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# Artificial Intelligence on Additive Manufacturing

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## ABSTRACT

**The use of 3D printing for creating three-dimensional objects is rapidly advancing in the manufacturing sector. Artificial intelligence is playing a key role in enhancing the efficiency and quality of 3D printing processes. This article delves into the ways in which artificial intelligence is impacting 3D printing. Prior to commencing a printing job, a machine learning-powered printability checker is used to assess the feasibility of a 3D object. Parallel slicing algorithms are employed to speed up the slicing process, while intelligent path planning further optimizes the process. Intelligent algorithms are also used to match demand with resources, supporting a Cloud service platform and evaluation model that allow customers to access services on demand. Additionally, three machine learning algorithms are discussed, which are designed to identify defects in products during cyber-attacks. The article also highlights the potential for further research in areas such as multi-indicator printability, simplifying complexity thresholds, expediting prefabrication, real-time control, enhancing security, and detecting defects in custom designs, particularly within the industrial context.4.0.**

**Keywords –Artificial Intelligence, Deep Learning, Machine Learning. Additive Manufacturing**

## INTRODUCTION

[1Additive manufacturing (AM) technology has experienced significant growth in usage across various industries in recent years. Unlike traditional subtractive techniques that rely on chip removal, forming, and joining processes, AM allows for the rapid creation of complex structures with minimal waste. Through the use of advanced design tools such as topology optimization (TO) or generative design (GD), it is possible to develop bio-mimetic components that push the limits of design. AM is versatile, capable of producing parts from a wide range of materials, including plastics, resins, ceramics, and metal alloys. It is particularly useful for creating spare parts, small-scale production runs, custom-made items, topologically optimized components, on-demand manufacturing of replacement parts, and parts with high strength-to-weight ratios. The field of AM encompasses a variety of techniques, including selective laser sintering (SLS), direct metal laser sintering (DMLS), and powder bed fusion (PBF) processes. These processes can use powders of iron, steel, titanium, and aluminum to produce solid objects with high strength. By leveraging the photopolymerization properties of resins, stereolithography (SLA) is able to produce components with intricate details and smooth finishes. Filament extrusion techniques, such as fused deposition modeling (FDM), are known for their low cost.

However, it is important to note that AM is a relatively new and evolving technology, and the research community is diligently working to establish best practices for achieving the highest quality in the final product. The lack of precise guidelines means that machine settings are largely dependent on the operator's skill, which can be effectively adjusted. For instance, the orientation of the part on the printing bed is one of the settings that, during the printing process, can significantly impact the quality of the final component. Choosing the right orientation for the part can reduce the need for supports in areas that overhang, leading to a higher-quality surface, fewer post-processing steps, and less material waste. Other factors that have been explored to optimize AM processes include defect detection, monitoring the process in real-time, simulating the printing process, optimizing component design, predicting topology optimization (TO) properties, and designing materials. Artificial intelligence (AI) plays a crucial role in optimizing the parameters needed for AM design and manufacturing. AI has advanced significantly in recent years, thanks to increased computing power and access to vast amounts of data. The term "AI" refers to the methods that enable "black-box" problem-solving, aiming to replicate systems that accurately predict an output in response to an input and complete tasks solely through data rather than analytical methods.[1].[2]Intelligent systems are specifically designed to adapt their characteristics and functions for particular uses. These systems comprise active and passive components, including materials capable of mimicking biological functions. Researchers are actively exploring new methods to improve behavior and predict properties for each unique application. However, overcoming challenges in manufacturing technologies is crucial for significantly enhancing the traditional design process.[2].[3]In additive manufacturing, assessing part quality for porosity or cracking is conventionally performed using costly and time-consuming X-ray tomography. Although attempts have been made to implement near real-time quality monitoring systems using image analysis and temperature measurements, their accuracy remains questionable. Acoustic Emission (AE) sensing technology stands out as a cost-effective and reliable solution for providing essential subsurface information about the additive manufacturing process in an efficient and non-destructive manner..The primary challenges in utilizing acoustic emission (AE) technology for structural health monitoring in additive manufacturing stem from weak signals and high levels of background noise. In response to this issue, we have developed a new methodology that combines AE with Machine Learning (ML). By leveraging highly sensitive AE sensors and ML techniques, we are able to discern meaningful information from AE signals even in noisy environments. This approach has been successfully used in various applications with substantial background noise, such as tribology and fracture mechanics. It's worth noting that while the examples cited in this contribution utilized a fiber-based detector with high sensitivity, the proposed approach is adaptable and compatible with various types of sensing devices, ranging from piezo-based contact sensors to airborne microphones. This summary encapsulates the progress we have made in this area.So far, our research group has made significant progress in the field of in situ additive manufacturing (AM) and laser welding (LW) monitoring by combining acoustic emission (AE) and machine learning (ML). We will begin by looking back at the initial feasibility study and then focus on the recent advancements in linking AE with the underlying physical mechanisms that lead to the formation of defects.[3]

