Exploring the Integration of Artificial Intelligence and Machine Learning in Metal Additive Manufacturing

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ABSTRACT

Additive manufacturing (AM) and artificial intelligence (AI) are both disruptive emerging technologies. while AI has permeated various aspects of our lives, its full potential in the realm of AM has yet to be fully explored. With its abundance of data and digital nature, AM presents significant opportunities for advancements in machine learning (ML) and consequently AI. This article offers a perspective on the applications of ML and AI in AM, particularly in powder bed AM technology. It discusses the various types and sources of data, potential variations in experimental and simulation data, and the suitability of these data for ML algorithms. Moreover, it presents novel ideas on how the integration of these two transformative technologies can profoundly impact the application of AM across diverse fields. Finally, it outlines a vision for the future direction of AM to fully harness the advantages of AI.

INTRODUCTION

The term "artificial intelligence" (AI) was first coined by John McCarthy to describe the ability of machines to exhibit intelligent behaviour. However, even before McCarthy, the renowned British mathematician, computer scientist, and philosopher Alan Turing posed the fundamental question of whether machines can possess intelligence. Turing introduced this concept through the concept of an imitation game, where he outlined a logical approach to analysing information and making intelligent decisions piece by piece. Prior to Turing, McCulloch and Pitts laid the groundwork for neural networks, drawing inspiration from the physiological functions of neurons, the propositional logic formulated by Russel and Whitehead in Principia Mathematica, and Turing's computational theory.

AI can be classified into two distinct approaches: symbolic or traditional intelligence, which involves problem-solving through reasoning and knowledge; and computational intelligence, which focuses on solving problems and making decisions based on example data. Within the realm of computational AI, there are several techniques encompassed, including artificial neural networks, fuzzy systems, and evolutionary programming, as defined by the IEEE Computational Intelligence Society.

Symbolic and computational intelligences can be acquired through various methods, including machine learning (ML) using experiments and simulations. AI encompasses subfields such as automated reasoning, where computer programs enable machines to engage in reasoning and decision-making processes. In many scenarios, machine logic and reasoning occur in uncertain circumstances, where decision-making becomes a probabilistic rather than deterministic action. Consequently, disciplines like fuzzy logic and Bayesian statistics play a vital role in comprehending and navigating these intricate situations.

The most prevalent form of AI involves the ability to emulate human behaviour and continuously improve upon it. Learning and improvement, which appear effortless for humans, are profoundly intricate cognitive phenomena that have evolved over millions of years, encompassing both cognitive and physiological aspects. Achieving general intelligence in machines necessitates fulfilling three essential requirements: the capacity to perform complex computational tasks, access to memory, and availability of data for learning (Figure 1). These three factors are crucial for both machines and humans to acquire knowledge and adapt. While our brains fulfil the criteria of memory and computational capabilities, both AI and the human brain rely on data processing and learning.

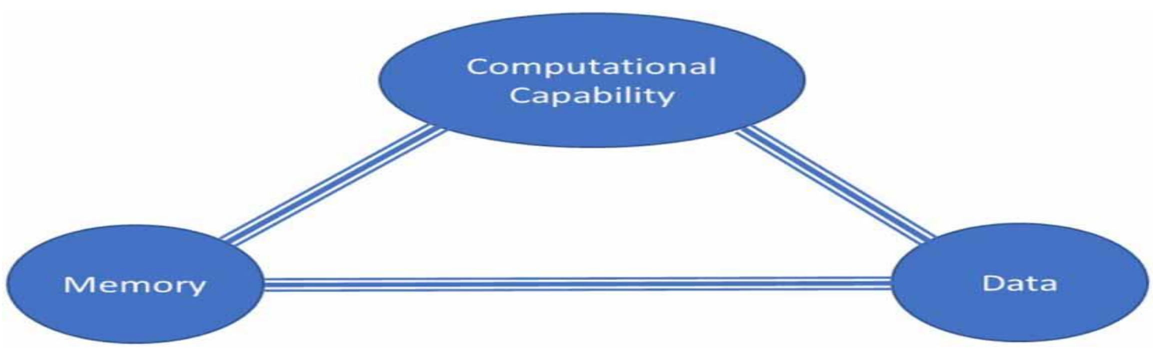

Figure1

We often come across terms like "data science," "AI," and "ML" in today's world, and it's crucial to understand the distinctions between these terms. Data science is an interdisciplinary and broad field that employs scientific methods, processes, and algorithms to extract knowledge from diverse sets of data. Its applications extend beyond AI.

As depicted in Figure 2, AI relies on the utilization of data science techniques, but it is not the sole application of data science. Data analysis techniques form the foundation for the development of AI.

