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MACHINE LEARNING AND DATA-DRIVEN ADDITIVE MANUFACTURING

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Abstract

Additive manufacturing has emerged as a disruptive digital manufacturing technology. However, its wild adoption in the industry is still impacted by high entry challenges of design for additive manufacturing, limited materials library, processing defects, and inconsistent product quality. Machine learning has recently gained increasing attention in additive manufacturing due to its exceptional data analysis performance, such as classification, regression, and clustering. This paper provides a review of the state-of-the-art machine learning applications in different domains of additive manufacturing.

Introduction

The additive manufacturing sector is rapidly adopting machine learning and data-driven approaches to further extend additive manufacturing capabilities. Additive manufacturing is a highly complicated technology that involves the intricate design, material, and process interactions over the course of a complex multistage process. It requires simultaneous consideration of physics, chemistry, materials science, computer science, electrical engineering, and mechanical engineering to fabricate a qualified part.

Additive manufacturing is a data-rich manufacturing technology. However, extracting practical information using traditional data analytics methods from the generated data has been an enormous challenge for this industry. Advanced machine learning techniques offer an outstanding capability to process additive manufacturing technology's high dimensional and complex data. Advanced machine learning techniques provide the opportunity to accelerate the additive manufacturing development timeline by decoding and identifying structure/process/property/performance relationships, discovering implicit (formerly unknown) knowledge, and transforming the existing additive manufacturing data into actionable and insightful information. In this paper, the state-of-the-art applications of machine learning techniques throughout the additive manufacturing lifecycle, from additive manufacturing material design to process and performance optimization, in-situ process monitoring and controlling, and inspection will be explored.

Machine Learning Techniques for Additive Manufacturing

Machine learning is an application of artificial intelligence that provides the systems with the ability to learn and improve from experience and data automatically. Machine learning models can be used for different purposes, such as classification, regression, forecasting, and optimization.

Machine learning algorithms are often categorized as supervised or unsupervised [1]. Supervised machine learning algorithms can uncover insights, patterns, and relationships from past experiences and apply the learned knowledge to predict future events. Starting from the analysis of a known training dataset, the learning algorithm produces an inferred function to make predictions about the output values. The system can provide targets for any new input after sufficient training. The learning algorithm can also compare its output with the correct, intended results to modify the model accordingly.

In contrast, unsupervised machine learning algorithms are used when the information used to train is neither classified nor labelled. Unsupervised learning studies how systems can infer a function to describe a hidden structure from unlabelled data. The system does not recognize the right output; however, it explores the data and can draw inferences from datasets to describe hidden structures from unlabelled data.

The supervised and unsupervised categories provide a high-level classification in which different machine learning algorithms can be further categorized. The decision between using a supervised or unsupervised machine learning approach will depend on the nature of each specific application.

Data-Driven Additive Manufacturing

The major distinctions between data-driven and conventional manufacturing are the generation, collection, and utilization of data, which have been considered as the key enabler to realize smart manufacturing [2]. In conventional manufacturing, by using theoretical, experimental, and numerical methods, human intelligence along with the experiences gained from the physical observations of the manufacturing system, derive physical models to better understand the mechanisms. However, due to the significant simplifications and assumptions for deriving physical models, also potentially unstable, biased, and partial experiences, these model-based methods can have limited effective range and accuracy [3]. In data-driven manufacturing, however, data generated through different steps of the manufacturing process is fully exploited to refine the manufacturing process and increase the flexibility and autonomy of the system. By taking full advantage of manufacturing data, the system is shifted from primary processes to smart processes, improving the production efficiency and the performance of a product [4].

A framework of data-driven additive manufacturing is presented in Figure 1. This framework is comprised of four modules: manufacturing, data, knowledge, and decision-making. The manufacturing module contains different stages of the design-to-product transformation cycle, in which a printed product is designed, manufactured, characterized, and inspected. In this module, various data is collected from human operators, production equipment, information systems, and industrial networks. In the data module, the manufacturing data is collected, stored, and visualized for the preparation of data processing. The data module provides the driving force for smart additive manufacturing throughout the different manufacturing data lifecycle stages. In the knowledge module, raw data is transformed into actionable insights and knowledge using data processing technologies to direct the actions (e.g., product design, production planning, and manufacturing execution) in the manufacturing module. In the decision-making module, through the utilization of intelligence, knowledge eventually informs decisions to make accurate and smart design, optimization, prediction, control to facilitate smart manufacturing.