## MATERIAL & METHODES

a) Power Bed Manufacturing –[4]Powder bed additive manufacturing (AM) technologies unequivocally employ a laser or electron beam to systematically melt layers of powder, shaping it based on a computer-aided design (CAD) model. This extensively established method has witnessed significant advancements over the years. The process commences with a CAD model input into software at the machine's interface, which then meticulously arranges the design and constructs support structures. Consequently, post-processing steps are often indispensable, including the removal of the part from the base plate, elimination of support structures, and occasionally, polishing and heat treating to mitigate residual stresses in the parts.In the context of applying AI in additive manufacturing (AM), it is imperative to categorize the applications into pre-process, process, and post-process stages. The pre-process stage involves utilizing machine learning (ML) in design space, raw materials design, and powder properties. ML applications are distinctly classified into experimental work on process monitoring and optimization, as well as simulation work in the process stage. Additionally, ML has made significant advancements in materials and design space through the Materials Genome Initiative (MGI) by the US government, which has been instrumental in driving computational materials science for the design and manufacturing of new materials with diverse properties.The comprehensive review of machine learning (ML) in materials, along with the extensive data available through databases, highlights the potential for ML to significantly enhance user interaction with machines and design software in the additive manufacturing (AM) field. Additionally, AI's capabilities in image and voice recognition have the power to revolutionize human-machine interaction. Furthermore, AI applications in image recognition for 3D scanning and modeling are proving to be invaluable. Recognition significantly improves the 3D scanning process for creating models of parts and facilitates user access to CAD models from internet databases. It also empowers the use of the internet of things and digital space for accessing available designs. Software must be adapted to fully leverage additive manufacturing process capabilities in microstructural design and bottom-up processing, enabling a more informed design process.The utilization of tailored and directional properties will revolutionize design optimization and lead to the development of cutting-edge design software. Recent advances in concurrent design involve dynamically modifying the design during the build process to effectively tackle issues like residual stresses or defects. This demands a profound understanding of how design parameters influence these factors. Furthermore, an in-situ process monitoring feedback loop is imperative to effectively guide the designprocess.[4][5]The most widely accepted definition of AI (artificial intelligence) states that it is the science of constructing programs for computerized machines to react and perform tasks similar to humans .AI involves making computerized machines intelligent and capable of decision-making comparable to humans through various programming methods. It is utilized in planning and operational systems, product design, and manufacturing applications. AI predicts, diagnoses, and detects damages and failures in manufacturing, aids in design optimization, and streamlines the repairing process. It also expedites the topology optimization process and contributes to sustainable computing. AI has a positive impact on additive manufacturing (AM) by analyzing and optimizing component printability, controlling process quality, and identifying part functionality. The integration of subtractive and additive manufacturing with AI techniques can effectively address optimization complexities.AI-based optimization encompasses various types, such as fuzzy logic, artificial neural networks, particle swarm optimization, and genetic algorithms, all playing a crucial role in additive manufacturing (AM) to optimize components. Implementing AI is essential to reduce manual work, provide quick solutions, and enhance tool life prediction accuracy. The systematic guidelines for integrating AI technologies into an industrial ecosystem involve four main steps: data technology, analytical technology, platform technology, and operations technology.[5][6]The concept of 4D printing involves the transformation of a 3D-printed object's shape, properties, and functionality over time in response to external stimuli. These stimuli can be physical (such as temperature, electromagnetic fields, humidity, UV light, and mechanical forces) or chemical (like pH and chemical reactions). Intelligent structures created through 4D printing can perform specific tasks, such as drug delivery or actuation through multistable topologies, by altering their shapes or enabling dynamic properties. These unique properties make 4D-printed components highly appealing across various fields, from engineering to medicine.For example, bio-inspired mechanisms designed to replicate natural movements, and microrobots that move in response to magnetic fields and light for drug delivery, are notable applications of 4D printing. Additionally, 4D-printed parts can be utilized in robotics for a broad range of applications, including actuators, grippers, sensors, and deployable structures.In tissue engineering, smart materials and composites are being developed to replace complex tissues with adaptable structures that can respond to specific stimuli to release drugs or particles for reducing inflammation, treating diseases, or targeting tumors. Additive manufacturing is used to create structures that can mimic the functions of natural tissues.The versatility of smart inks in 4D printing allows for the creation of soft devices that can change shape in response to external stimuli. Integration of artificial intelligence can open new possibilities for shape programming, enabling the fabrication of wearable devices that can adjust to body movements or implants that can adapt to their anatomical location.Beyond the realm of 4D printing, it is seen as a key technology for emulating the characteristics of living organisms, such as sensing and self-repair capabilities, which are highly sought after for structural applications in sectors like aerospace and bioengineering.[6]