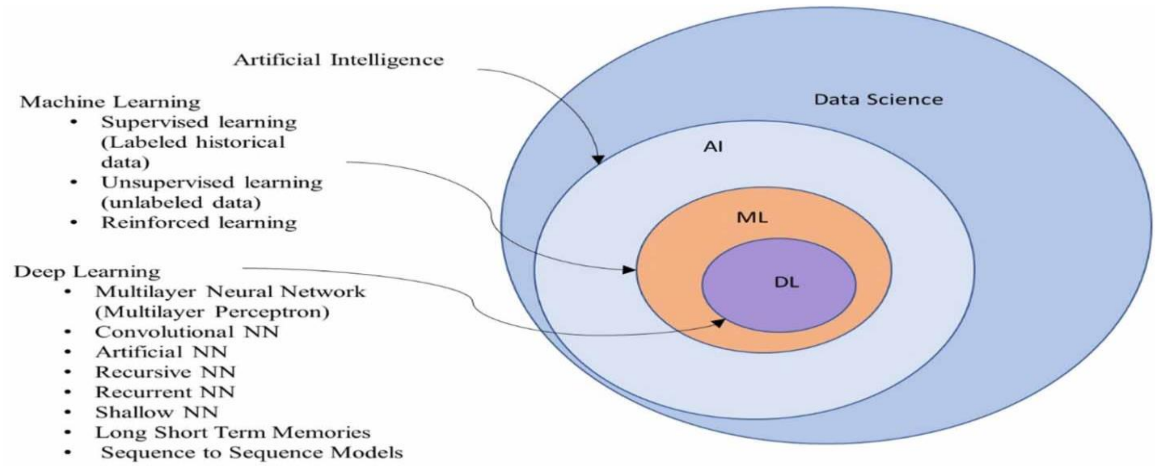

Figure 2

Over the years, significant progress has been made in AI through the contributions of mathematicians, philosophers, physiologists, neuroscientists, cognitive scientists, computer scientists, electrical engineers, and various other disciplines. Each field has influenced the evolution of tools and techniques in AI. Philosophers have drawn parallels between the brain and machines, while physiology, neuroscience, and cognitive sciences have enhanced our understanding of how the human brain functions and processes information. Computer science has provided the groundwork for developing mathematical programs, logical frameworks, and rational reasoning algorithms to implement these ideas. With the availability of advanced computers capable of sophisticated computations and data storage, along with abundant data resources resulting from digitization, the internet, and media advancements, we have made significant strides in AI. However, it's important to note that we have thus far achieved only weak AI, with general or strong AI and artificial superintelligence still remaining as future aspirations.

Figure 2 illustrates that machine learning (ML) is a subdomain of AI. ML plays a crucial role in the development of AI, and it encompasses supervised, unsupervised, and reinforced learning. Various learning algorithms exist, with deep learning algorithms being the most common ones, as depicted in the deep learning subdomain.

ML can be categorized based on the type of data used: supervised learning and unsupervised learning. In supervised learning, models are trained using labelled historical data to make predictions or fit new input.

Classification of labelled data and trend prediction based on previously labelled data are employed to determine the model's output. On the other hand, unsupervised ML utilizes data clustering techniques to discover patterns and groupings. Reinforcement learning combines aspects of supervised and unsupervised learning methods. Neural networks (NN) are a fundamental technique used in ML, and Figure 2 showcases various approaches developed for NN.

AI has made significant advancements across a wide range of applications, including speech recognition, autonomous vehicles, robotics, game development, computer graphics, and cybersecurity. Manufacturing is poised to be profoundly impacted by AI, making it the second-largest spending category for AI after banking, finance, and insurance services, as indicated by the data provided in Figure 3.

