ML Technique	Reference
Classification of dimensional variation from laser scanned 3D point cloud data	Sparse representation, k-NN, NN, Naïve Bayes SVM, Decision tree	Tootani et al., 2017 [56]
Defect detection (porosity)	Augmented layer-wise spatial log Gaussian Cox process (ALS-LGCP)	Liu et al., 2018 [57]

Tootooni et al. [56] developed a new method to classify dimensional variations in parts made with FDM based on spectral graph theory. They used Laplacian Eigenvalues as extracted features from laser-scanned 3D point cloud data, followed by supervised ML techniques to classify dimensional variation, including sparse representation, k-NN, NN, naïve Bayes, SVM, and decision tree. The sparse representation technique provided the highest classification accuracy (F-score > 95 percent). Their approach requires a priori knowledge of the part for training, thus limiting applications to other parts.

Liu at al. [57] proposed an augmented layer-wise spatiotemporal log Gaussian Cox process (ALS-LGCP) model to quantify the spatial distribution of pores within each layer of an AM part and track sequential evolution across layers. They applied the ALS-LGCP to binder-jetted parts, and used Bayesian predictive analytics to predict porosity prone areas in successive layers, achieving statistical fidelity approaching 85 percent.

Senin and Leach [58] developed a smart information-rich surface metrology technique using multi-sensor data fusion and ML. They identified AM as an example where advanced measurement techniques are needed due to complex geometries and lack of uniform material properties.

7. CONCLUSION

This paper presents a detailed review of ML applications throughout the AM design-to-product transformation cycle. We have categorized the literature based on the applications as they pertain to the different phases in the AM product lifecycle. With most of the reviewed research published in 2017 or later, the ML methods identified throughout this paper are the beginnings of what is sure to be a growing effort of ML applications for AM. We observed why ML methods are well suited to solve problems in the AM domain and which methods are most commonly being used. To date, ML for AM research has been opportunistic, where researchers have identified areas rich with data, such as in in-situ process monitoring and control. The high dimensionality and complexity of AM data makes it well-suited for popular ML algorithms. For instance, supervised learning techniques, such as NN and SVM, are most popular due to the availability of labeled datasets. This paper lays a foundation for a more methodical approach to ML for AM moving forward.

While ML techniques are rapidly being adopted into AM applications, there are many opportunities for improved future applications. For instance, unsupervised learning techniques are not as widely adopted. However, with the increasing amounts of unlabeled AM datasets, these techniques are likely to become more popular and thus should be further investigated. Alternatively, as ML algorithms require training data, increased interest in ML for AM will lead to new approaches for supervised ML.

ML models are very poor at diagnosing conditions that have not been previously encountered. This limitation puts an emphasis on collecting data for training by creating scenarios that will address a wide range of operating conditions and dimensionality space. A major challenge in the maturation of ML for AM is the lack of availability of accurate, accessible, and extensive databases for AM processes, products, and materials [26]. While each build can generate terabytes of data, there is a lack of standard practices for handing datasets characterized by high volume and velocity in real time.

Absence of a common data structure, and standard methods for data integration and fusion, prevents rich, multifaceted, data-driven analysis. Furthermore, generating exemplar data via experimentation is difficult and expensive. Even if data is available, poor quality of data makes it unsuitable for ML algorithms. Low resolution of in-situ optical data, limited fields of view, and high temporal load result in poor quality data sets [6]. This hinders feature selection for ML algorithms. The development of feature libraries for AM feature characterization would help address some of the current challenges that make it difficult to select a suitable ML algorithm compatible with the available data.

8. FUTURE WORK

As reviewed in this paper, there already are many AM applications that are benefitting from ML techniques. However, even more applications areas remain unexplored. For instance, in the domain of AM design, deep learning techniques could be used to train on voxelized CAD models to make better predictions of DfAM attributes such as part mass, support structures, and build time. The in-situ, monitoring-and-control domain could benefit from the advantages of deep learning techniques for use in fault detection and build failures. CNN, for example, can detect and classify both macroscopic and microscopic faults using layer-wise, optical-sensor data. Moving forward, potential opportunities like these will continue to be identified.

