KSÜ Mühendislik Bilimleri Dergisi, 28(1), 2025
Derleme Makale

KSU J Eng Sci, 28(1), 2025
Review Article

Kahramanmaras Sutcu Imam University
Journal of Engineering Sciences

Geliş Tarihi : 03.12.2024
Kabul Tarihi :27.12.2024

Received Date : 03.12.2024
Accepted Date : 27.12.2024

A LITERATURE REVIEW OF LASER ENGINEERED NET SHAPING IN ADDITIVE MANUFACTURING USING ARTIFICIAL NEURAL NETWORKS

YAPAY SİNİR AĞLARI KULLANILARAK KATMANLI ÜRETİMDE LAZERLE TASARLANMIŞ AĞ ŞEKİLLENDİRME ÜZERİNE BİR LİTERATÜR İNCELEMESİ

Filiz KARAOMERLIOGLU[1,2*] (ORCID: 0000-0002-4677-4365)
Mustafa UCAR[2] (ORCID: 0000-0002-1851-2317)

[1]Department of Electrical Electronics Engineering, Mersin University, Mersin, Turkey
[2]Department of Nanotechnology and Advanced Materials, Mersin University, Mersin, Turkey

*Sorumlu Yazar / Corresponding Author: Filiz KARAOMERLIOGLU, filizkrm@mersin.edu.tr

ABSTRACT

This review explores the integration of machine learning (ML) and artificial neural networks (ANNs) in optimizing alloy production modeling and print control within Laser Engineered Net Shaping (LENS), a key additive manufacturing process. It investigates theoretical foundations, methodologies, case studies, and emerging trends to enhance process efficiency, improve product quality, and accelerate production cycles. A comprehensive literature review was conducted across academic databases and industry reports using keywords such as "machine learning," "artificial neural networks," and "Laser Engineered Net Shaping." Both theoretical and experimental perspectives were analyzed to provide a well-rounded discussion. Findings indicate that ML and ANN models enhance understanding of alloy production, optimizing configurations and reducing defects. Real-time ML-driven optimization enables adaptive adjustments to process parameters, ensuring improved quality and accuracy. ANNs effectively predict key alloy microstructure properties, supporting informed decision-making and process refinement. Integrating ML and ANNs into LENS facilitates adaptive manufacturing, dynamically responding to changing conditions and alloy compositions.

Keywords: Artificial neural networks, laser engineered net shaping, 3d print control, process optimization

ÖZET

Bu derleme, makine öğrenimi (ML) ve yapay sinir ağlarının (YSA), önemli bir eklemeli üretim süreci olan Laser Engineered Net Shaping (LENS) içinde alaşım üretim modellemesi ve baskı kontrolünü optimize etmek amacıyla entegrasyonunu incelemektedir. Süreç verimliliğini artırmak, ürün kalitesini iyileştirmek ve üretim döngülerini hızlandırmak için teorik temeller, metodolojiler, vaka çalışmaları ve yeni ortaya çıkan trendler araştırılmıştır. Akademik veri tabanları ve endüstri raporları üzerinde kapsamlı bir literatür taraması gerçekleştirilmiş, "makine öğrenimi", "yapay sinir ağları" ve "Laser Engineered Net Shaping" gibi anahtar kelimeler kullanılmıştır. Konuya dengeli bir bakış açısı sunmak amacıyla hem teorik hem de deneysel çalışmalar analiz edilmiştir. Bulgular, ML ve YSA modellerinin alaşım üretim süreçlerini daha iyi anlamayı sağladığını, konfigürasyonları optimize ettiğini ve kusurları azalttığını göstermektedir. Gerçek zamanlı ML tabanlı optimizasyon, işlem parametrelerinin adaptif olarak ayarlanmasını sağlayarak kaliteyi ve doğruluğu artırır. YSA'lar, alaşım mikro yapısına ilişkin temel özellikleri başarılı bir şekilde tahmin ederek bilinçli karar alma ve süreç iyileştirmeye katkıda bulunur. ML ve YSA'ların LENS'e entegrasyonu, değişen koşullara ve alaşım bileşimlerine dinamik olarak uyum sağlayan adaptif üretimi mümkün kılar.

Anahtar Kelimeler: Yapay sinir ağları, lazerle tasarlanmış net şekillendirme, 3d baskı kontrolü, süreç optimizasyonu

ToCite: KARAOMERLIOGLU, F., & UCAR, M., (2025). A LITERATURE REVIEW OF LASER ENGINEERED NET SHAPING IN ADDITIVE MANUFACTURING USING ARTIFICIAL NEURAL NETWORKS. *Kahramanmaraş Sütçü İmam Üniversitesi Mühendislik Bilimleri Dergisi*, 28(1), 551-582.

INTRODUCTION

Additive manufacturing (AM), commonly referred to as 3D printing, has been experiencing a surge in popularity in recent years due to its numerous advantages over traditional manufacturing methods. Among the leading AM techniques, Laser Engineered Net Shaping stands out as a versatile tool capable of producing complex components with fine-tuned geometries for various industrial applications (Sames et al., 2016; Bennett et al., 2016; Gorunov, 2018). However, the quality of parts produced by LENS is strongly influenced by process parameters such as laser power, scanning speed, beam spot size and powder feed rate. If these parameters are not optimised, they can lead to defects such as porosity and cracks, causing problems with the mechanical properties and structural integrity of the final components (Grasso and Colosimo, 2017; Fu et al., 2016; Sterling et al., 2016).

Based on expertise and experience, traditional optimisation methods often struggle to provide a comprehensive understanding of the relationships between process parameters and part properties, given the inherent complexity of the AM process (Kumar et al., 2022).

The advent of machine learning techniques, in particular Artificial Neural Networks, offers a promising solution to overcome these challenges. ANNs excel at recognising complex patterns and developing deterministic relationships, thus eliminating the need for physical models. Unlike traditional approaches, machine learning-based optimisation facilitates decision-making processes, allowing informed choices to be made about critical factors such as component and support structure design.

The wide range of applications and increasing applicability of machine learning techniques, previously considered impractical, have facilitated their integration into the modern era. With its adoption in manufacturing, industries have started to use machine learning more frequently to realise economic benefits. Today, the manufacturing sector is undergoing significant transformations driven by smart manufacturing and Industry 4.0. Despite this progress, some sectors, especially mid and low-capitalisation companies, continue to show reluctance due to the costs associated with implementation and concerns about training.

Recent studies have shown the effectiveness of machine learning in optimizing AM process parameters and predicting the properties of printed parts. Chen et al. (2021) used machine learning to develop a model for predicting the porosity of LENS printed parts, while Zhang et al. (2021) and Yang et al. (2015) used machine learning to predict fatigue life and crack growth rate, respectively. These studies highlight the growing interest and potential of machine learning in improving the quality, reliability, and efficiency of the AM process.

This review paper aims to comprehensively analyse the current state-of-the-art machine learning-based optimisation of AM processes. By synthesising findings from various studies, it explores the benefits offered by these advanced techniques, including reduced manufacturing time and cost, improved part quality and reliability, improved support structure design and part orientation. The insights gained from this review will serve as valuable guidance for researchers and practitioners seeking to utilise machine learning to improve the efficiency, quality and sustainability of AM production.

RATIONALE

This study is needed to explore the application of machine learning (ML) and artificial neural networks (ANNs) to enhance alloy production modelling and print control within Laser Engineered Net Shaping (LENS), an additive manufacturing process. The objective is to investigate theoretical foundations, methodologies, case studies, and emerging trends in leveraging ML and ANNs to optimize process parameters, improve product quality, and accelerate production cycles in LENS technology.

THE AUDIENCE IT IS INTENDED FOR

The target audience for this study includes researchers, practitioners, and industry professionals interested in the application of machine learning and artificial neural networks to enhance alloy production modelling and print control within Laser Engineered Net Shaping (LENS), an additive manufacturing process. The study aims to provide valuable insights and guidance for those seeking to leverage ML and ANNs to optimize process parameters, improve product quality, and accelerate production cycles in LENS technology.

SURVEY METHODOLOGY

The objective of this survey is to provide a comprehensive overview of the current state of research on the integration of Machine Learning (ML) techniques in Additive Manufacturing (AM). To achieve this, a systematic approach was employed to gather, analyze, and synthesize relevant literature, ensuring an unbiased representation of the field.

LITERATURE SEARCH STRATEGY

A multi-faceted literature search strategy was implemented to identify pertinent studies. The following steps were undertaken:

Database Selection: Key academic databases were selected for the literature search, including IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, and Web of Science. These databases were chosen due to their extensive collections of peer-reviewed articles, conference papers, and technical reports relevant to both Machine Learning and Additive Manufacturing.

Keyword Identification: A comprehensive list of keywords and phrases was developed to capture the breadth of the topic. Keywords included “Machine Learning”, “Additive Manufacturing”, “3D printing”, “process optimization”, “quality control”, “intelligent manufacturing”, “artificial neural networks”, “Laser Engineered Net Shaping”, “alloy production modelling”, “3D print control”, “real-time monitoring”, “adaptive manufacturing” and “metal 3D printing”. Boolean operators (AND, OR) were utilized to refine the search results and ensure that relevant articles were not overlooked.

Inclusion and Exclusion Criteria: Clear inclusion and exclusion criteria were established to filter the literature. Studies were included if they:
• Focused on the application of Machine Learning techniques in Additive Manufacturing.
• Were published in peer-reviewed journals or reputable conference proceedings.
• Provided empirical data, case studies, or theoretical frameworks relevant to the topic.
Conversely, studies were excluded if they:
• Were not published in English.
• Focused on traditional manufacturing processes without an emphasis on Additive Manufacturing.
• Did not include a significant discussion of Machine Learning applications.

DATA EXTRACTION AND ANALYSIS

Systematic Review Process: The literature was reviewed systematically, with each study evaluated for its relevance, methodology, findings, and contributions to the field. A standardized data extraction form was used to capture key information from each article, including authorship, publication year, research focus, ML techniques employed, and outcomes related to AM.

Thematic Analysis: The extracted data were subjected to thematic analysis to identify common themes, trends, and gaps in the literature. This analysis facilitated the categorization of studies into various domains, such as process parameter optimization, quality control, material discovery, and predictive modeling.

Quality Assessment: To ensure the reliability and validity of the included studies, a quality assessment was conducted using established criteria, such as the rigor of the methodology, the robustness of the results, and the clarity of the conclusions. This assessment helped to mitigate bias and enhance the credibility of the survey findings.

ENSURING COMPREHENSIVE AND UNBIASED COVERAGE

To ensure comprehensive and unbiased coverage of the literature, several strategies were employed:

Diverse Sources: The literature search encompassed a wide range of sources, including journals from different disciplines (engineering, computer science, materials science) to capture interdisciplinary perspectives on the integration of ML in AM.

Timeframe Consideration: The search included both recent studies and seminal works in the field, allowing for a thorough understanding of the evolution of research on ML applications in AM.

Citation Tracking: The reference lists of key articles were examined to identify additional relevant studies that may not have been captured in the initial search. This snowballing technique helped to uncover influential works and ensure a more exhaustive literature review.

Expert Consultation: Feedback from academic peers and advisors with expertise in Machine Learning and Additive Manufacturing was sought to validate the relevance and comprehensiveness of the literature included in the survey.