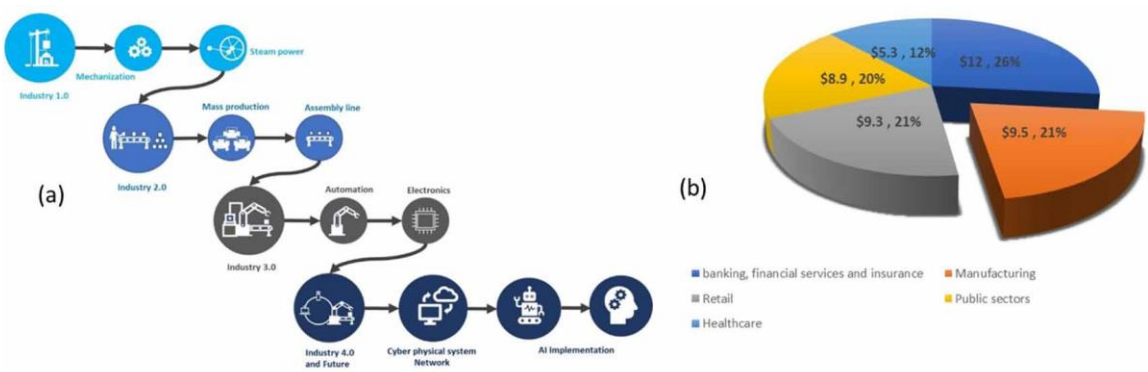

Figure 3

The implementation of AI in manufacturing necessitates the adoption of smart manufacturing, where sensors provide real-time information. Smart manufacturing is not a new concept and can be enhanced through the use of digital twin technology. Digital twin involves creating a digital representation of a physical system, such as a process, machine, or part, using digital data. It establishes a two-way interaction between the real-world system and its digital counterpart, enabling improved system outcomes and predictability. The concept of digital twin has found widespread use in various industries, and its application in additive manufacturing (AM) began with activities focused on process modelling. For example, a digital twin of a laser-based directed energy deposition AM system includes a transient, three-dimensional model that calculates temperature and velocity fields, cooling rates, solidification parameters, and deposit geometry. The integration of cyber-physical systems and digital twin has paved the way for the development of ML and AI algorithms.

AM, being a digital technology, can greatly benefit from advancements in data science, ML, and AI. The entire AM process is conducted digitally, which facilitates data collection and organization. However, the highly automated nature of AM during the design, process preparation, and printing stages generates vast amounts of system data that are challenging for humans to visualize and interpret. The enclosed environment of AM further complicates the observation and monitoring of the process. Additionally, the high speed of the process poses difficulties in monitoring. ML can play a crucial role in data visualization, image recognition, and system modelling to improve our understanding of the AM process. Furthermore, the labour-intensive tasks involved in the preparation and post-processing stages can be assisted through process automation using intelligent analysis algorithms for planning and decision-making.

AI and ML can be applied to optimize process quality and reduce defect density in AM. Considerable research has focused on improving feedback control systems to enhance process quality. Concurrent design is another application of AI, where the information acquired during the build process is utilized to continuously and adaptively improve the design. Design improvements may target objectives such as reducing residual stress, weight reduction, and enhancing strength in areas where defects have developed. The integration of design and process in concurrent design provides ample opportunities for creativity and innovation. Given the digital nature of AM and the critical role of digitization and computer models, the application of AI becomes highly relevant in this field. This manuscript specifically concentrates on the application of AI in powder bed processes for metals.

1. Powder bed processes

Powder bed additive manufacturing (AM) technologies involve the use of a laser or electron beam to melt layers of powder and create a shape based on a computer-aided design (CAD) model. These processes have been in existence for a few decades, with the concept of laser sintering in powder bed processes originating from Dr. Carl Deckard and Dr. Joe Beaman at the University of Texas at Austin in the mid-1980s. Since then, significant advancements have been made in this technology. Laser technology has improved, enabling higher laser powers and the development of selective melting processes like selective laser melting (SLM). European innovators have also utilized electron beams instead of lasers for melting.

The powder bed AM process begins with a CAD model, which is fed into software interfaced with the machine. The software layers the design and creates support structures. During the process, powder is typically spread on top of a build plate using a rack or roller. In the next step, a laser or electron beam pre-heats and melts the powder. Various intermediary steps have been developed to enhance the process, such as preheating the base plate in electron beam machines to reduce stress in the final part.

Ideally, AM should produce parts that require minimal post-processing. However, several post-process steps are often necessary to prepare the part for its final application. These steps include removing the part from the base plate, removing support structures, and sometimes performing additional treatments like polishing and heat treating to reduce residual stresses in the parts.

2. AL and ML application in AM

To effectively apply artificial intelligence (AI) in additive manufacturing (AM), it is useful to categorize the applications into pre-process, process, and post-process stages, as depicted in Figure 4. In the preprocess stage, machine learning (ML) techniques can be utilized in various areas such as design space, raw materials design, and powder properties. ML advancements have enabled the prediction of material properties and the design of new and innovative materials. AM's unique manufacturing capabilities can be leveraged to bring these designs to life, even those that were previously considered infeasible. However, the application of ML in the pre-process stage, particularly in the design space (geometrical design and topology optimization) and powder properties, is still relatively limited, with a particular gap in exploring powder properties. The following section will provide more detailed information on each of these categories.