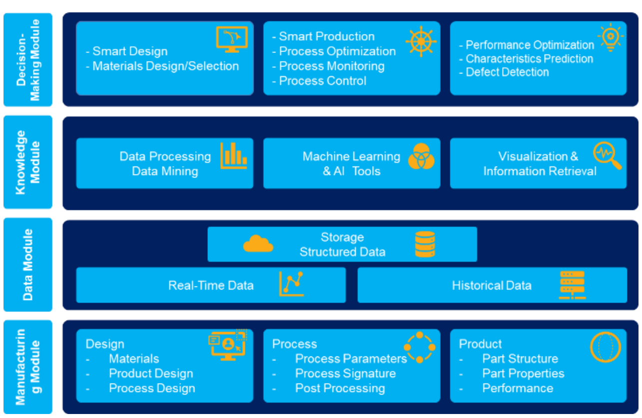

Figure 1. Data-driven additive manufacturing framework

Applications of Data-Driven Additive Manufacturing

Additive Manufacturing Design

The additive manufacturing design stage is comprised of several functions, including product design, tolerancing and manufacturability, and materials design and selection.

Product Design: Product design is the first and very critical step in additive manufacturing processing. However, there are always deviations between the design models, and the printed parts and compensation is usually performed to obtain a final product with high accuracy. Different approaches for the part geometric design accuracy have been proposed, combining experiments, finite-element method simulation, and machine learning algorithms, which help counterbalance thermal shrinkage and deformation in the manufactured part. The machine learning model is trained to learn the effect of the processing parameters and make the required geometric corrections on the product design, which results in a dimensional-accurate finished product [5,6]. Machine learning techniques have also been used to predict the build time [7] and develop cost-estimation frameworks for additive manufacturing processes [8].

Design Tolerancing & Manufacturability: Tolerancing the product designs can be assessed using machine learning techniques to estimate geometric deviation patterns by statistical learning from different shape data and supporting more accurate tolerances for additive manufacturing parts [9]. Researchers also are using machine learning to assess the manufacturability of design models. Deep learning is used to learn different Design for Manufacturing rules from labelled voxelized CAD models, without additional shape or process information [10].

Materials Design and Selection: Material selection impacts the physics of additive manufacturing from start to finish, from the interactions of energy sources with the material to the final parts' performances. However, the range of materials for additive manufacturing processing is very limited and developed materials for traditional manufacturing techniques are not suitable for additive manufacturing.

Designing materials for additive manufacturing, either altering the chemistries of known materials or discovering new ones, requires considering the material properties' implications with additive manufacturing processing. Machine learning techniques have great potentials to uncover knowledge about the fundamental physical, mechanical, electrical, electronic, chemical, and engineering properties of materials. Machine learning approaches utilize analytical forms that can significantly accelerate the prediction and optimization process in materials design compared with other computational methods. Recently, studies have shown that machine learning 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.

Additive Manufacturing Process

The mapping of process, structure, property, and performance relationships is significantly important for the process parameter selection and optimization of additive manufacturing parts' performance. This relationship is often significantly nonlinear due to the high numbers of the input variables, and it is challenging to identify the underlying mathematical formula.

Machine learning techniques have a robust capability to successfully discover complex process-structure-property-performance relationships, overcoming many of the conventional analysis methods' limitations. The scope of such techniques generally focuses on understanding either process response or performance response by using a data-driven approach or a combination of both physics-based and data-driven techniques. Table 1 summarizes the application of machine learning models used for the additive manufacturing process and performance optimization.

Additive Manufacturing Monitoring and Control

In situ monitoring, feedback, and control has been consistently ranked as one of the most-needed technologies for additive manufacturing. The combination of rapid solidification and the small length scales of additive manufacturing solidification can make traditional process monitoring approaches difficult. Process monitoring involves acquiring real-time signals that can reveal information about a wide variety of phenomenon and product quality during manufacturing. Accurate and simultaneous analysis of these real-time signals can lead to complete closed-loop control. Machine learning models can predict the state of the final part by using these signals to characterize a part's current state.