ADDITIVE MANUFACTURING TECHNIQUES

ISO/ASTM 52900:2021, a comprehensive standard for additive manufacturing, categorises the various additive manufacturing techniques under 7 headings in alphabetical order in section "3.2 Process Categories". These categories cover a range of innovative processes that transform the production environment:

Binder Jetting (BJT) (Standard Heading No: 3.2.1): Binder Spraying involves the selective release of a liquid binder to join powder materials and offers a versatile approach to forming complex components.

Directed Energy Deposition (DED) (Standard Heading No: 3.2.2): Directed Energy Deposition utilises focused thermal energy, such as a laser or electron beam, to melt and fuse materials as they are deposited, enabling precise and efficient production.

Material Extrusion (MEX) (Standard Heading No: 3.2.3): Material Extrusion is a process in which material is selectively dispensed through a nozzle or orifice, allowing complex structures to be formed layer by layer.

Material Jetting (MJT) (Standard Heading No: 3.2.4): Material Spraying involves selectively depositing droplets of raw materials such as photopolymer resin and wax to form the desired object with high precision and detail.

Powder Bed Fusion (PBF) (Standard Heading No: 3.2.5): Powder bed fusion selectively fuses regions of a powder bed using thermal energy and offers a method for producing complex and functional parts with high accuracy.

Sheet Lamination (SHL) (Standard Heading No: 3.2.6): Sheet Lamination provides a cost-effective and efficient way to produce components with varying geometries by combining layers of material to form a part.

Vat Photopolymerisation (VPP) (Standard Heading No: 3.2.7): Vat Photopolymerisation involves the selective curing of liquid photopolymer in a container through light-activated polymerisation, enabling the creation of detailed and complex parts at high resolution.

These standardised processes play an important role in the development of additive manufacturing technologies, offering diverse capabilities to meet the evolving needs of modern manufacturing industries.

DIRECTED ENERGY DEPOSITION (DED)

Directed Energy Deposition (DED) is a revolutionary additive manufacturing process that harnesses the power of high-energy beams to precisely join metal powders or wires layer by layer on a substrate. This innovative technique has emerged as a game-changer in the manufacturing environment, offering unique capabilities in the production of complex parts with exceptional strength and surface quality.

Main features

Accelerated Deposition Speed: DED's ability to deposit material quickly allows for significant reductions in production time and costs, making it an attractive option for manufacturers looking to streamline their operations.

Unparalleled Geometric Complexity: The versatility of DED enables the creation of complex parts with features that are impossible or extremely challenging to produce using conventional manufacturing methods, opening up new possibilities for designers and engineers.

Improved Material Properties: The resulting parts exhibit superior strength and surface finish. This makes them ideal for applications where performance and reliability are paramount.

Material Diversity: DED's compatibility with a wide range of materials, including metals, composites and ceramics, expands its potential applications in various industries.

Industry applications

Aviation: DED is used in the production of critical aircraft components such as turbine blades, landing gear and structural components where high strength, low weight and precise surface finish are required.

Automotive: This technology is well suited to the production of complex automotive parts where high performance and durability are paramount, including engine blocks, transmission components and suspension parts.

Medical: DED is ideal for creating medical devices such as implants, prostheses and surgical instruments where biocompatibility, precision and surface quality are critical.

Benefits

Cost Savings: DED offers manufacturers significant cost-saving opportunities by enabling the production of complex parts with less material wastage and accelerated production cycles.

Improved Part Quality: The ability of the technology to produce parts with consistent properties, high strength and excellent surface quality ensures that the final product meets the highest quality and performance standards.

Freedom of Design: The capabilities of DED allow designers to push the boundaries of part design, creating complex geometries that are not possible or practical to produce by conventional methods.

Environmental Benefits: WIA contributes to a more sustainable production environment by reducing material wastage and energy consumption.

Challenges and limitations

Initial Investment Cost: The high cost of HIA equipment can be a significant barrier to entry for small businesses or start-ups.

Operator Training: The technology requires specialised training which may limit the availability of qualified operators.

Process Control: Ensuring consistent quality and performance in the complex HIA process can be challenging and requires careful process control and monitoring.

Material Availability: The limited availability of certain materials in powder or wire form can limit the application range of DED.

Despite these challenges, Directed Energy Deposition is a technology with enormous potential, offering manufacturers a powerful tool for creating complex parts with exceptional properties. As technology continues to develop, it is likely to play an increasingly important role in shaping the future of manufacturing.

LASER ENGINEERED NET SHAPING (LENS)

LENS is a versatile additive manufacturing technique that uses directed energy deposition to produce complex metal parts, repair high-value components and enable hybrid manufacturing approaches. Developed and patented by Optomec Inc., LENS has been widely adopted in various industries due to its unique capabilities.

Main features

The LENS process involves the controlled exposure of metal powder to a high-energy laser beam. The powder is melted and fused with a substrate or pre-deposited layers to form a three-dimensional structure. The coaxial powder delivery system used in LENS provides precise control over material deposition, enabling increased part quality and accuracy.

An important feature of the LENS technology is the coaxial powder distribution system. In this configuration, metal powder is fed directly into the laser beam through a coaxial nozzle. This setup ensures a consistent and accurate powder flow, enabling the production of complex geometries and high-quality parts.

The LENS technology is compatible with a wide range of metal powders, including stainless steel, titanium alloys and nickel-based superalloys. These powders are carefully selected and designed to have specific properties, such as particle size distribution and flowability, to optimise the material deposition process and provide the desired part properties.

The LENS process uses a high-power laser to create a focused beam that provides the heat necessary to melt and fuse the metal powder. The laser system includes advanced controls for precise power modulation, scanning speed and beam diameter, allowing fine-tuning of process parameters to achieve the desired results.

The LENS technology offers several advantages over traditional manufacturing techniques. The ability to produce near-net shape parts reduces material wastage and the need for extensive machining. In addition, LENS provides excellent material properties, improved part accuracy and the flexibility to integrate multiple materials into a single structure.

Industry applications

Some examples of industrial products that can be produced using LENS technology in additive manufacturing are as follows:
Aviation Components: The LENS technology can be used in the manufacture of complex components such as turbine blades, engine parts and structural components for the aerospace industry. The ability to produce complex geometries and high-quality metal parts makes LENS suitable for aerospace applications.

Power Transmission Parts: Industrial products such as power transmission components such as gears, shafts and housings can be manufactured using LENS technology. The precision and material properties offered by LENS make it ideal for producing durable and high-performance parts for power transmission systems.

Heavy Industry Equipment: LENS technology is applicable in the production of heavy industrial equipment, including specialised machine parts, tooling components and wear-resistant surfaces. The versatility of LENS in the manufacture of large-scale parts with complex geometries makes it valuable in heavy industry applications.

Precision Components: LENS technology can be used to produce precision components for a variety of industrial sectors, including automotive, medical and instrumentation. The high accuracy and material properties achievable with LENS make it suitable for manufacturing components that require tight tolerances and complex designs.

In summary, industrial products such as aerospace components, power transmission parts, heavy industrial equipment, optical components and precision parts can be effectively manufactured using LENS technology in additive manufacturing processes.

LENS technology has been applied in various industrial sectors, including
Aerospace: LENS technology has been used in the repair and manufacture of aerospace components such as compressor blades and exhaust ducts.

Power Generation: LENS technology is applied in the power generation sector for the manufacture of components such as enclosures and other parts.

Oil and Gas: LENS technology is used in the oil and gas industry for the repair and manufacture of components such as pipes and valves.

Medical: LENS technology is applied in the medical sector for the manufacture of specialised implants and other medical devices.

Automotive: LENS technology is used in the automotive industry for the repair and manufacture of components such as engine parts and other vehicle components.

Heavy Industry: LENS technology has been applied in the heavy industry sector for the manufacture of large, complex components such as gears and other mechanical parts.

Smart Technologies: LENS technology has been applied in the smart technologies sector to manufacture components such as sensors and other electronic devices.

Electronics: LENS technology is used in the electronics industry for the manufacture of components such as printed circuit boards and other electronic devices.

Defence: LENS technology is applied in the defence sector in the manufacture of components such as military equipment and other defence-related devices.

These examples demonstrate the versatility and industrial applicability of LENS technology in additive manufacturing, which can be used in the manufacture of a wide range of components and products in various industries.

Benefits

The main benefits of using LENS technology in additive manufacturing for industrial applications are as follows:
Reduced Production and Material Costs: LENS technology offers lower manufacturing and material costs compared to conventional manufacturing methods. The DED process used in LENS can be more cost-effective than other additive manufacturing techniques.

Compared to other additive manufacturing techniques, the cost of LENS technology is advantageous in terms of depositing different materials in a single structure and adding metal at a lower cost. LENS and other DED technologies offer cost advantages over conventional manufacturing methods in terms of material deposition efficiency and potentially reduced overall costs. This cost efficiency can be attributed to the ability of LENS technology to deposit different materials in a single structure, increasing manufacturing flexibility and cost-effectiveness.

Reduced Processing Time: The LENS process can enable faster production of parts and components by reducing the overall production time compared to conventional methods.

Reduced Environmental Impact: LENS technology has less environmental impact compared to conventional manufacturing as it can lead to less material wastage and more efficient production processes.

Improved Product Performance: LENS technology is capable of producing parts with superior material properties such as high density, minimal heat-affected zones and the ability to process a wide range of metals, including non-reactive and reactive materials. This will result in improved performance of final industrial products.

Ability to Produce Complex Geometries: The LENS process enables the manufacture of parts with complex geometries and intricate designs that can be useful for industrial applications requiring customised or specialised components.

Repair and Refurbishment Capabilities: LENS technology can be used to repair and refurbish high-value industrial components, extending their life and reducing the need for replacement. This will be cost-effective for industrial operations.

Challenges and limitations

Limitations of LENS Technology can be summarised as follows;
Optimising Material Properties: One of the limitations of LENS technology is the challenge of optimising material properties to meet specific requirements that can affect the final quality and performance of the manufactured parts.
Residual Stresses and Distortion: LENS technology faces challenges in reducing residual stresses and distortion during the manufacturing process that can affect the structural integrity and dimensional accuracy of manufactured components.

Ensuring Consistent Part Quality: Maintaining consistent part quality throughout the additive manufacturing process can be a limitation of LENS technology and requires meticulous attention to detail and precise control over various parameters.

Process Optimisation: The need for continuous process optimisation is a major limitation of LENS technology, as fine-tuning parameters such as laser power, scanning speed and powder distribution is necessary to achieve the desired results.

Control over Powder Distribution: Effective control over powder distribution, especially with complex geometries or intricate parts, can be challenging with LENS technology and is important enough to affect the uniformity and integrity of the final product.

Heat Management: Proper heat management is crucial in LENS technology to avoid problems such as overheating, warping or inconsistent material properties, emphasising the importance of precise temperature control throughout the process.

Compatible Material Range: While LENS technology offers versatility in material selection, there will be limitations in the range of compatible materials that can be used effectively, restricting the applicability of this technology in certain industries or applications.

Consequently, while LENS technology offers numerous advantages in additive manufacturing, including precision material deposition and the fabrication of complex geometries, addressing these limitations through careful management of material properties, process optimisation and quality control measures is essential to maximise its effectiveness and applicability in production.

BENEFITS OF ON-SITE PROCESS MONITORING

LENS requires on-site process monitoring techniques to ensure quality control. These techniques will include thermal imaging, spectroscopy and real-time feedback systems, allowing the detection of defects and adjustment of process parameters. Ongoing research at LENS focuses on achieving full process control, improving material properties and expanding the range of compatible materials. With advances in powder dispensing systems, in-situ monitoring and hybrid manufacturing approaches, the future of LENS is promising.