Identifying new opportunities in the AM lifecycle is simply a precursor to the data challenges that will arise when seeking to take advantage of these opportunities. For instance, further research is needed for in-situ data sensor fusion. The fusion of thermal, acoustic, optical and other build environmental data can create a more holistic, reliable and accurate information source for real-time defect detection and correction with feedback control. Other opportunities include using ML to build models correlating in-situ and ex-situ data, such as IR videos with NDE X-CT data. Such an approach could enable the “qualify-as-you-build” goal for AM and reduce dependence on post build NDE qualification. As new AM data sets continue to emerge so will new opportunities to leverage ML techniques to improve the fabrication of AM parts.

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REFERENCES

[1] Berman, B., 2012, “3-D Printing: The New Industrial Revolution,” Bus. Horiz., **55**(2), pp. 155–162.

[2] ASTM International, 2015, “Standard Terminology for Additive Manufacturing – General Principles – Terminology,” ASTM ISO/ASTM52900-15.

[3] Gao, W., Zhang, Y., Ramanujan, D., Ramani, K., Chen, Y., Williams, C. B., Wang, C. C. L., Shin, Y. C., Zhang, S., and Zavattieri, P. D., 2015, “The Status, Challenges, and Future of Additive Manufacturing in Engineering,” Comput.-Aided Des., **69**, pp. 65–89.

[4] *Wohlers Associates, Inc., 2016, Wohlers Report 2016: Additive Manufacturing and 3D Printing State of the Industry, Wohlers Associates, Fort Collins, CO.*

[5] Kim, D. B., Witherell, P., Lipman, R., and Feng, S. C., 2015, “Streamlining the Additive Manufacturing Digital Spectrum: A Systems Approach,” Addit. Manuf., **5**, pp. 20–30.

[6] Everton, S. K., Hirsch, M., Stravroulakis, P., Leach, R. K., and Clare, A. T., 2016, “Review of In-Situ Process Monitoring and in-Situ Metrology for Metal Additive Manufacturing,” Mater. Des., **95**, pp. 431–445.

[7] Mani, M., Lane, B., Donmez, A., Feng, S., Moylan, S., and Fesperman, R., 2015, "Measurement Science Needs for Real-Time Control of Additive Manufacturing Powder Bed Fusion Processes", NIST IR 8036, National Institute of Standards and Technology, Gaithersburg, MD, USA.