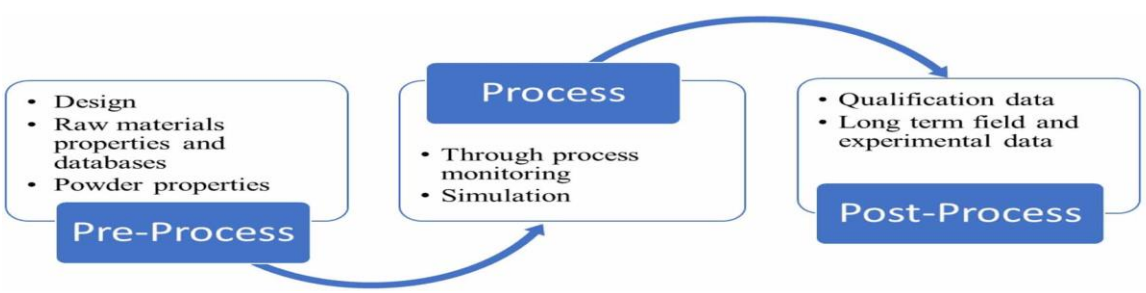

Figure 4

Within the process stage of additive manufacturing (AM), the application of machine learning (ML) can be further categorized into experimental work on process monitoring and optimization, as well as simulation work in the same domain. Experimental process monitoring and optimization have received significant attention in research, and this area is discussed in detail in section 2.2 of the paper. On the other hand, the application of ML in post-process data analysis is relatively new and has gained less focus. Most of the existing research has been centered around establishing connections between post-process data and the manufacturing process itself. Limited studies have been conducted in this particular area. Therefore, section 2.3 of the paper provides a brief review of the application of artificial intelligence (AI) and ML in postprocess analysis.

2.1. AI application in pre-process

In the pre-process step of additive manufacturing (AM), machine learning (ML) has already made significant advancements in the materials and design space. Under the materials domain, these advancements have been largely driven by initiatives such as the Materials Genome Initiative (MGI) introduced by the US government. MGI focuses on leveraging computational materials science to design and manufacture new materials with unique properties, and ML has played a crucial role in enabling progress in this field. ML techniques have been extensively applied to a wide range of materials, including metals and alloys commonly used in AM processes. Detailed insights into ML in materials can be found in the comprehensive review provided in, and materials data is readily available through various databases.

Within the design space, which encompasses digital design, computer-aided design (CAD), and related fields, ML has the potential to transform two major aspects. Firstly, it can revolutionize the interaction between users and machines, making AM accessible to users of all ages and skill levels, from K-12 students to professional engineers. To integrate AM into daily activities seamlessly, users must be able to interact with machines easily. AI and ML can facilitate this by enabling image and voice recognition, allowing users to interact with machines through verbal communication rather than technical programming steps. AI applications in image recognition, for example, can improve the 3D scanning process commonly used to generate models of parts. AI can also enhance the utilization of internet databases for retrieving CAD models, enabling the harnessing of available designs (such as STL and other CAD files) through the internet of things and digital space.

Secondly, ML can contribute to the improvement of design software and its integration with the process design. Software can be modified to leverage the unique capabilities of AM in microstructural design and bottom-up processing. By incorporating AM's ability to create customized and directional properties, the design optimization space can be transformed, leading to the development of programs and software for optimized design. Recent advancements in concurrent design, where the design is adaptively modified during the build process to address issues like residual stresses or defects, have also emerged. However, achieving this requires a deep understanding of how design parameters impact residual stresses and defects, as well as an in-situ process monitoring feedback loop to inform the design process.

2.2.1. Defects detection and reduction

In the manufacturing of parts through additive manufacturing (AM), the detection and avoidance of defects are of utmost importance, particularly for critical applications like aerospace where defects can lead to premature failure or fatigue and pose significant risks. One factor that has garnered attention in the past decade is the melt pool temperature, as it is closely associated with defect generation during the AM process. Temperature measurement has been a focal point for manufacturers and researchers, leading to the development of analytical tools such as in-situ infrared (IR) cameras for measuring melt pool temperature. However, temperature data alone is insufficient for defect detection, and it needs to be correlated with actual defect data through process learning.

Several approaches have been explored for defect identification during the ongoing AM process. Image processing technologies have been utilized to detect defects using layer-wise images captured during the process. For instance, researchers have employed linear support vector analysis with binary classifiers to assign characteristics to pixels (flaw vs. nominal formation). Challenges arise when translating and correlating the coordinates of flaws observed in in-situ images to post-build CT scan images, as part expansion and reduced residual stresses after part removal can introduce errors. Another approach involves using a bi-stream deep convolutional neural network (DCNN) to extract relevant embedded patterns from images captured after powder spread and selective laser melting (SLM) of each layer. This method accounts for the impact of surface irregularities in the powder spread, achieving a high accuracy of 99.4% in defect detection.