LENS technology has revolutionised the field of metal additive manufacturing, offering a unique combination of precision, accuracy and material properties. Its wide range of applications and advantages over conventional manufacturing techniques make it an attractive solution for industries looking to produce complex metal parts.

EFFECTS OF LENS TECHNOLOGY ON THE ACCURACY OF THE FINAL PRODUCT

The LENS technology significantly impacts the accuracy of the final product by offering precise control over material deposition and enabling complex geometries to be produced with high accuracy. The technology's ability to create a focused laser beam that melts and fuses metal powder onto a substrate allows parts with tight tolerances and complex designs to be produced. In addition, LENS technology provides advanced controls for power modulation, scan speed and beam diameter, improving the accuracy of the manufacturing process. The surface finish, microstructure and mechanical properties of the final product are influenced by the optimisation of the LENS technology, ensuring that the manufactured components meet the required specifications with high precision and accuracy.

COST-SAVING MEASURES BY USING LENS TECHNOLOGY

Efficient Material Accumulation: Optimising the material deposition process in LENS technology will help to reduce material wastage and improve efficiency, leading to cost savings in additive manufacturing Achieving precise control over material usage and deposition will help to minimise material costs.

Reduced Finishing: Minimising the need for extensive post-processing steps will contribute to cost savings when using LENS technology. By producing parts with high surface quality and precision directly from the additive manufacturing process, the dependency on costly finishing processes will be reduced.

Supply Chain Optimisation: Utilising the capabilities of LENS technology to streamline production and reduce the number of parts to be stored and transported will lead to cost savings in the supply chain. This optimisation will lead to lower storage and transportation costs, contributing to overall efficiency and expense reduction.

Efficient Production of Low-Volume Parts: LENS technology is particularly beneficial for low-volume and small-scale production, where the benefits of additive manufacturing can outweigh the costs associated with mass production. Cost savings can be achieved by focusing on efficiently producing customised, low-volume parts.

Design Flexibility and Innovation: Taking advantage of the design flexibility offered by LENS technology can lead to cost savings through innovative part designs that optimise material utilisation and production efficiency. Designing parts specifically for additive manufacturing will help reduce costs associated with traditional manufacturing constraints.

In summary, the application of measures such as efficient material deposition, reduced post-processing, supply chain optimisation, focus on low-volume production and exploiting design flexibility using LENS technology can help to achieve cost savings in additive manufacturing processes.

POTENTIAL OF USING ML AND ARTIFICIAL NEURAL NETWORK (ANN) FOR PRINT CONTROL IN LENS

The manufacturing process in DED methods has emerged as a promising additive manufacturing technique, offering the ability to produce complex geometries and functional parts directly from computer-aided design (CAD) models. However, maintaining precise control over the printing process remains a significant challenge. Factors such as laser power, scanning speed, powder feed rate and flap gap can significantly affect the quality and consistency of printed parts (Gu, 2018). Improper adjustment of these parameters can lead to defects such as porosity, lack of fusion and residual stresses. These are conditions that can jeopardise the mechanical properties and performance of the final product (Vaezi et al., 2013).

To overcome these challenges, researchers have investigated the potential of ML and ANNs to improve print control in DED. Machine learning algorithms can learn from data and identify models that can be used to optimise process parameters and predict part quality (Tapia and Elwany, 2017). For example, Gobert et al. (2018) demonstrated the use of convolutional neural networks (CNNs) to detect defects in real-time during the LENS process, enabling immediate corrective measures to be taken.

Inspired by the structure and function of the human brain, ANNs also hold promise for improving print control in LENS. ANNs can learn complex relationships between input parameters and output responses, making them well-suited for modelling and predicting the behaviour of the LENS process. Researchers have used ANNs to optimise process parameters such as laser power and scanning speed to achieve desired part features (Ding et al., 2016). In addition, ANNs have been used to predict melt pool geometry and temperature distribution in LENS, which are critical factors in determining the quality and integrity of printed parts (Heralić et al., 2012).

Despite these developments, the integration of ML and ANN into LENS systems is still in its infancy. Challenges such as the need for large datasets, computational complexity, and model interpretability need to be addressed before these technologies can be widely adopted in industrial settings (Caiazzo and Caggiano, 2018). Furthermore, the development of robust and reliable in situ monitoring systems is crucial to provide the necessary data for ML and ANN models to learn and adapt to changing process conditions (Everton et al., 2016).

In conclusion, the feasibility of print control in LENS is significantly improved by the application of ML and ANNs. These technologies offer the potential to optimise process parameters, predict part quality and enable real-time process control, ultimately leading to increased consistency and reliability of parts produced by LENS. However, further research and development is needed to overcome the challenges associated with the application of ML and ANNs in LENS systems.

OPTIMISING PROCESSES, INCREASING PRODUCTIVITY AND QUALITY WITH MACHINE LEARNING IN ADDITIVE MANUFACTURING

The manufacturing industry, especially the Additive manufacturing (AM) and 3D printing sectors is generating large amounts of data during this fourth industrial revolution, often referred to as "Industry 4.0" (Alabi, 2018; Xing et al., 2020). AM technologies are important elements of the Industry 4.0 concept and enable the creation of physical objects from 3D modelling data by layering or solidifying materials (Guo and Leu, 2013; Kulkarni et al., 2000). As shown in Table 1, AM has been successfully used in the development of 3D structures using various materials. However, optimising AM processes in design, manufacturing and process control requires significant knowledge transfer from operators and designers (Wang et al., 2020). To fully utilise the benefits of AM, design, process and manufacturing are becoming increasingly complex (Jia et al., 2021; Wang et al., 2020). Major design changes often require an in-depth understanding of variables and their corresponding effects on part behaviour, which is time-consuming and computationally intensive.

Table 1. Metals/Alloys Commonly Used For Commercial Use Of AM (Frazier, 2014)

Titanium	Aluminum	Tool Steels	Super Alloys	Stainless Steel	Refractory
Ti-6Al-4V	Al–Si–Mg	H13	IN625	316 ve 316L	MoRe
ELI Ti	6061	Cermets	IN718	420	Ta-W
CP Ti			Stellite	347	CoCr
γ-TiAl				PH 17–4	Alümina

Limited orthogonalisation (steepening) is reported in AM processes, where increasing one parameter can adversely affect another. For example, increasing extrusion temperatures can improve layer adhesion but also increase shrinkage. Fine-tuning workflow variables for specific parts or innovative materials can be time-consuming and uneconomical (Qi et al., 2019). In industries that support AM integration, such as aerospace, component consistency is crucial. However, variations in component quality will prevent wider acceptance. Managing and evaluating large amounts of data and information is part of these challenges. Machine Learning (ML) algorithms have the potential to help alleviate these issues by reducing the amount of human or computational work required to achieve satisfactory results (Kumar et al. 2023).

Compared to conventional manufacturing methods, AM offers several advantages for the manufacture of components with increasingly complex structures and designs at macro, medium and micro scales, and the ability to adapt to mass-produced parts (Ahlers et al., 2019). Despite these advantages, there are also some disadvantages such as the lack of basic consistency (Dowling et al., 2020). This has made certification problematic in various industries (Thompson et al., 2016). Another limitation is the lack of accurate and sufficient information on design guidelines (Thompson et al., 2016).

Beyond the ability to generate predefined predictions through data modelling, experts are exploring creative and novel techniques to incorporate ML algorithms into AM processes (Kumar et al., 2023). ML techniques, applications and frameworks are used by AM professionals to improve quality, optimise manufacturing processes and reduce costs (Sutton and Barto, 2015).

Although AM has been around since the 1980s, it gained popularity after the expiry of important patents (20 years of patent protection), especially for consumer-grade 3D printing technology. Research in machine learning has been conducted since around 1960 (Widrow and Lehr, 1990). However, it has recently gained attention due to the outstanding results produced by research organisations and commercial organisations such as Google. Different studies are now specialising in additive manufacturing research that can address fundamental and complex challenges through machine learning approaches. This era is witnessing the creation of large databases as a significant amount of information is generated daily in various networks, including manufacturing, online networks, pharmaceuticals, aerospace, 3D printing, automotive and telecommunications.

Machine Learning (ML), a discipline of Artificial Intelligence (AI), enables devices to learn from various datasets and perform intelligent tasks by leveraging existing data rather than following pre-programmed instructions (Kumar et al., 2023). ML has a crucial role in managing the large amount of data collected during the Additive Manufacturing (AM) creation process. As the demand for industrial additive machines and 3D desktop printing devices increases, there are challenges in producing defect-free components or finished products that meet high-quality standards. Recent studies have identified parameter variations during construction as factors influencing defects in the AM sector. Addressing these variations can help to identify potential problem areas in the final product and improve construction procedures and cost reduction strategies. Computer vision, estimation and information retrieval are key components directly applicable to AM processes. Advances in graphics hardware have facilitated in-depth investigations and enabled rapid optimisation of machine learning algorithms on extensive datasets (Shinde and Shah, 2018). These developments pave the way for the effective use of ML solutions in AM to increase productivity.

Figure 1a shows the ML taxonomy and its applications in AM. Among the machine learning approaches, Artificial Neural Networks (ANNs) have grown tremendously in importance with the advances in processing power, especially with the use of GPUs for improved computational capabilities. An ANN consists of multiple layers, each containing elementary neurons (Figure 1b).

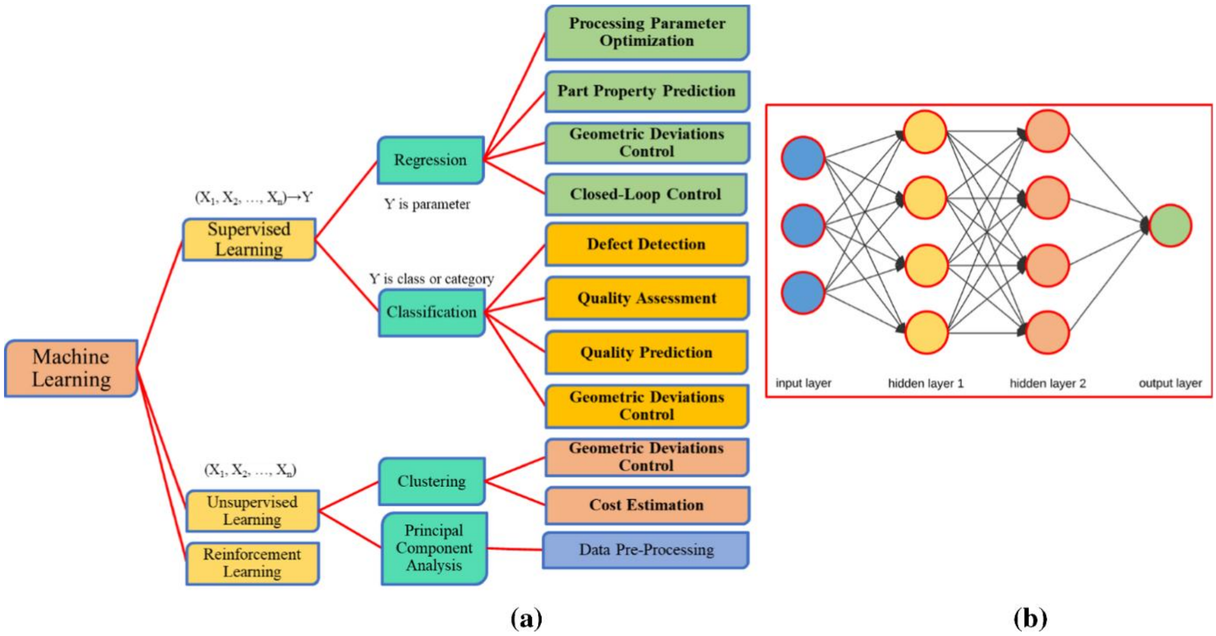

Figure 1. (a) Shows The Classification Of Machine Learning Applications In The AM Domain (Meng et al., 2020). X1; X2; ...; Xn Represents The Input Vector Containing Various Input Features And Y Represents The Output. (b) An ANN With An Input Layer, 2 Hidden Layers And A Fully Connected Output Layer (Grierson and Quayle, 2021).