[8] Witherell, P., 2018, “Emerging Datasets and Analytics Opportunities in Metals Additive Manufacturing,” *Direct Digital Manufacturing Conference*, Berlin, Germany.
[9] Dehoff, R., 2015, “In-Situ Process Monitoring and Big Data Analysis for Additive Manufacturing of Ti-6All-4V,” *Titanium USA Conference 2015*, ITA, Orlando, FL, USA
[10] Wuest, T., Weimer, D., Irgens, C., and Thoben, K.-D., 2016, “Machine Learning in Manufacturing: Advantages, Challenges, and Applications,” Prod. Manuf. Res., **4**(1), pp. 23–45.
[11] Wang, J., Ma, Y., Zhang, L., Gao, R. X., and Wu, D., 2018, “Deep Learning for Smart Manufacturing: Methods and Applications,” J. Manuf. Syst., **48**, pp. 144–156.
[12] Yang, J., Chen, Y., Huang, W., and Li, Y., 2017, “Survey on Artificial Intelligence for Additive Manufacturing,” *2017 23rd International Conference on Automation and Computing (ICAC)*, IEEE, Huddersfield, United Kingdom, pp. 1–6.
[13] Hastie, T., Tibshirani, R., and Friedman, J., 2009, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer.
[14] Yao, X., Moon, S. K., and Bi, G., 2017, “A Hybrid Machine Learning Approach for Additive Manufacturing Design Feature Recommendation,” Rapid Prototyp. J., **23**(6), pp. 983–997.
[15] Murphy, C., Meisel, N., Simpson, T. W., and McComb, C., 2018, “Predicting Part Mass, Required Support Material, and Build Time via Autoencoded Voxel Patterns” [Online]. Available: engrxiv.org/8kne7
[16] Munguía, J., Ciurana, J., and Riba, C ., 2008, "Neural-Network-Based Model for Build-Time Estimation in Selective Laser Sintering", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, **223**(8), 995–1003.
[17] Di Angelo, L., and Di Stefano, P., 2011, “A Neural Network-Based Build Time Estimator for Layer Manufactured Objects,” Int. J. Adv. Manuf. Technol., **57**(1–4), pp. 215–224.
[18] Chan, S. L., Lu, Y., and Wang, Y., 2018, “Data-Driven Cost Estimation for Additive Manufacturing in Cybermanufacturing,” J. Manuf. Syst., **46**, pp. 115–126.
[19] Gaynor, A. T., 2015, “Topology Optimization Algorithms for Additive Manufacturing,” Ph.D. thesis, Department of Civil Engineering, Johns Hopkins University.
[20] Chowdhury, S., and Anand, S., 2016, “Artificial Neural Network Based Geometric Compensation for Thermal Deformation in Additive Manufacturing Processes,” *ASME 2016 International Manufacturing Science and Engineering Conference MSEC2016*, ASME, Blacksburg, Virginia, USA.
[21] Zhu, Z., Anwer, N., Huang, Q., and Mathieu, L., 2018, “Machine Learning in Tolerancing for Additive Manufacturing,” CIRP Ann.
[22] Ling, J., Hutchinson, M., Antono, E., DeCost, B., Holm, E. A., and Meredig, B., 2017, “Building Data-Driven Models with Microstructural Images: Generalization and Interpretability,” [Online]. Available: ArXiv171100404 Cond-Mat.