In addition to optical surface imaging, other researchers have focused on measuring melt pool dimensions and temperature distribution using infrared imaging technology. ML algorithms such as decision trees, K-nearest neighbours, support vector machines, linear discriminant analysis, and quadratic discriminant analysis have been employed to determine the dimensions of the melt pool and subsequently identify porosity and defects in powder bed-based AM processes. These approaches involve characterizing the melt pool using a pyrometer and performing x-ray tomography after the build to determine defects and label the melt pool images as defective or non-defective. Comparative studies have shown that the K-nearest neighbour method provides the best accuracy in classifying melt pools, while decision trees excel in identifying normal melt pools incorrectly as defective.

In addition to temperature and visual inspection, researchers have explored the use of plume and splatter characteristics in conjunction with near-infrared imaging to understand the relationship between process parameters, melt pool geometry, and defects. Deep Belief Network learning methods have been employed to characterize the melt pool, achieving efficiency in determining different melting states for a significant portion of the time.

Defect detection in AM processes is not limited to temperature or visual inspection alone. Ongoing research involves the use of acoustic emission combined with convolutional neural network analysis to assess part quality, including sublayer pores and defects. Different machine settings are employed to generate varying pore densities, and acoustic emission data is collected and categorized into training and testing sets. The acoustic signals are transformed into images representing different colour ranges of stored energy, which are then used to train the algorithms. The trained algorithms are subsequently employed to classify the quality of built parts into three categories: poor, medium, and good. Classification accuracies of 83%, 85%, and 89% have been achieved for high, medium, and poor quality, respectively.

As evident from these examples, there is a wide range of approaches for defect detection in AM, utilizing different measurement techniques and algorithms. Some approaches involve direct measurements like acoustic emission, while others rely on indirect measurements such as temperature to infer information about the process. Direct quantification of defects offers advantages by reducing errors associated with data processing and interpretation. Different algorithms provide distinct advantages, with some offering higher accuracy and others offering speed and lower memory requirements. Factors such as training data size, model interpret

2.2.2. Reducing stress residuals and failure during and after build

When it comes to physical defects such as voids, cracks, or un-melted powder in additive manufacturing (AM), imaging and acoustic techniques have proven to be reliable methods. However, assessing stresses and strains in parts, even in normal conditions outside the melt pool, poses significant challenges. Stresses cannot be directly measured, and only strains, as an indirect effect of stresses, can be measured. Traditional strain measurement techniques, which are mostly contact measurements using strain gauges or extensometers, are not suitable for AM processes due to the high temperature environment, process speed, vibrations, and other variables. Non-contact techniques such as Moiré interferometry, digital image correlation, laser measurements, x-ray diffraction, convergent electron beam diffraction, and neutron diffraction residual stress measurement have been employed in traditional applications but have yet to be extensively applied in AM.

These non-contact techniques are often sensitive to environmental parameters such as temperature and vibration. Currently, no strain measurement techniques have been adapted for in-situ use within the build chamber during AM processes. Among the mentioned techniques, x-ray diffraction and electron beam diffraction have the most potential for applications in laser powder bed and electron beam powder bed methods, respectively, since lasers and electron beams are used for material melting.

Due to the challenges and lack of experimental data in stress and strain measurements during AM, the most promising approach for efficient and accurate machine learning (ML) and process improvement is through simulation and modelling, or by obtaining historical data from post-process analysis. Simulation is a valuable tool when experiments are not feasible, and well-established physics-based simulations can provide insights into the impact of process parameters on solid formation, residual stresses, and deformation in parts. This knowledge can inform and optimize ML algorithms, and the simulation predictions can be validated by correlating them with experimental results. By adopting a joint computational and experimental approach, a continuous improvement in the learning process can be achieved.

Significant advancements have been made in the simulation domain over the last decade, enabling multi-physics and multi-scale modelling of AM processes. The ability to model the intrinsic elastic and plastic behaviour of materials at different temperatures, coupled with multi-scale metallurgical and phase deformation models, provides valuable information that can reduce the need for extensive experimentation. Simulation-assisted ML, which leverages simulations to train ML algorithms and minimize the reliance on experimental data, has gained attention in various fields, including biomedical, gaming, and manufacturing applications.

The combination of ML and simulations is applied in two different scenarios. In the first scenario, simulations are integrated into ML as an additional resource for training, typically to augment data in scenarios where available data is insufficiently represented [Rueden et al., 2020]. The second scenario involves using ML within simulations to save computational resources, replacing complex simulations with simpler surrogate models [Rueden et al., 2020]. In the manufacturing context, for example, researchers developed a surrogate model to represent weld behaviour and predict weld distortion in pipe girth welds. The surrogate model allowed for avoiding running full simulation models for a large number of weld orientations, leading to efficient determination of factors influencing weld distortion.