The perceptron developed by Rosenblatt in 1958 is one of the pioneering works in the field of ANN (Rosenblatt, 1958). The Heaviside step function serves as an activation function that calculates responses based on input values and identifies neurons according to their weights. During the training phase of a multilayer ANN, backpropagation is used to adjust neuron weights by changing the gradient of the loss function, which represents the difference between the output of the ANN and the training data. This process makes it possible to create feed-forward neural networks (FNN) or recurrent neural networks (RNN) if backward connections exist between layers. Long short-term memory networks (LSTMs) are used in the training of RNNs to solve the problem of gradients lost in backpropagation. Deep learning is based on multilayer ANNs, including hidden layers, convolutional layers and pooling layers. Neurons are arranged in layers, and CNNs are formed by connecting these layers together. In the current AM industry, variability in component functionality, depending on various processing variables such as print speed and layer thickness, poses a significant challenge. Several review papers have investigated the relationship between process, structure and property (Kumar and Kar, 2021; Kumar and Kishor, 2021; Singh et al., 2017). High-fidelity simulations or experiments are options that can be used to overcome this challenge, obtain reliable data, and assist in tuning processing parameters. However, these methods can be time-consuming or costly (Kumar et al., 2022).

In-situ monitoring systems offer another approach to ensure part quality and process reliability. However, effective defect detection based on data, such as images, requires robust and accurate data processing tools. These challenges are addressed by machine learning, a branch of artificial intelligence. With reliable datasets, ML algorithms are able to extract information from training sets to make informed decisions. Trained ML algorithms can predict and identify optimal operational settings and detect defects in real time using in-situ data. Recent studies have tested various ML applications, including geometric variation control, cost estimation, and quality analysis (Jin et al., 2020; Razvi et al., 2019). In essence, ML applications can be considered as a form of data processing, which makes ML integration an important component of Industry 4.0.

To better understand the benefits of ML in manufacturing processes, three broad categories are proposed and illustrated in Figure 2. These categories aim to show how they influence successful AM integration, information preservation planning and planning. As compiled by Shinde and Shah (2018), the main application areas of machine learning techniques include computer vision, prediction, semantic analysis, natural language processing and information retrieval.

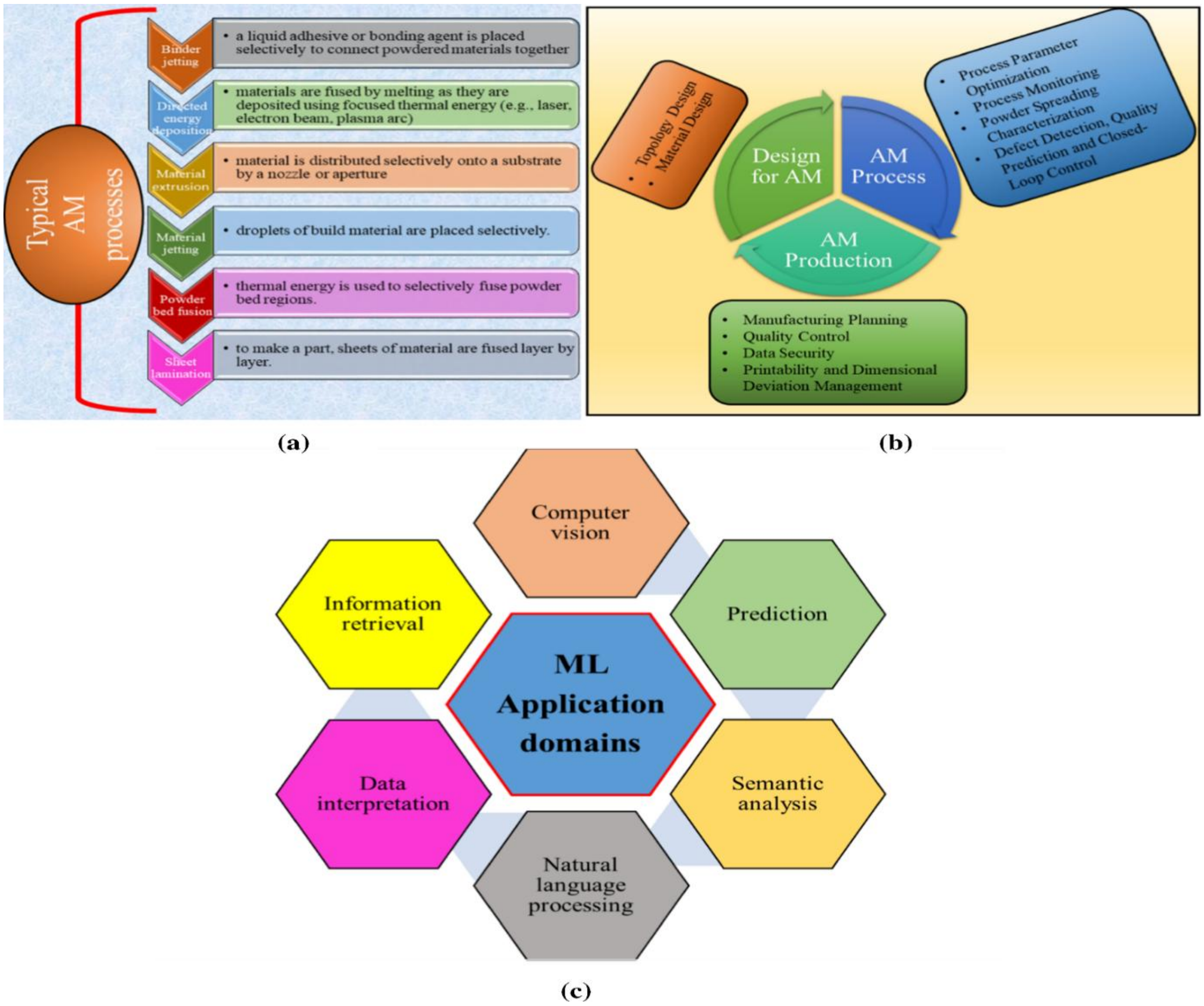

Figure 2. (a) Classification Of Typical AM Processes According To STM F42. (b) Application Of ML Techniques In Numerous AM Domains. (c) Major Application Areas For Machine Learning

The data that can be evaluated and used for the Process-Structure-Property (PSP) relationship chain is shown in Figure 3. In Figure 3, the data available for machine learning is represented by the text in the boxes. Some known machine learning applications in AM are indicated by the highlighted text. The source and terminal of each arrow reflect the source and outgoing values respectively (Meng et al., 2020)

In conclusion, the integration of machine learning into additive manufacturing holds significant promise for increasing productivity, improving quality and driving innovation in the manufacturing sector. By leveraging ML algorithms to optimise processes, manufacturers will be able to overcome challenges, reduce costs and remain competitive in the evolving additive manufacturing landscape.

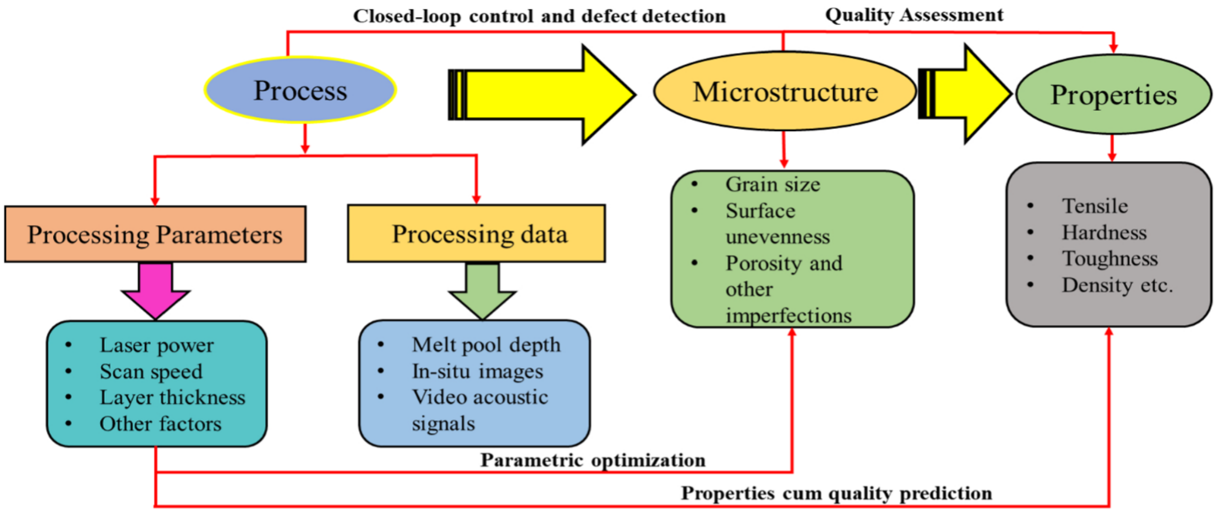

Figure 3. The Link Between Process, Structure And Feature In Additive Manufacturing (Meng et al., 2020).

Topology design and optimisation

Topology Optimisation (TO) is a method used in the design of structures to optimise the material distribution within a given region, taking into account specific stresses and constraints (Bendsoe, 1999). MTR processes often involve multiple design iterations and prototyping, making them technologically intensive, especially for large-scale and complex components. Machine Learning (ML) models offer a promising way to improve CTR procedures by complementing the traditional CTR approach, offering innovative ideas without starting from scratch. Although research on ML for topology design in AM applications is limited, Yao et al. (2017) introduced an integrated ML methodology for AM design feature recommendations using a clustering algorithm in the design phase.

Advanced machine learning techniques in topology optimisation

Recent studies have found that Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) have the optimal integration in topology optimisation for AM applications. CNN models are trained to predict optimal designs at an intermediate stage. This significantly speeds up the optimisation process compared to conventional methods such as Solid Isotropic Material with Penalty (SIMP). GAN, a generative programming approach incorporating deep learning techniques, is able to predict optimised structures without the need for extensive TO iterations (Figure 4). This technology will allow the creation of complex designs that efficiently meet specifications (Kumar et al., 2022).

Future directions and challenges

Although ML cannot completely replace traditional MTR techniques, it serves as a valuable tool to reduce the number of iterations and speed up the optimisation process in "Design for Manufacturing and Assembly" (DfMA). ML-centred CTR techniques improve the efficiency of the design process by providing fast and approximate predictions of the initial data. However, further research and experimentation are required to fully explore the potential of ML in additive manufacturing and its ability to streamline and optimise design and manufacturing processes. The integration of Machine Learning into Additive Manufacturing Design offers exciting opportunities to revolutionise the design process, optimise structures and improve the efficiency of additive manufacturing technologies (Kumar et al., 2022). By utilising advanced machine learning techniques, designers will be able to push the boundaries of traditional manufacturing and experience new possibilities in product design and manufacturing.