[23] DeCost, B. L., Jain, H., Rollett, A. D., and Holm, E. A., 2017, “Computer Vision and Machine Learning for Autonomous Characterization of AM Powder Feedstocks,” JOM, **69**(3), pp. 456–465.
[24] Balu, A., Lore, K., Gavin, Y., Krishnamurthy, A., and Sarkar, S., 2016, “A Deep 3D Convolutional Neural Network Based Design for Manufacturability Framework,” [Online]. Available: ArXiv:1612.02141v1 [cs.CV].
[25] Ramakrishna, S., Zhang, T.-Y., Lu, W.-C., Qian, Q., Low, J. S. C., Yune, J. H. R., Tan, D. Z. L., Bressan, S., Sanvito, S., and Kalidindi, S. R., 2018, “Materials Informatics,” J. Intell. Manuf.
[26] Smith, J., Xiong, W., Yan, W., Lin, S., Cheng, P., Kafka, O. L., Wagner, G. J., Cao, J., and Liu, W. K., 2016, “Linking Process, Structure, Property, and Performance for Metal-Based Additive Manufacturing: Computational Approaches with Experimental Support,” Comput. Mech., **57**(4), pp. 583–610.
[27] Baturynska, I., Semeniuta, O., and Martinsen, K., 2018, “Optimization of Process Parameters for Powder Bed Fusion Additive Manufacturing by Combination of Machine Learning and Finite Element Method: A Conceptual Framework,” Procedia CIRP, **67**, pp. 227–232.
[28] Lu, Z. L., Li, D. C., Lu, B. H., Zhang, A. F., Zhu, G. X., and Pi, G., 2010, “The Prediction of the Building Precision in the Laser Engineered Net Shaping Process Using Advanced Networks,” Opt. Lasers Eng., **48**(5), pp. 519–525.
[29] Fathi, A., and Mozaffari, A., 2014, “Vector Optimization of Laser Solid Freeform Fabrication System Using a Hierarchical Mutable Smart Bee-Fuzzy Inference System and Hybrid NSGA-II/Self-Organizing Map,” J. Intell. Manuf., **25**(4), pp. 775–795.
[30] Zhang, W., Mehta, A., Desai, P. S., and III, C. F. H., “Machine Learning Enabled Powder Spreading Process Map for Metal Additive Manufacturing (AM),” p. 15.
[31] Yang, Z., Eddy, D., Krishnamurty, S., Grosse, I., Denno, P., Witherell, P. W., and Lopez, F., 2018, “Dynamic Metamodeling for Predictive Analytics in Advanced Manufacturing,” Smart Sustain. Manuf. Syst., **2**(1).
[32] Yan, W., Lin, S., Kafka, O. L., Lian, Y., Yu, C., Liu, Z., Yan, J., Wolff, S., Wu, H., Ndip-Agbor, E., Mozaffar, M., Ehmann, K., Cao, J., Wagner, G. J., and Liu, W. K., 2018, “Data-Driven Multi-Scale Multi-Physics Models to Derive Process–Structure–Property Relationships for Additive Manufacturing,” Comput. Mech., **61**(5), pp. 521–541.
[33] Kappes, B., Moorthy, S., Drake, D., Geerlings, H., and Stebner, A., 2018, “Machine Learning to Optimize Additive Manufacturing Parameters for Laser Powder Bed Fusion of Inconel 718,” *9th International Symposium on Superalloy 718 & Derivatives: Energy,*