## RESULTS

Machine learning (ML) and artificial intelligence (AI) have been underutilized in the later stages of additive manufacturing (AM) due to missed opportunities for in-process control and improvement. However, data collected during processing can still refine future production processes. Quality issues, such as defects and surface smoothness, can be attributed to initial design and materials. Fatigue is a critical concern for AM parts, especially in high-temperature environments like jet engines. Researchers are exploring machine learning to predict long-term material behavior and fatigue life. Additive manufacturing processes are susceptible to defects, and studies have focused on evaluating porosity using machine learning algorithms. Furthermore, a study has analyzed the significant impact of part location and pressure drop on the mechanical properties of printed parts. There is a significant opportunity to leverage machine learning to assess surface roughness and microstructural variations in additive manufacturing. Integrating knowledge-based optimization techniques, such as artificial neural networks (ANN), genetic algorithms (GA), particle swarm optimization, and fuzzy logic, with additive manufacturing (AM) and artificial intelligence (AI) can significantly improve the design process, enhance process efficiency, and facilitate decision-making. Utilizing AI techniques in various AM applications can lead to better design optimization, particularly for complex geometries, and support the overall restoration process. Effective hybrid techniques must leverage the strengths of individual algorithms, possess a reliable database, and prioritize supporting product design and cost optimization for restoration purposes from the outset.

The rise of machine learning has enabled the integration of artificial intelligence into additive manufacturing, leading to the development of closed-loop AM systems and digital twins (DT). This inhibits various components of a closed-loop system and acknowledges artificial intelligence as a key driver for advancing manufacturing into the fourth industrial revolution. Technological advancements in data capture and cloud computing play instrumental roles in this evolution. While redesign optimization of large parts using Additive Manufacturing (AM) may not be cost-effective due to high costs, it can still enhance performance. However, challenges exist in estimating the remaining useful life of complex components and implementing design optimization in the AM field. Environmental concerns, such as reducing energy consumption, materials, and pollutants, are also important. Prioritizing early design for product restoration and the circular economy is crucial.

Training a neural network (ANN) necessitates a substantial amount of data or training samples. The success of training an ANN depends on the size and quality of the dataset. More data leads to higher prediction accuracy. Training is considered complete when the network can accurately predict outcomes based on user-defined criteria. However, training ANNs can be time-consuming. Therefore, there's a significant need to reduce the time it takes to train ANNs without compromising the quality and accuracy of the predictions.

## CONCLUSIONS

The emergence of machine learning has paved the way for the integration of artificial intelligence into additive manufacturing, enabling the development of closed-loop AM systems and digital twins (DT). Various components of a closed-loop system are outlined in this comprehensive paper. Artificial intelligence is recognized as a key driver for advancing manufacturing into the fourth industrial revolution. Technological progress in data capture and cloud computing is also instrumental in this evolution. Redesign optimization of large parts using Additive Manufacturing (AM) may not be cost-effective due to high costs, but it can still improve performance. Challenges include estimating the remaining useful life of complex components and implementing design optimization in the AM field. Environmental concerns such as reducing energy consumption, materials, and pollutants are also important. Prioritizing early design for product restoration and the circular economy is crucial.

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