Material design and machine learning

Materials experts and researchers have made significant progress in the creation of metamaterials, which are composites with unique and distinguishable properties. The traditional manual development of metamaterials using the Edison method is laborious and challenging. However, modern Machine Learning (ML) approaches have revolutionised the synthesis of metamaterials, significantly accelerating the process (Gu et al., 2018). Recent advances in ML are empowering materials experts and researchers to predict material properties and develop new metamaterials. In addition, Additive manufacturing (AM) techniques have enabled the realisation of previously unattainable design concepts.

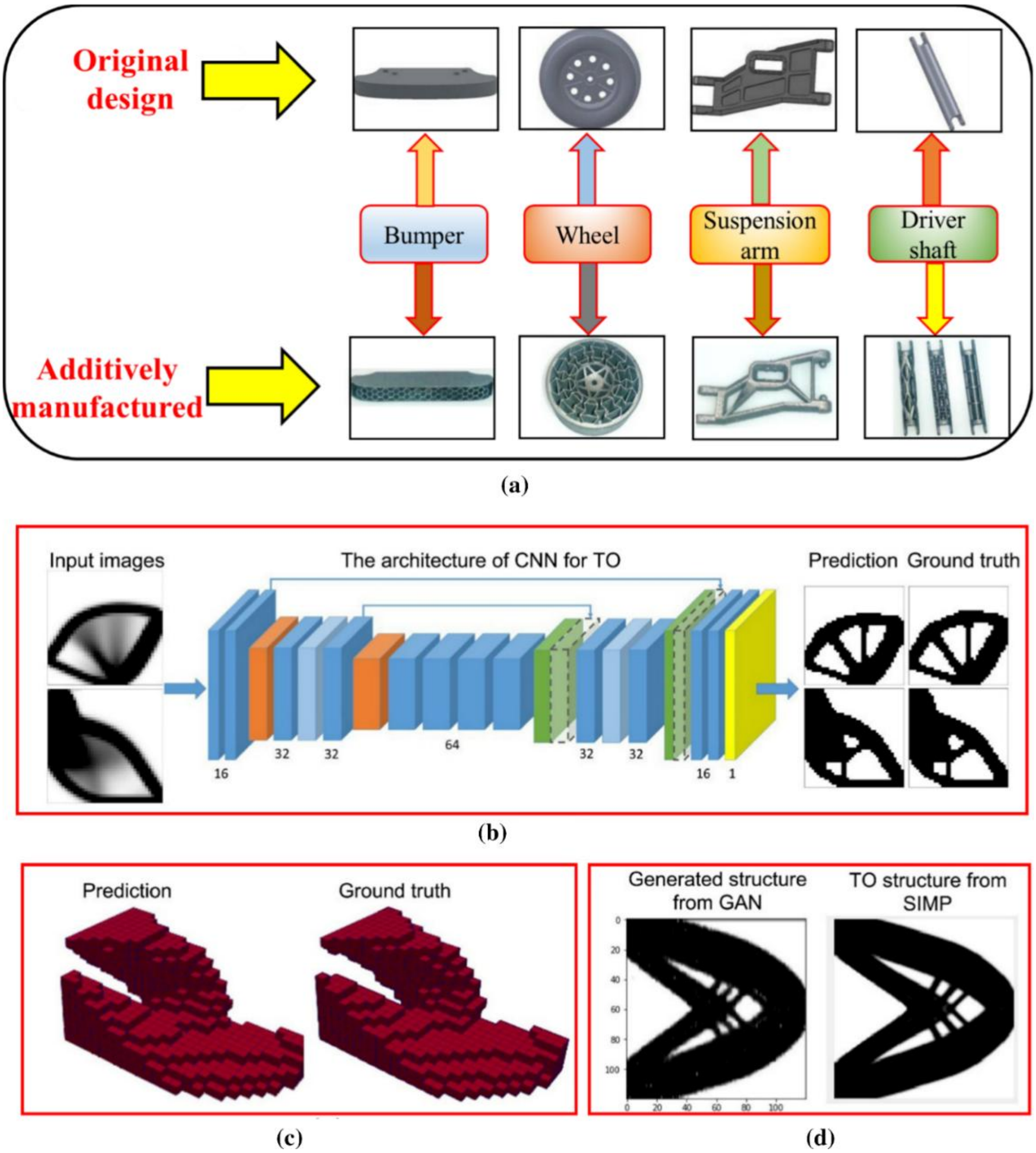

Figure 4. (a) Redesigned SLM-Built Components With Existing Target Component Design After A Guideline For Hybrid Machine Learning (Wang et al, 2020; Yao et al, 2017). (b) Use of CNN To Predict The Best Structures From Intermediate Topologies Serving As Input (Wang et al, 2020). (c) A Similar Approach Is Also Used For 3D Structures (Banga et al, 2018). (d) Using GAN To Generate To Structures (Rawat and Shen, 2018)

Automated metamaterial design

Chen et al. (2017) introduced a fully automated method for determining optimal meta-material designs, which was experimentally validated using the PEBA2301 elastic material and selective laser sintering (SLS) process (Figure 5). The system uses ML techniques to generate customised microstructures that meet the desired specifications by determining elastic material parameters such as Young's modulus, Poisson's ratio and shear modulus. Gu et al. (2018) investigated the creation of 100,000 microstructures using three types of unit cells on an 8 by 8 lattice structure, representing a very small fraction of all possible combinations. Convolutional Neural Networks (CNN) were used to train a database containing mechanical parameters calculated through the Finite Element Method (FEM). This resulted in innovative microstructural models for a composite meta-material that is twice as strong and forty times stiffer. Their concept was validated using the multi-material spray AM method (Figure 6). Notably, FEM simulations required about five days for mechanical characteristic calculations, while CNN took only ten hours to learn and a few seconds to generate output (Kumar et al., 2023).

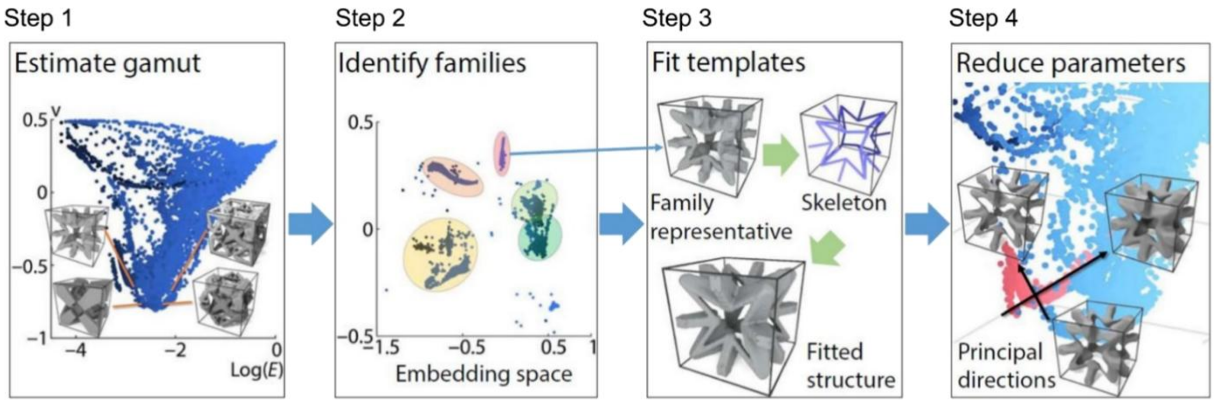

Figure 5. Computational Workflow Defining Extreme Microstructure Families Based On Elastic Material Parameters (Desai et al., 2018; Wang et al., 2020)

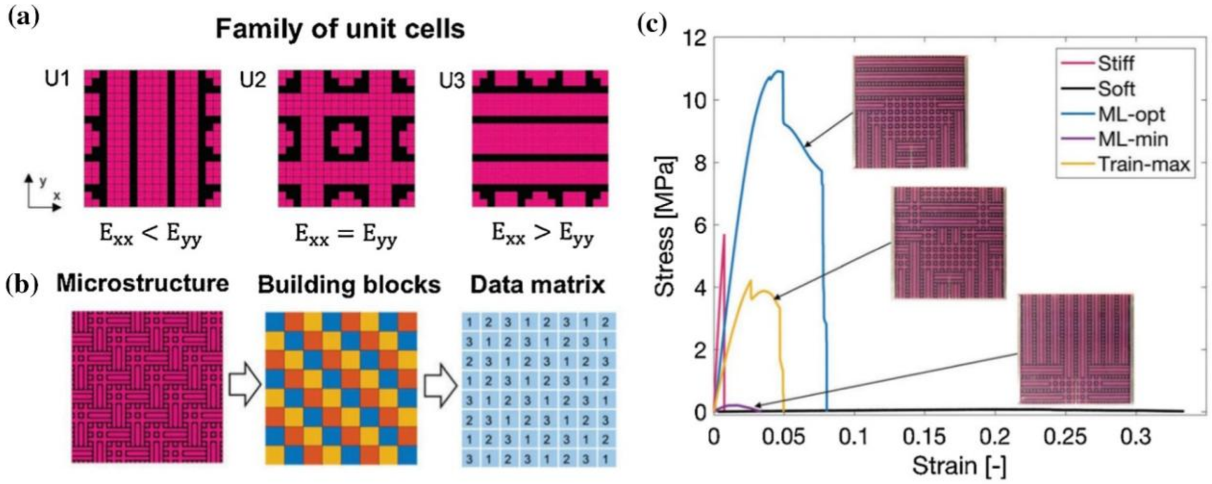

Figure 6. Optimisation Of Microstructure With Machine Learning (Gu et al., 2018; Wang et al., 2020).

Machine learning for additive manufacturing processes

Processing parameters such as extruder temperature in Material Extrusion (ME), laser power in Laser Powder Bed Fusion (L-PBF), printing speed and layer thickness significantly affect the quality, reliability and productivity of printed components (Figure 3). Structural design plays an important role in production costs and geometrical variations in manufactured products. In-situ images and acoustic emissions (AE) can be utilised by monitoring systems for real-time identification and elimination of problems (Meng et al., 2020).

By training ML models on datasets containing interconnected categories of data within the PSP network, conclusions can be drawn from the input data. This approach is widely used in ML model applications to effectively analyse and optimise additive manufacturing processes.

The integration of ML into material design, and additive manufacturing processes has provided new opportunities for innovation, efficiency and quality improvement in the manufacturing industry. By leveraging ML techniques, researchers and engineers will be able to improve material design, optimise manufacturing processes and support advances in additive manufacturing technologies.

Process parameter optimisation

In additive manufacturing, developers often lack the ability to predict the quality of a part produced with a given set of machining parameters until that part is actually produced. This uncertainty necessitates several steps to guarantee product performance, such as printing samples and verifying their efficiency. This makes the design process costly, time-consuming and unpredictable. Therefore, it would be highly advantageous to establish a direct link between management variables and product performance. While tests and calculations are valuable tools to establish this link, it is difficult to determine the most appropriate variables when multiple input parameters are intertwined. To improve operational efficiency, Machine Learning (ML) techniques can be utilised in the form of substitution models (Wang et al, 2018b, 2019).