Aerospace, and Industrial Applications, Springer International Publishing, pp. 595–610.
[34] Garg, A., and Tai, K., 2014, "An Ensemble Approach of Machine Learning in Evaluation of Mechanical Property of the Rapid Prototyping Fabricated Prototype," Appl. Mech. Mater., **575**, pp. 493–496.
[35] Yang, Z., Eddy, D., Krishnamurty, S., Grosse, I., and Lu, Y., 2018, "A Super-Metamodeling Framework to Optimize System Predictability," *ASME 2018 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, ASME, Quebec City, Canada.
[36] Sarah Anderson Goehrke, 2017, "Metal 3D Printing with Machine Learning: GE Tells Us About Smarter Additive Manufacturing," 3DPrintcom Voice 3D Print. Addit. Manuf.
[37] Imani, F., Montazeri, M., Gaikwad, A., Rao, P., Yang, H., and Reutzel, E., 2018, "Layerwise In-Process Quality Monitoring in Laser Powder Bed Fusion," *ASME 2018 13th International Manufacturing Science and Engineering Conference*, ASME, College Station, USA.
[38] Aminzadeh, M., and Kurfess, T. R., 2018, "Online Quality Inspection Using Bayesian Classification in Powder-Bed Additive Manufacturing from High-Resolution Visual Camera Images," J. Intell. Manuf.
[39] Scime, L., and Beuth, J., 2018, "Anomaly Detection and Classification in a Laser Powder Bed Additive Manufacturing Process Using a Trained Computer Vision Algorithm," Addit. Manuf., **19**, pp. 114–126.
[40] Scime, L., and Beuth, J., 2018, "A Multi-Scale Convolutional Neural Network for Autonomous Anomaly Detection and Classification in a Laser Powder Bed Fusion Additive Manufacturing Process," Addit. Manuf., **24**, pp. 273–286.
[41] Zhang, Y., Hong, G. S., Ye, D., Zhu, K., and Fuh, J. Y. H., 2018, "Extraction and Evaluation of Melt Pool, Plume and Spatter Information for Powder-Bed Fusion AM Process Monitoring," Mater. Des., **156**, pp. 458–469.
[42] Shevchik, S. A., Kenel, C., Leinenbach, C., and Wasmer, K., 2018, "Acoustic Emission for in Situ Quality Monitoring in Additive Manufacturing Using Spectral Convolutional Neural Networks," Addit. Manuf., **21**, pp. 598–604.
[43] Ye, D., Hong, G. S., Zhang, Y., Zhu, K., and Fuh, J. Y. H., 2018, "Defect Detection in Selective Laser Melting Technology by Acoustic Signals with Deep Belief Networks," Int. J. Adv. Manuf. Technol., **96**(5–8), pp. 2791–2801.
[44] Grasso, M., Gallina, F., and Colosimo, B. M., 2018, "Data Fusion Methods for Statistical Process Monitoring and Quality Characterization in Metal Additive Manufacturing," Procedia CIRP.
[45] Rao, P. K., Liu, J. (Peter), Roberson, D., Kong, Z. (James), and Williams, C., 2015, "Online Real-Time Quality Monitoring in Additive Manufacturing Processes Using Heterogeneous Sensors," J. Manuf. Sci. Eng., **137**(6).
[46] Petrich, J., Gobert, C., Phoha, S., Nassar, A. R., and Reutzel, E. W., 2017, "Machine Learning for Defect Detection for PBFAM Using High Resolution Layerwise Imaging Coupled with Post-Build CT Scans," *28th Annual International Solid Freeform Fabrication Symposium,* Austin, TX, USA.
[47] Gobert, C., Reutzel, E. W., Petrich, J., Nassar, A. R., and Phoha, S., 2018, "Application of Supervised Machine Learning for Defect Detection during Metallic Powder Bed Fusion Additive Manufacturing Using High Resolution Imaging.," Addit. Manuf., **21**, pp. 517–528.
[48] Uhlmann, E., Pontes, R. P., Laghmouchi, A., and Bergmann, A., 2017, "Intelligent Pattern Recognition of a SLM Machine Process and Sensor Data," Procedia CIRP, **62**, pp. 464–469.
[49] Wu, H., Wang, Y., and Yu, Z., 2015, "In Situ Monitoring of FDM Machine Condition via Acoustic Emission," Int. J. Adv. Manuf. Technol.
[50] Wu, H., Yu, Z., and Wang, Y., 2016, "A New Approach for Online Monitoring of Additive Manufacturing Based on Acoustic Emission," *Volume 3: Joint MSEC-NAMRC Symposia*, ASME, Blacksburg, Virginia, USA.
[51] Wu, H., Yu, Z., and Wang, Y., 2017, "Real-Time FDM Machine Condition Monitoring and Diagnosis Based on Acoustic Emission and Hidden Semi-Markov Model," Int. J. Adv. Manuf. Technol., **90**(5–8), pp. 2027–2036.
[52] Liu, C., Roberson, D., and Kong, Z., 2017, "Textural Analysis-Based Online Closed-Loop Quality Control for Additive Manufacturing Processes," *2017 Industrial and Systems Engineering Conference*, Blacksburg, VA, USA.
[53] Yao, B., Imani, F., and Yang, H., 2018, "Markov Decision Process for Image-Guided Additive Manufacturing," IEEE Robot. Autom. Lett., **3**(4), pp. 2792–2798.
[54] Sames, W. J., List, F. A., Pannala, S., Dehoff, R. R., and Babu, S. S., 2016, "The Metallurgy and Processing Science of Metal Additive Manufacturing," Int. Mater. Rev., **61**(5), pp. 315–360.
[55] Imani, F., Yao, B., Chen, R., Rao, P., and Yang, H., 2018, "Fractal Pattern Recognition of Image Profiles for Manufacturing Process Monitoring and Control," P*roceedings of the ASME 2018 13th International Manufacturing Science and Engineering Conference*, ASME, College Station, TX, USA.
[56] Samie Tootooni, M., Dsouza, A., Donovan, R., Rao, P. K., Kong, Z. (James), and Borgesen, P., 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).
[57] Liu, J. (Peter), Liu, C., Bai, Y., Rao, P., Williams, C., and Kong, Z. (James), 2018, "Layer-Wise Spatial Modeling of Porosity in Additive Manufacturing," IISE Trans.
[58] Senin, N., and Leach, R., 2018, "Information-Rich Surface Metrology," Procedia CIRP.