Current efforts towards using machine learning for real-time control for additive manufacturing processes primarily focus on monitoring the state of either the built part or the additive manufacturing machine (machine monitoring) itself. In the latter approach, the in-situ monitoring is performed by observing the machine logs or build conditions instead of monitoring the part. Machine learning models can extract time and frequency domain features from machine logs using acoustic data to identify normal and abnormal machine states [25,26]. This monitoring method can be used as a diagnostic tool to identify failures.

Developments in in-situ monitoring control will significantly enhance part defect detection and prediction in additive manufacturing processes. Additive manufacturing parts can have different types of defects, including porosity, poor surface finish, layer delamination, cracking, and geometric distortion. Through traditional offline inspection methods, the identification of defects can be subject to inaccuracy, inconsistency, and delays. Studies have explored establishing effective and reliable in-process detection of defects for a framework of zero-defect additive manufacturing processes by using advanced machine learning and data mining techniques. Different machine learning models using visual data, acoustic data, and multi-sensor data have been developed to analyze underlying patterns and features within datasets and detect multiple and different types of defects (porosity detection [27], quality of fusion and defect detection [28], anomaly detection and classification [29], melt pool features and spatter detection [30], defect detection and classification [31], fault detection from multi-sensor data [32], quality monitoring using heterogeneous sensors [33], defect detection for LPBF using in-situ images coupled with ex-situ CT scans [34]). Improving real-time control of additive manufacturing processes also has the benefit of minimizing the post-processing and inspection tasks.

Conclusion and Future Developments

The development, integration, and application of machine learning and data-driven approaches into the additive manufacturing product lifecycle can address many of the issues currently facing the technology's advancement. The high dimensionality and complexity of additive manufacturing data make it well-suited for popular machine learning algorithms. While machine learning techniques are rapidly being adopted into additive manufacturing applications, there are many opportunities for improved future work. Success in applying data-driven approaches is significantly dependent on the availability and quality of the training data. Machine learning algorithms perform poorly at diagnosing conditions without enough data to signify a prediction pattern. This limitation should be addressed by collecting data from different processing scenarios representing a wide range of operating conditions and dimensionality space.

Another significant challenge in the advancement of machine learning for additive manufacturing is the lack of accurate, accessible, and extensive databases for additive manufacturing processes, products, and materials. 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. The absence of a common data structure, and standard methods for data integration and fusion, prevents rich, multifaceted, data-driven analysis.

Also, generating high-quality data via experimentation is difficult and expensive. The data must be collected with the highest care and precision since low quality or incorrectly-inconsistently labelled data hinders feature selection for machine learning models. The development of libraries for additive manufacturing feature characterization would also help address some of the current challenges that make it difficult to select a suitable machine learning algorithm compatible with the available data.

Table 1. Machine learning applications in additive manufacturing processes

Tech	Target Property	Processing Parameters	Ref.
SLS	Density	Laser power, scan speed, scan spacing, layer thickness	[11]
SLS	Dimension	Laser power, scan speed, scan spacing, layer thickness	[12]
SLS	Build time	Z height, volume, bounding box	[13]
SLS	Shrinkage ratio	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	[14]
SLS	Open porosity	Layer thickness, laser power, scan speed	[15]
SLS	Tensile strength	Laser power, scan speed, hatch spacing, layer thickness, powder temperature	[16]
SLS	Density	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	[17]
SLA	Dimensional accuracy	Layer thickness, border overcure, hatch overcure, fill cure depth, fill spacing and hatch spacing	[18]
FDM	Compressive strength	Layer thickness, orientation, raster angle, raster width, air gap	[19]
FDM	Wear volume	Layer thickness, orientation, raster angle, raster width, air gap	[20]
FDM	Volumetric error	Orientation, slice thickness	[21]
FDM	Dimensional accuracy	Layer thickness, orientation, raster angle, raster width, air gap	[22]
FDM	Dimensional accuracy	Layer thickness, orientation, raster angle, raster width, air gap	[23]
BJ	Surface roughness	Layer thickness, printing saturation, heater power ration, drying time	[24]
BJ	Shrinkage rate (Y-axis)	Layer thickness, printing saturation, heater power ration, drying time	[24]
BJ	Shrinkage rate (Z-axis)	Layer thickness, printing saturation, heater power ration, drying time	[24]