Traditionally, process parameter development and optimisation for additive manufacturing of new materials has been performed using the design of experiments or simulation methods. However, developing an experimental strategy in the case of metal Additive Manufacturing (AM) often requires a long and costly research process (Wang et al., 2018b, 2019). Physics-based simulations can demonstrate the theoretical basis for the production of various properties during machining. However, macro-scale models such as Finite Element Method (FEM) may contain errors in experimental results due to their simplified assumptions. More advanced approaches, such as computational fluid dynamics, often focus on single tracks or several tracks and layers. This makes it difficult to predict the mechanical properties of parts on a macro scale or on a continuum (Kumar et al., 2023).

Several researchers have investigated the potential of using ML to overcome the aforementioned challenges in metal AM process optimisation as shown in Table 2. ML has primarily been used as a link between process parameters and quality criteria at two levels, mid-scale and macro-scale. Some academics have considered process maps as a means of identifying process windows. These process maps can be valuable tools for further analyses (Kumar et al., 2023). At the medium scale of high-energy AM, singular pathways are the main structural elements. The topology of the melt pool can significantly influence the final quality of the product, such as its shape, continuity and consistency. Due to insufficient empirical observations, powder-based or wire-based Directed Energy Deposition (DED) processes were estimated using a Multilayer Perceptron (MLP). Process variables were found to be inextricably linked to melt pool morphologies. This indicates that a specific geometry can be obtained by adjusting the parametric combinations in the opposite direction (Kumar et al., 2023). Tapia et al. (2017) used a Gaussian Process-based (GP) surrogate model to generate 3D response maps of process settings versus melt pool depths, allowing the identification of parametric combinations to eliminate the occurrence of keyhole melting (Figure 7 a-c). Their approach utilised the combination of an empirical dataset and two additional literature datasets consisting of 139 data points (Kumar et al., 2023). Several custom filters were applied to reduce anomalies, resulting in 96 valid data points with an acceptable preview error of 6.023 µm. In AM-made parts, medium-scale porosity is another major issue. Since the mechanical behaviour of components is strongly influenced by porosity, especially fatigue, total density is the main target in metal AM. The Multilayer Perceptron (MLP) is able to predict complex, non-linear interactions, although it provides little information on how the predictions are generated. In Figure 7(d-e), MLP and GP combined with Bayesian approaches were used to predict porosity in Selective Laser Melting (SLM) based on combinations of process factors (Tapia et al., 2016). Support Vector Machines (SVM) and MLP algorithms were also used to predict the open porosity of PLA samples during the Selective Laser Sintering (SLS) process.

Machine Learning techniques can also be used to investigate macro-scale properties of AM-made objects. Adaptive neuro-fuzzy inference systems (ANFIS) can usually only handle partial values. However, since there are too many unknowns in the fatigue process, it is useful to analyse the fatigue characteristics. Zhang et al. (2019) obtained 139 SS316L fatigue data produced under 18 different treatment configurations on the same SLM equipment. ANFIS was effectively used with the "process-based" model and "feature model" to predict high cyclic fatigue, with a mean root mean square error of 11-16%. When they used the training set containing 66 data points to predict fatigue life, the performance of their algorithm decreased due to the variability from machine to mechanical systems. Therefore, it is recommended to use both empirical and bibliographic inputs in model training to improve generalisation ability (Kumar et al., 2023).

Wang et al. (2018b) emphasised that studying the surface morphology can help narrow the Electron Beam Melting (EBM) process window. Support Vector Machines (SVM) work well in cases where the closeness between classes is evident. However, overfitting (memorisation) is easy to occur.

Aoyagi et al. (2019) proposed a simple method to create EBM flowcharts using only 11 datasets. It should also be noted that in this study, SVM was only used to fit the data to determine decision boundaries. Since the training dataset was very small, it was a problem to assign a training dataset to evaluate the accuracy of the model.

Table 2. Machine Learning Approaches To Optimise Parameters In The AM Process (Wang et al., 2020)

AM Processes	Materials	Builds	Sensors	Input Features	ML Methods	Output targets	References
Acoustic –Based Monitoring							
SLM	SS304	Single tracks	Microphone	Acoustic signals	DBN,MLP,SVM	Classify melting states	Ye et al., 2018a)
SLM	SS	10 × 10 x 20mm^3 cubes	Fibre Bragg grating sensor	Acoustic signals	Special CNN	Classify of build qualities	Shevchik et al., 2018)
FDM	ABS	-	Acoustic emission sensor	Acoustic signals	K-means clustering	Identify failure mode	Wu & Yu, 2016)
FDM	-	-	Acoustic emission sensor	Acoustic signals	Hidden semi-Markov model	Identify extruder state	Wu et al., 2016a)
Optical-Based Monitoring							
SLM	SS316 L	Single tracks	High-speed camera	Layer-wise images of melt pools, plume and spatter	SVM,CNN	Detect anomalies of melt tracks	Zhang et al., 2018)
SLM	Zinc	5 × 5 x 5mm^3 cubes	IR camera	IR images(plumes and laser-heated zones)	Unsupervised ML	Detect unstable melting conditions	Grasso et al., 2018)
SLM	In718	Single Tracks, unsupported overhangs	High-speed camera, optical microscope (ex-situ)	In-situ and ex-situ morphologies of the melt pool	SVM	Detect keyhole porosities and balling instabilities	Scime & Beuth, 2019)
SLM	SS	Step cylinder	Digital single lens reflex camera, CT scan (ex-situ)	Layer-wise images under 8 lighting conditions, ex-situ CT scan data	SVM	Detect and locate anomalies	Gobert et al., 2018)
SLM	In625	40.5 “ unsupported overhangs	Photodetector, high-speed camera, IR camera	Intensity, morphology, thermal profile of melt pools	MLP,SVM,KNN	Distinguish between the overhang and bulk build states	Montazeri & Rao, 2018)
SLM	SS304	Single tracks	Near –IR camera	Plume and spatter signatures	DBN,CNN,MLP	Classify melting states	Ye et al., 2018b)
SLM	SS304	8.5 × 8.5 x 4mm3 cubes	High- speed camera	Images and locations of melt pools	DBN	Classify MP images concerning laser power	Kwon et al., 2018)
SLM	In718	Tensile Bars	Visible light and IR photodiode sensors	Plasma emission and thermal radiation of melt pools	Gaussian mixture model	Detect faulty bars	Okaro et al., 2019)
SLM	SS316 L	Ø16 × 44 mm3 cylinder,50 × 50 × 50 mm3 lattice structure	High- speed camera	Intensity profile of melt pools	K-means clustering	Detect and locate defects due to overheating	M. G, V. L, Q. S, B.M C. xxxx)
SLM	-	Hollow cylinders	Optical camera	Layer-wise surface images before and after powder coating	RF,SVM	Detect elevated regions after laser exposure	Jacobsmühlen & zur, 2015)
SLM	In718	Ø40 × 20 mm3 cylinder	Digital single-lens reflex camera	Layer-wise surface images before and after powder coating	CNN,SVM	To recognize defects induced by process non-conformities	Caggiano et al., 2019)
DED	Ti-6Al-4 V	Thin walls	Pyrometer, IR camera, CT scan(ex-situ)	Thermal profile and location of the melt pool	SOM	Detect the location and size of pores	Jafari-Marandi et al., 2019)
DED	Ti-6Al-4 V	Thin walls	Pyrometer, IR camera, CT scan(ex-situ)	Morphological and thermal characteristics of the melt pool	SOM	Detect location of pores	Khanzadeh et al., 2019)
FDM	PLA,ABS	DNA model	Optical camera	Images of parts at specified checkpoints	SVM	Classify good and defective parts	Delli & Chang, 2018)
FDM	-	Parts with different types of infills	Cameras mounted on both extruder and frame of printer	Simulated images from software, real images from camera	KNN, RF, unsupervised ML	Detect malicious infill structure	Wu et al., 2017)

Recurrent Neural Networks (RNN) are used to predict time series. Mozaffar et al. (2018) used RNN for training FEM data to determine the high thermal history of the complex components of the DED process, considering the time dependence of the inputs. In addition, both MLP and SVM were used to predict thin wall deposits for DED. The study focused on the mechanical properties of macroscopic dimensions in the AM extrusion material process. For carefully examined process parameters, Fused Deposition Modelling (FDM) includes layer thickness, temperature and structure guidance. Here MLP is the most widely used methodology. A sufficiently trained MLP is preferred for the accuracy and prediction of the nonlinear data of the system. The use of compressive strength, wear rate, elasticity dynamics, creep and restorative properties in the prediction of material shrinkage parameters of PLA and PC-ABS materials has been extensively evaluated.

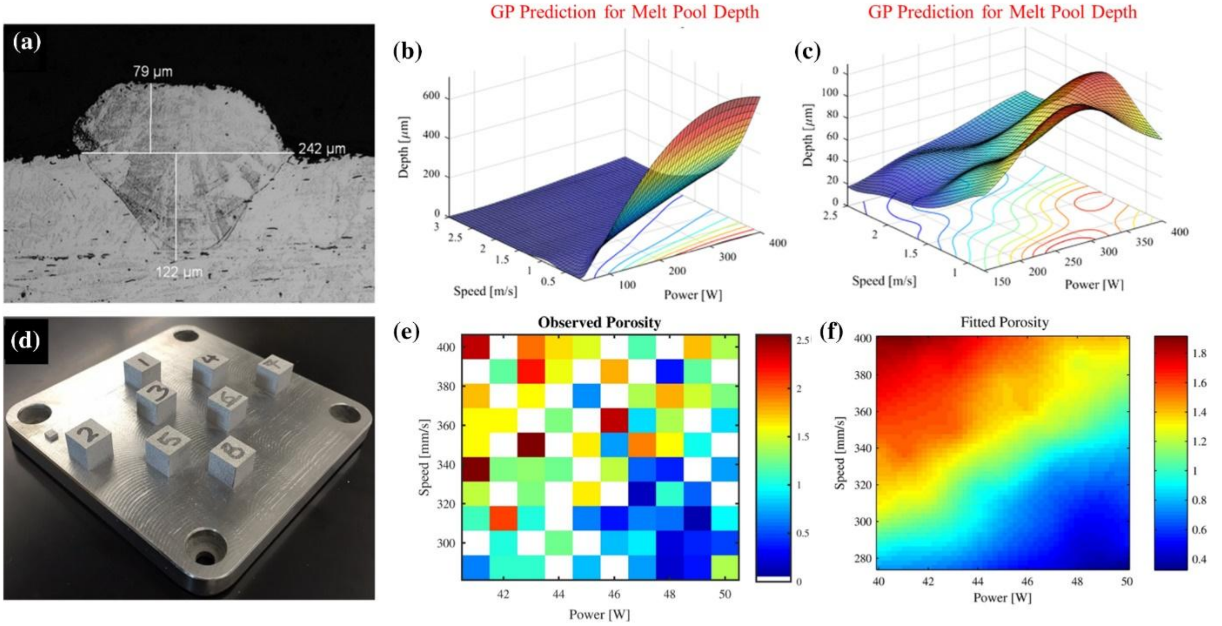

Figure 7. A GP-Based Model For Predicting Medium-Scale Properties Of SLM Fabricated Parts (Wang Et Al., 2020). SS316L Samples: (a) Single Trace Optical Micrograph. (b) Predictions Of Melt Pool Depth From Experiments, (c) Modelling. PH Samples From SS17-4 (Tapia et al., 2016). (d) Samples With Exactly The Desired Shape. (e) Spatial Behaviour Of The Observation Along The Process Parameter Table. (f) Porosity Prediction For Power-Speed Combination (Tapia et al., 2017)

Process monitoring

Although parameter optimisation can improve process predictability, it cannot completely eliminate defects (Kwon et al., 2018). Since printing issues contribute significantly to the cost of Additive manufacturing (AM) parts, process monitoring approaches that can detect build errors and defects are crucial. To overcome this challenge, several Machine Learning (ML) solutions have been developed (Kumar et al., 2023), categorised according to the type of input data (optical and acoustic monitoring).