2.2.3. In situ metrology and design accuracy

Dimensional accuracy is a crucial parameter in additive manufacturing (AM) and is influenced by various factors. These factors include initial geometry and design, material properties and behaviour in a heated environment, build parameters (e.g., spot size, powder size, hatch spacing, layer thickness), and more. Understanding the combined effect of these factors can help achieve accurate parts. It is also important for designers to know the deviation of the final part from the initial design so that they can adjust the dimensions accordingly. In order to achieve this, real-time measurement of part dimensions during the building process is necessary. By utilizing analytical tools and devices inside the build chamber to accurately measure dimensions, machine learning (ML) algorithms can compare the ongoing build with the design specifications and provide immediate feedback to adjust the process parameters accordingly. Given the spatial and temporal scales of the powder bed AM process, rapid inspection methods are necessary. Each layer is built in a matter of microseconds, during which the dimensions are changing. Therefore, a high-speed inspection method with a large field of view and high accuracy is required.

However, studies focusing on in situ metrology of powder bed processes are limited, and most of the explored methods are based on optical imaging or thermal measurements. Optical imaging techniques often provide two-dimensional surface information and lack depth information. Imaging the entire layer is often impractical due to camera limitations and image sizes. Some techniques, such as linear approximation and phase shifting fringe projection, have been used to measure planar dimensions and area height profiles of each layer. While these methods show promise in detecting surface characteristics, they have limitations and complexities to overcome. Other techniques like Optical Coherence Tomography have been proposed for measuring surface curvature and porosity but are not used for in situ metrology. Enhanced phase measuring profilometry has been used in combination with 3D surface imaging to detect geometrical signatures in powder bed processes but does not provide depth information for the build. Recently, Fringe Projection Profilometry has been utilized for in situ 3D inspection of powder bed parts, using a camera and projector to capture and analyse the fringe pattern and extract 3D shape information.

Advancements in image processing and ML have allowed researchers to optimize the use of optical images to detect geometrical defects and deviations from the nominal geometry. Image segmentation techniques can be employed to compare the captured images with the original design and generate a deviation map. However, this method may not detect deviations that occur after the production of the monitored layer, and it has limitations when the distortions are small compared to camera resolution and uncertainty. Laser physics advancements have also been leveraged to determine surface and subsurface geometrical attributes such as melt pool depth. By correlating the characteristic oscillation frequency of the surface ripples of the melt pool with laser penetration depth, information about the melt pool depth can be obtained. This method has shown promising results in correlating oscillation frequencies with molten pool characteristics and can provide insights into the quality of the build.

2.2.4. Microstructural design

In powder bed additive manufacturing processes, if no deliberate control of parameters is implemented, a columnar microstructure typically forms along the build orientation due to the re-melting and solidification of multiple layers. However, due to the bottom-up nature of the process and the ability to control temperature and thermal gradients, it is possible to manipulate grain growth and orientation. Researchers have conducted studies to intentionally change the microstructure to a more equiaxed type by controlling the ratio of thermal gradient to solidification rate through process control. Furthermore, the formation of specific phases can also be controlled through the additive process.

The ability to design microstructures is a unique advantage of additive manufacturing, particularly in powder bed processes. This capability is especially valuable in applications where specific microstructures are required. For instance, in situations where components experience cyclic loading and high temperatures leading to creep and fatigue, such as turbine blades in jet engines, having a single crystal microstructure is crucial. Single crystal metals exhibit reduced microstructural defects, such as dislocations and grain boundaries, which helps mitigate fatigue and creep damage and extends the life expectancy of the blades and engine. Traditional methods of producing single crystal materials are expensive, but additive manufacturing offers the potential to design and tailor such microstructures, making it an attractive option for aerospace applications.

Early studies examined the columnar grain growth structure and explored variations of this microstructure. Researchers also investigated the control of local microstructure by varying process parameters, leading to site-specific grain growth control. More recently, a breakthrough study demonstrated the processing of single crystal materials using additive manufacturing technology. This was achieved through a scanning strategy, geometry control, and the use of a special parameter setting called μ-Helix in an electron beam melting machine. The μ-Helix setting enables the control of solidification paths to resemble a micrometer-sized helix.