SLS: Selective Laser Sintering, SLA: Stereolithography
FDM: Fused Deposition Modeling, BJ: Binder Jetting

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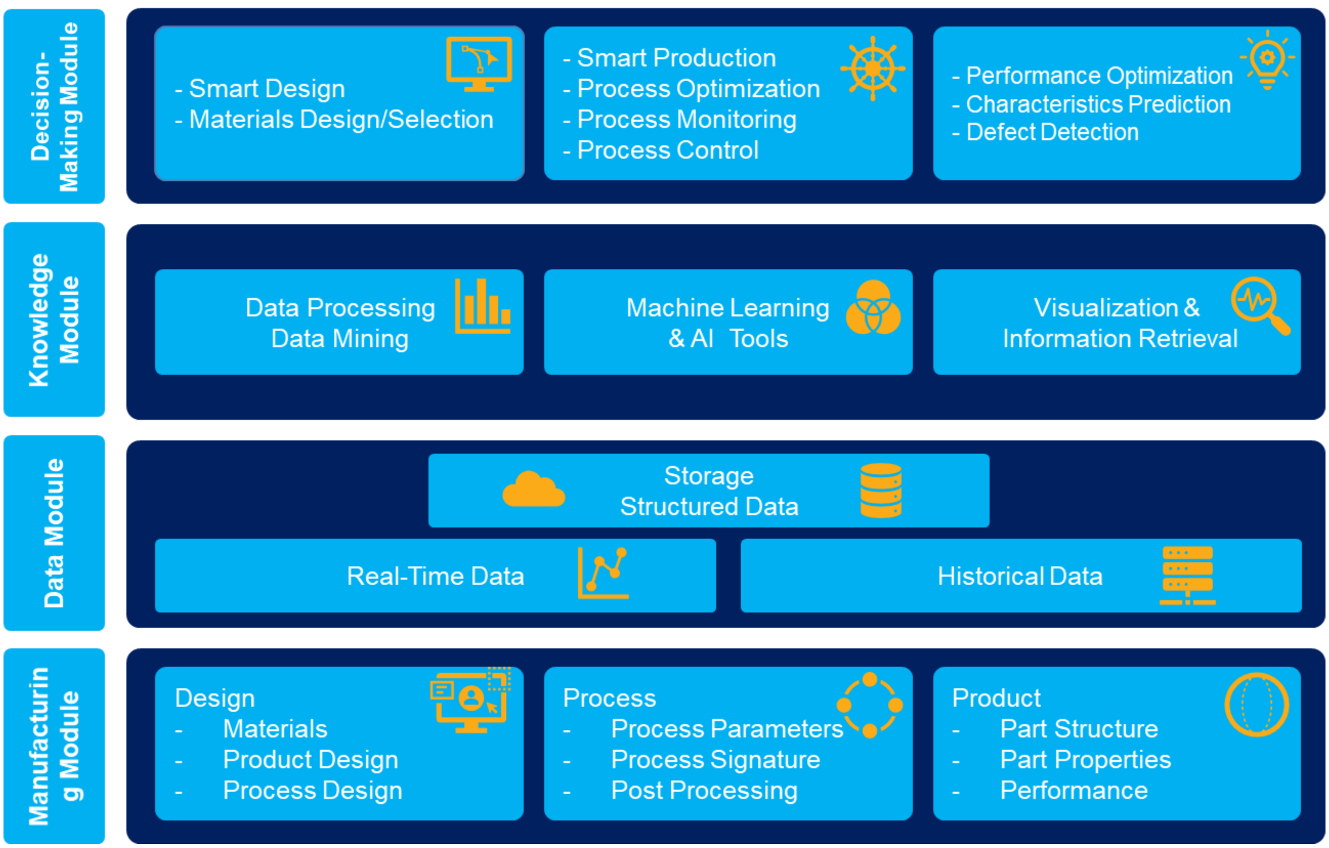

Figure 1. Data-driven additive manufacturing framework