Optical Tracking: Optical monitoring solutions utilising data from digital, high-speed or infrared cameras are widely used in AM processes. Monitoring the melt pool, a critical aspect in Powder Bed Fusion (PBF) operations, has been the focus of much monitoring research. Kwon et al. (2018) used melt pool thermal data to train a Convolutional Neural Network (CNN) based software to distinguish between high and low-quality structures. In this study, a failure rate of less than 1.1% was achieved, potentially saving time and cost. Zhang et al. (2018b) integrated melt pool, smoke and splash data to effectively categorise component quality. Long Short-Term Memory (LSTM) networks have demonstrated improved prediction capabilities in this context (Zhang et al., 2021). Optical monitoring has also been useful in other AM techniques such as binder spraying and material extrusion. Gunther et al. (2020) used an optical tool to analyse defects in binder jet parts, while Wu et al. (2016b) achieved an accuracy of 95% using optical tracking to detect filler print defects in material extrusion.

Acoustic Monitoring: Acoustic monitoring, a newer and cost-effective method, is based on acoustic signals related to part porosity and melt states in PBF and material extrusion processes. Compared to optical monitoring, acoustic monitoring systems use cheaper sensors. The machine learning algorithms used range from supervised CNNs to clustering solutions. Acoustic monitoring effectively detects problematic structures, reducing the need for post-print inspection, and has achieved confidence levels of up to 89% for porosity classification and 94% for defects related to the melt pool. Wu et al. (2015b) used acoustic monitoring and a Support Vector Machine (SVM) classifier to assess material extrusion and achieved 100% accuracy in detecting material extrusion and 92% accuracy in identifying extruder obstacles.

Powder spreading characterisation and defect detection

In Powder Bed Fusion (PBF) processes, the consistency of powder distribution is critical to the quality of the final products. Improper powder distribution can lead to a variety of problems, such as warping and swelling, which can cause the entire structure to fail. Examples of powder dispersion problems include recoater impact on curled or bumpy components, recoater entrainment of foreign material, recoater blade damage and debris on the powder bed. It is highly desirable to eliminate the need for man-made detectors for certain anomalies. In this work, a mechanism for independently detecting and classifying dust propagation defects during the construction process is introduced to address this problem. Scime and Beuth used modern computer vision techniques such as k-means clustering (Scime and Beuth, 2018a) and multiscale Convolutional Neural Networks (CNN) (Scime and Beuth, 2018b) to learn the algorithm accurately. Using photographs recorded during the Selective Laser Melting (SLM) process, they classified image fragments into seven types. This technology also enabled in-process repair of defects in the AM process when a feedback control system was used (Kumar et al., 2023).

Defect detection, quality prediction and closed loop control

In-situ monitoring devices have been developed to the extent that real-time data can be collected for defect detection and closed-loop control in additive manufacturing. Real information such as spectroscopy, images, Acoustic Emission (AE) and computed tomography (CT) can be used in various ways with machine learning models;

- Faulty (potentially with categories of defects) or error-containing data are identified by experimental testing or human expertise. Supervised learning models are then trained to detect defects and project real-time performance, a common application of ML classification techniques.
- For clustering of abnormal data, cluster analysis is performed with unsupervised learning approaches and defects are detected without labelling.
- ML regression models are built using data from some real-time adjustable process conditions to vary these processing parameters in real time. This approach is illustrated by voltage level control in the Material Jetting (MJ) process. The charge-coupled device (CCD) camera first captures dynamic photographs of the droplet. Second, the images are used to extract four droplet features (satellite, bond, quantity and velocity), which are then combined with current-voltage to form a neural network (NN), ML algorithm. Finally, the trained ML model is used to determine the appropriate voltage level and send it to the voltage modification system that regulates the droplet spray pattern (Figure 8) (Meng et al., 2020; Wang et al., 2018a).

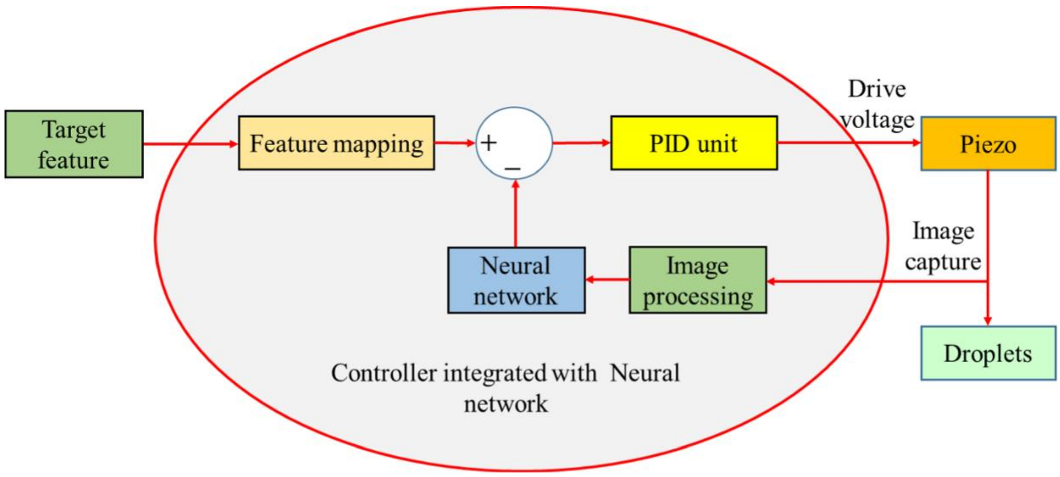

Figure 8. Closed-Loop Voltage Regulation Architecture Of The MJ Programme (Meng et al., 2020; Wang et al., 2018a).

The integration of Machine Learning into powder dispersion characterisation, defect detection, quality prediction and closed-loop control in additive manufacturing processes plays a crucial role in improving product quality, reducing waste and optimising production efficiency. By utilising advanced machine learning techniques, researchers will be able to develop robust, appropriate, monitoring systems and feedback control mechanisms to ensure consistent powder distribution, detect defects in real-time, and adapt process parameters accordingly.

Geometric deviation control and cost estimation

Additive manufacturing (AM) parts often exhibit low geometric accuracy and surface integrity, causing challenges in various industries such as aerospace and pharmaceuticals (Grasso, 2017). To address these geometric imperfections, machine learning (ML) models have the potential to play an important role in recognising geometric defects, quantifying deviations, and providing recommendations for correcting these defects. Francis et al. (2019) developed a geometric error compensation framework for the Laser Powder Bed Fusion (L-PBF) process using a Convolutional Neural Network (CNN) ML model. This framework predicts degradation by analysing thermal data and process variables and feeds the degradation results back to the Computer-Aided Design (CAD) model for defect detection and correction. By adjusting the CAD model based on ML predictions, the geometric accuracy of the produced items can be significantly improved, as shown in Figure 9. The geometric error compensation approach for Ti-6Al-4 V in the L-PBF process is shown (Meng et al., 2020). The distortion predicted using the deep learning model is the output data. The distortion in the CAD model is reversed to compensate for errors. CAMP-BD is a convolutional and ANN for predicting Additive manufacturing using big data (Francis and Letters, 2019)

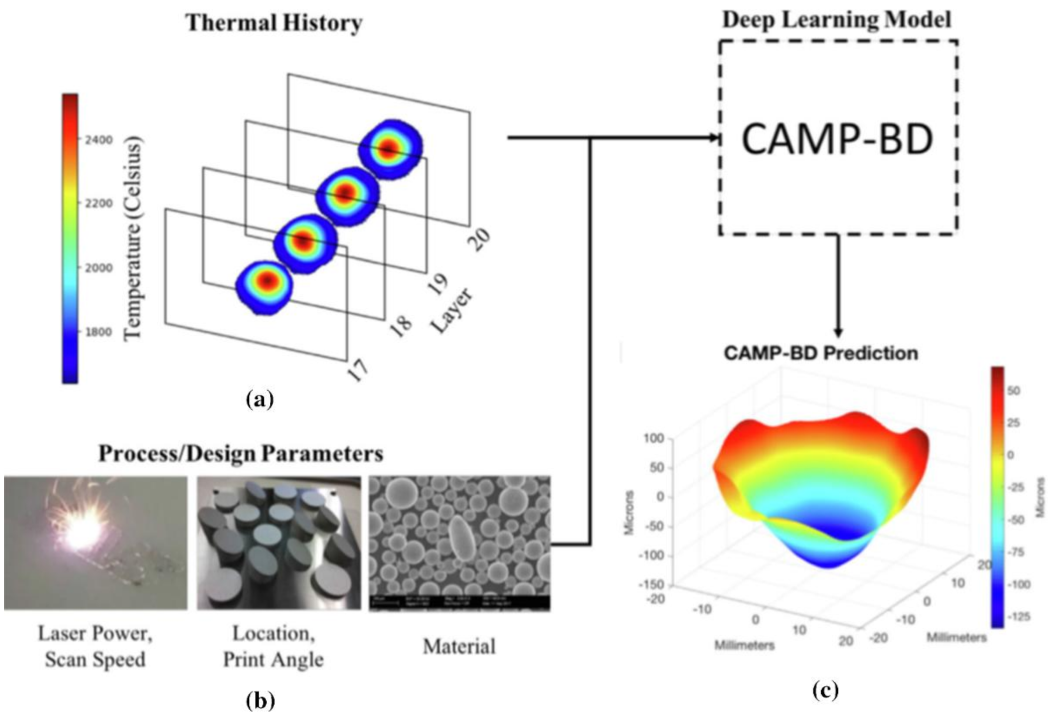

Figure 9. Input Data (a) Thermal History, (b) Processing Parameters (Francis and Letters, 2019)

Cost Estimate: Understanding the costs and time required for 3D printing is crucial for manufacturers, customers and supply chain stakeholders. While the dimensions of a proposed shape can provide some estimates, a precise and effective cost estimation technique is still required. Chan et al. (2018) presented an innovative cost estimation framework outlined below:

- A customer submits a production order containing a three-dimensional model.
- The three-dimensional model is converted into an input vector and fed to machine learning algorithms trained for cost estimation using clustering analysis based on similar workloads.
- If requested by the customer or in case there is not enough data available for training the ML algorithm, the 3D model is processed using modelling techniques to predict the costs that serve as a training source for the ML algorithms.
- After integrating the ML estimates, the gross expected cost is calculated.
- The final cost estimate is presented to the customer.

This cost estimation framework, shown in Figure 10, enables accurate and effective cost estimates for 3D printing projects. It increases transparency and facilitates informed decision-making for all stakeholders involved in the additive manufacturing process (Chan and Lu, 2018; Meng et al., 2020)

Planning and quality control

Additive manufacturing (AM) is recognised as a costly manufacturing process and many end users demand a significant return on their investment. A precise pre-production strategy is needed for the manufacturing process, from Computer-Aided Design (CAD) to final product quality testing. As a result, some projects have utilised machine learning (ML) to assist in AM planning. Tang et al. (2016) showed that the manufacturability of a component for

Fused Deposition Modelling (FDM) printed grid structures can be assessed using ML in pre-fabrication. They also designed a multimodal learning system combining Convolutional Neural Networks (CNN) and Multilayer Perceptron (MLP). This system was constructed based on concepts, materials and process parameters for the successful production of the metal part by Selective Laser Melting (SLM).