As additive manufacturing processes become more controllable with advancements in machine manufacturing, the use of machine learning (ML) in the design and implementation of advanced grain structures becomes increasingly feasible. However, in situ monitoring of grain structure and orientation is still a challenging task. Evaluation of grain orientation is typically performed through electron backscatter diffraction (EBSD) analysis, which is a meticulous and challenging microscopic technique. Currently, it is not possible to use EBSD in situ to provide unsupervised learning data for ML. Other technologies such as x-ray microscopy have the potential for in situ use, although they also have limitations regarding specimen size and field of view. Consequently, the data required for ML processes applied to grain structure refinement and design can currently only be obtained through post-process microstructural characterization of specimens, providing supervised learning data for ML algorithms.

2.2.5. Alloy design and optimization

The field of alloy design has been of interest to the materials community for a long time, and more recently, machine learning (ML) has been extensively employed to design alloys with specific desirable properties. ML has been used to improve mechanical properties, tailor properties for biomedical applications, and even create new series of metals based on novel compositions. For example, a recent study published in Nature utilized ML to develop a β-Ti alloy with a minimum elastic modulus, and the projected composition showed promising results in experiments. In a comprehensive analysis of steel alloys, 16 different descriptors were used in an ML platform to predict the yield strength and ultimate tensile strength of 5,473 thermo-mechanically controlled processed (TMCP) steel alloys. The study explored the accuracy and usefulness of different ML algorithms and found that the optimization process effectively controlled the amount of key alloying elements, such as C, Mn, Nb, and Si, leading to improved strength for TMCP applications. However, experimental verification of these ML-based alloy designs is still required.

It is important to note that the design of a material and its successful manufacturing are two separate challenges. While many materials can be designed theoretically, limitations in manufacturing approaches can hinder their actual production. This is where additive manufacturing (AM) becomes highly valuable. Traditional methods like casting have always struggled with controlling the microstructure and phases of materials. Phase formation does not always occur under equilibrium conditions, and in casting, phase formation is specific to the cooling rate, which can be difficult to control, especially for complex parts and new designs. The cooling rate has a significant influence on the phases formed in materials.

AM, with its local and bottom-up build nature, offers precise control over the cooling rate in the melt pool, enabling the achievement of desired phases. This brings us closer to the actual manufacturing of complex alloys that require controlled environments. Various factors impact the cooling rate, including geometry (heat path through solid vs. powder), thermo-physical properties of the materials (e.g., diffusivity, emissivity, reflectivity in solid, powder, or molten form), distance from the base plate, laser or electron beam parameters (e.g., power, speed, spot size), and the type of atmosphere used in the process (e.g., vacuum or inert gas). Many of these parameters are dependent on the machine or the materials being used. Therefore, controlling the process parameters, such as beam power and speed, may be the most practical approach. By considering a specific process, material, geometry, and machine, a thermal finite element simulation can provide information on the process parameter range necessary to achieve a desired thermal gradient and cooling rate in the part.

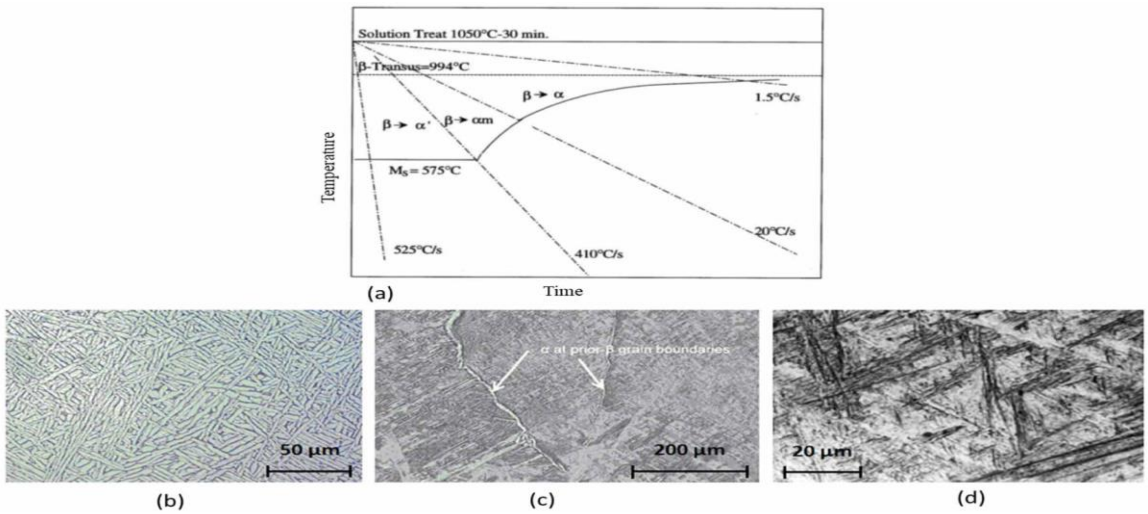

Figure 5

However, despite its numerous benefits, additive manufacturing (AM) also presents challenges and difficulties in achieving the desired microstructure and alloy compositions. Some of these challenges include:

Evaporation of Low Melting Temperature Components: The high local temperatures and occasional use of vacuum environments inside the AM chamber can lead to the evaporation of low melting temperature components. This evaporation can alter the initial intended composition of the material. Currently, there is no systematic way to control this evaporation, resulting in potential differences between the composition of the final parts and the intended composition.

Limited Post-Processing Opportunities: Parts manufactured using traditional techniques often undergo additional post-processing steps such as extrusion, which work harden the material and enhance the strength of the parts. However, in AM, parts are typically fabricated to near-net shape or net shape, reducing the need for extensive post-processing. While this may limit the strength of AM parts, it also provides an opportunity for researchers to explore ways to enhance the strength of AM parts through the AM process itself.

The future development of machine learning (ML) and artificial intelligence (AI) in additive manufacturing holds promise for addressing these challenges and achieving high-quality final parts. ML and AI can enable closer control over variations in the manufacturing process, leading to improved control over microstructure and alloy compositions, and ultimately resulting in higher quality parts.

2.3. Application of ML and AI in post process

The application of machine learning (ML) and artificial intelligence (AI) in post-processing steps of additive manufacturing (AM) has been limited. This is mainly because by the time parts reach the post-processing stage, the opportunity for in situ control and improvement has already passed. However, information obtained during post-processing can still be utilized to optimize future builds.

There are specific areas within post-processing where ML and AI can play a role, particularly in evaluating quality factors such as defect density, surface roughness, dimensional accuracy, and reliability indices like fatigue strength. Fatigue life is a critical reliability factor for many AM applications, especially in aerospace where cyclic loads are common. Researchers have explored the use of ML to optimize the long-term behaviour and fatigue strength of AM materials based on process parameters. For example, adaptive neuro-fuzzy inference systems have been trained using literature data to determine the fatigue strength of stainless steel. Other studies have focused on fatigue prediction of AM parts using ML models based on theoretical considerations and the types of defects generated during the AM processes.

The microstructure of AM parts and the presence of defects, such as porosity and surface defects, significantly impact fatigue life. Powder bed processes are particularly prone to such defects, leading to research on evaluating porosity as a process quality index. X-ray tomography is commonly employed to measure porosity and defect density. Many studies have focused on ML algorithms to optimize the generation and interpretation of x-ray tomography images. In a meticulous study, micrographs of metallic components manufactured using laser powder bed processes were utilized to train ML algorithms for the classification of porosity types. To overcome limitations and costs associated with in situ monitoring, a research effort focused on statistical analysis to establish relationships between downstream mechanical properties and process inputs for quality repeatability. The study revealed that the combination of part location and post-chamber pressure drop significantly influenced the mechanical properties of printed parts.

Considering the significance of surface roughness and microstructural variations in the long-term behaviour of AM parts, there are opportunities to apply ML in evaluating these process outcomes. However, currently, the number of studies focusing on these aspects is quite limited.

CONCLUSION

Additive manufacturing (AM) has the potential to extensively benefit from the applications of machine learning (ML) and artificial intelligence (AI). However, the integration of AM into other manufacturing techniques or making it more accessible to users through ML and AI is still a future goal. AI can contribute to AM in areas such as process optimization, design correlation, design improvement, defect reduction, and microstructural design. AM can learn from the approaches developed for other processes, but the main challenge lies in the availability and reliability of the data required to train ML algorithms.

The current experimental data for AM, collected by the research community or AM manufacturers, varies and is not always publicly available. Therefore, it is crucial to establish reliable data collection, storage, and sharing practices for the development of ML algorithms in AM. Creating a platform or venue for data storage within the manufacturing community is important. To ensure the usefulness of the data and proper functioning of ML algorithms, it is essential to disclose the conditions under which the data was generated. This includes providing information on process parameters, raw materials (such as powder or feedstock), their composition, properties (e.g., powder flowability, particle size), machine specifications, and any other relevant data needed for data recreation and labelling.

Furthermore, the challenges posed by the AM process itself, such as high temperatures and speeds, make monitoring and measurements difficult. Most available technologies rely on thermal or optical imaging of the material's surface, with limited depth information. It is important for manufacturers and researchers to develop tools that can accurately and rapidly monitor various parameters and conditions of the AM process. Challenges remain in areas such as defect detection, real-time 3D imaging during the build process, and monitoring of microstructure and grain orientations. Addressing these challenges requires the dedication and efforts of an enthusiastic and dynamic community.

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