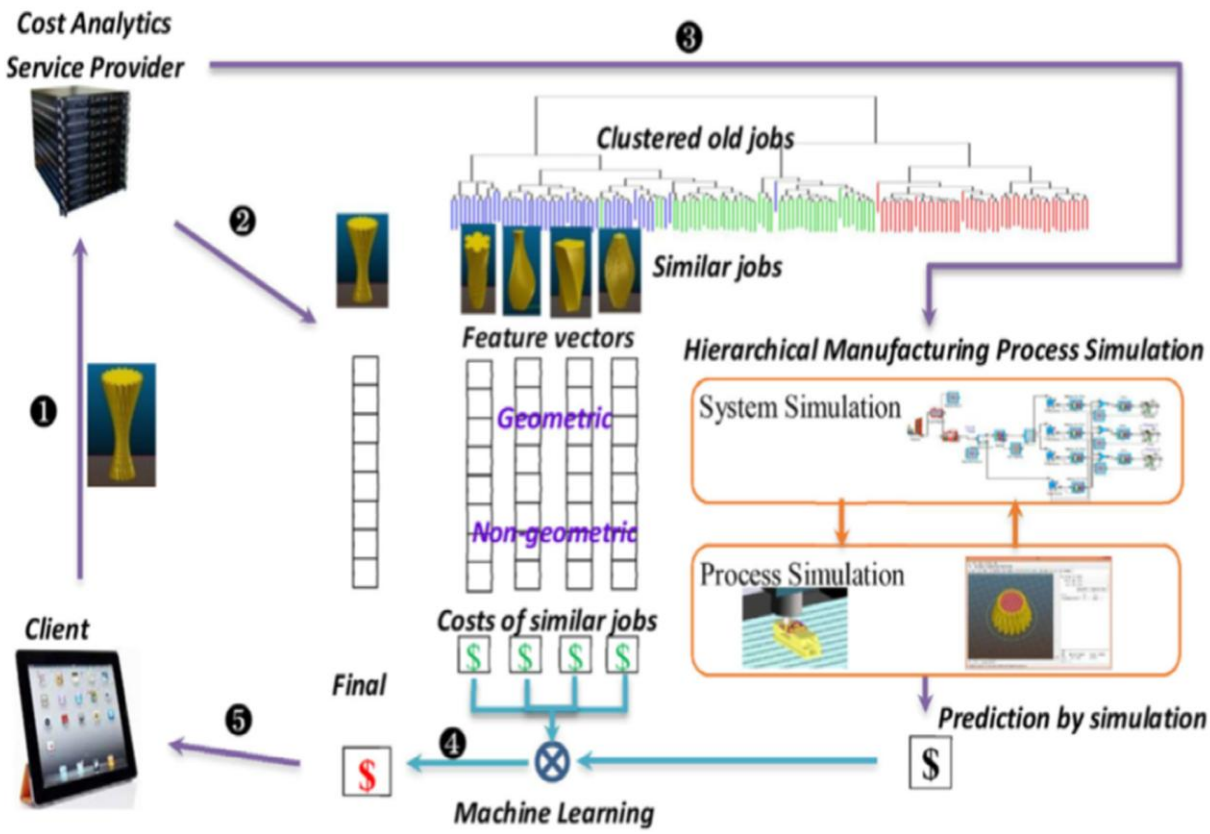

Figure 10. A Framework For Cost Analysis Due To Geometry And Process Similarities (Chan and Lu, 2018; Meng et al., 2020)

Additive manufacturing quality control

A significant barrier to AM quality assurance is the variability in production quality between different machines in the same process, even from production to production. Differences in dimensional accuracy, density, process stability and material properties can result from these disparities (Kumar and Wu, 2020, 2021b; Kumar et al., 2020b). As a result, numerous studies have attempted to use ML algorithms to establish quality in AM parts. The three methods of eliminating geometric errors are rescaling all components, replacing their original CAD, and using quality measures. Before production, MLP or CNN can be used to estimate the scaling ratio and change the overall size of the components. Shape-dependent geometric changes due to heat stress can be modelled using ML algorithms that allow appropriate geometric adjustments to the CAD model. MLP was used to correct geometric distortion to reduce the thermal consequences caused by SLM (Chowdhury et al, 2018). Finite Element Method (FEM) modelling output was generated to predict the distorted regions and modify the available CAD data (Figure 11).

Noriega et al. (2013) used a similar method in FDM printing and replaced simulated data with test results. To achieve process control, Self-Organising Maps (SOM) are able to link different geometric deviations with specific process parameters. Compared to many existing supervised machine learning algorithms, this method, when combined with a laser scanner, will be able to reduce the point cloud data required to measure the dimensional accuracy of additively manufactured components. In addition, single traces can be modified on a macro-scale by adjusting the Directed Energy Deposition (DED) process parameters to minimise geometric imperfections. After laser exposure of each layer formed in the Powder Bed Fusion (PBF) process, the acquired surface images can train ML algorithms to quickly recognise deformed parts before powder coating (Kumar et al., 2023).

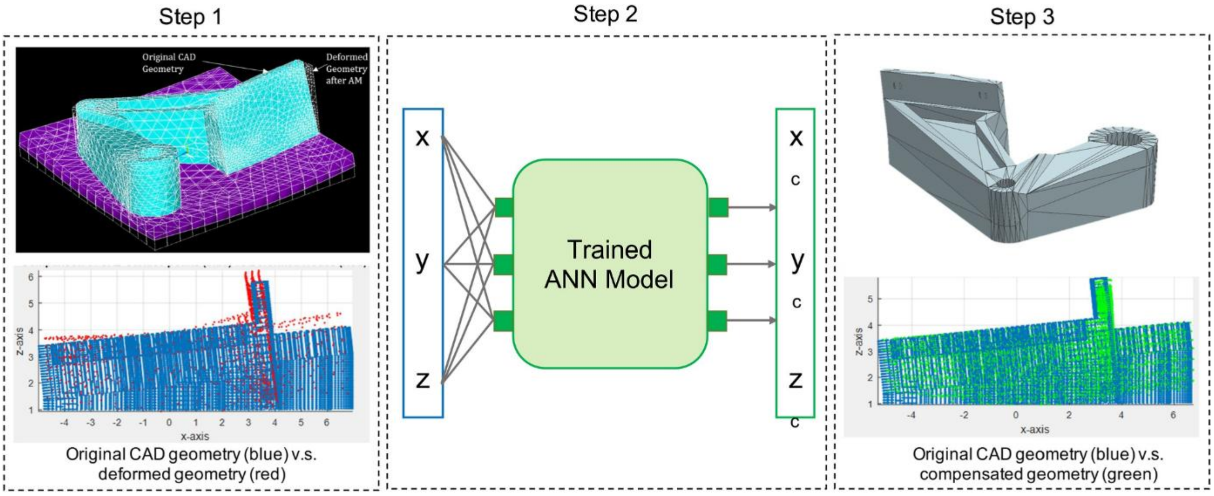

Figure 11. ML Approach To Minimise Thermal Degradation In The SLM Process (Chowdhury et al, 2018; Wang et al, 2020)

In-process inspection involving various sensors and cameras is used to improve the quality of additively manufactured components. Signal emissions, mainly visual and auditory, can be recorded and analysed to train multiple ML systems to manage the 3D structure. ML has the potential to help diagnose printing status and failure mechanisms, melting conditions, porosity detection, shrinkage property prediction and surface roughness prediction in AM.

Additive manufacturing data security and dimensional deviation management

Intellectual property (IP) protection is vital in the manufacturing sector, where companies invest heavily in the protection of their data. The cyber and physical domains are two important parts of digital manufacturing, as shown in Figure 12a. Data theft most commonly occurs in the cyber domain, but can also occur in the physical domain (such as side channels) as Additive manufacturing (AM) technology emits various signals when creating 3D structures. It is possible to use Machine Learning (ML) techniques to monitor outgoing channels in IP surveillance and extract Computer Aided Design (CAD) data. Until recently, ML could only record acoustic signals during printing to reconstruct 3D models with data from side channels. But now, thanks to transducers, it can capture acoustic signals from stepper motors in Melt Deposition Modelling (FDM), as seen in Figure 12b, similar to G-code in that it leaks data on the FDM process, including axis motion, nozzle speed, temperature and material discharge. Al Faruque et al. (2016) were able to utilise features extracted from these captured sound files to develop ML algorithms. They were able to reconstruct a model with 78% prediction accuracy and 18% prediction error for axis prediction. In the case of IP theft, the thief can even place the mobile phone close to the device to capture audio data. As an example, these data were used in the study by Hojjati et al. (2016) to accurately reconstruct an aircraft model of about one mm in length with an angular error of one degree.

PRINTABILITY AND DIMENSIONAL DEVIATION MANAGEMENT

Convolutional neural networks (CNNs) and support vector machines (SVMs) can be used to create models for the determination of part printability in material extrusion processes and Powder Bed Fusion (PBF). The use of Neural Networks (NNs) can reduce print time estimates for PBF processes from 20-35% to 2-15% and allow for better equipment control. In AM systems, material, machine and layer production are all three-dimensional elements. In the process of converting a CAD model to STL file format, for example, the resolution will be reduced. In PBF, ML was initially used to correct these by optimising the orientation of components, reducing the mismatch due to the machine and adjusting the computer design to the thermal effects of the material. Khanzadeh et al. (2019) used Self-Organising Maps (SOM), an unsupervised learning algorithm, to analyse and evaluate point cloud data for dimensional deviation of components produced by extrusion procedures. Their application allowed partial differences to be classified into discrete clusters based on the severity of the differences present, allowing the identification of sub-optimal conditions in the process. Noriega et al. (2013) used NNs to compensate for dimensional variation by varying the size of the part for material extrusion. The two NN implementations were able to reduce the deviation by 50 per cent for the outer dimensions and 30 per cent for the inner dimensions, respectively. Charalampous et al. (2021) used AM of T4 spine vertebrae as a case study and achieved a 25% reduction in dimensional deviation at a 1:1 scale and a 33% reduction at a 3:1 scale. Numerous studies have investigated how to limit geometric deviation in Directed Energy Deposition (DED) and binder jetting. Rawat & Shen (2018) conducted a study using CNNs to predict and compensate for geometric deviation by tilting, resizing and rotating the CAD geometry of a dental crown to be made using bond sputtering procedures. During the operational study, the CNN used a voxel-based method where each voxel was rated as reliable or defective. The average of the F1 scores, a single-valued metric used to assess prediction accuracy, was found to be 94%. However, despite these results, no actual samples were produced, making these results unreliable. The most typical method used for dimensional bias correction in DED is to use process parameter optimisation to optimise the geometric properties of individual traces. However, although this method partially corrects component and machine problems, it cannot solve document formatting problems. Caiazzo and Caggiano (2018) created an optimisation model to analyse the results.

The integration of Machine Learning into Additive manufacturing data security and dimensional deviation management will offer significant benefits in protecting intellectual property, improving product quality and optimising manufacturing processes. By leveraging advanced machine learning techniques, researchers and industry professionals will be able to detect potential IP theft, identify printability issues and compensate for dimensional deviations, enabling safer and more efficient AM operations.

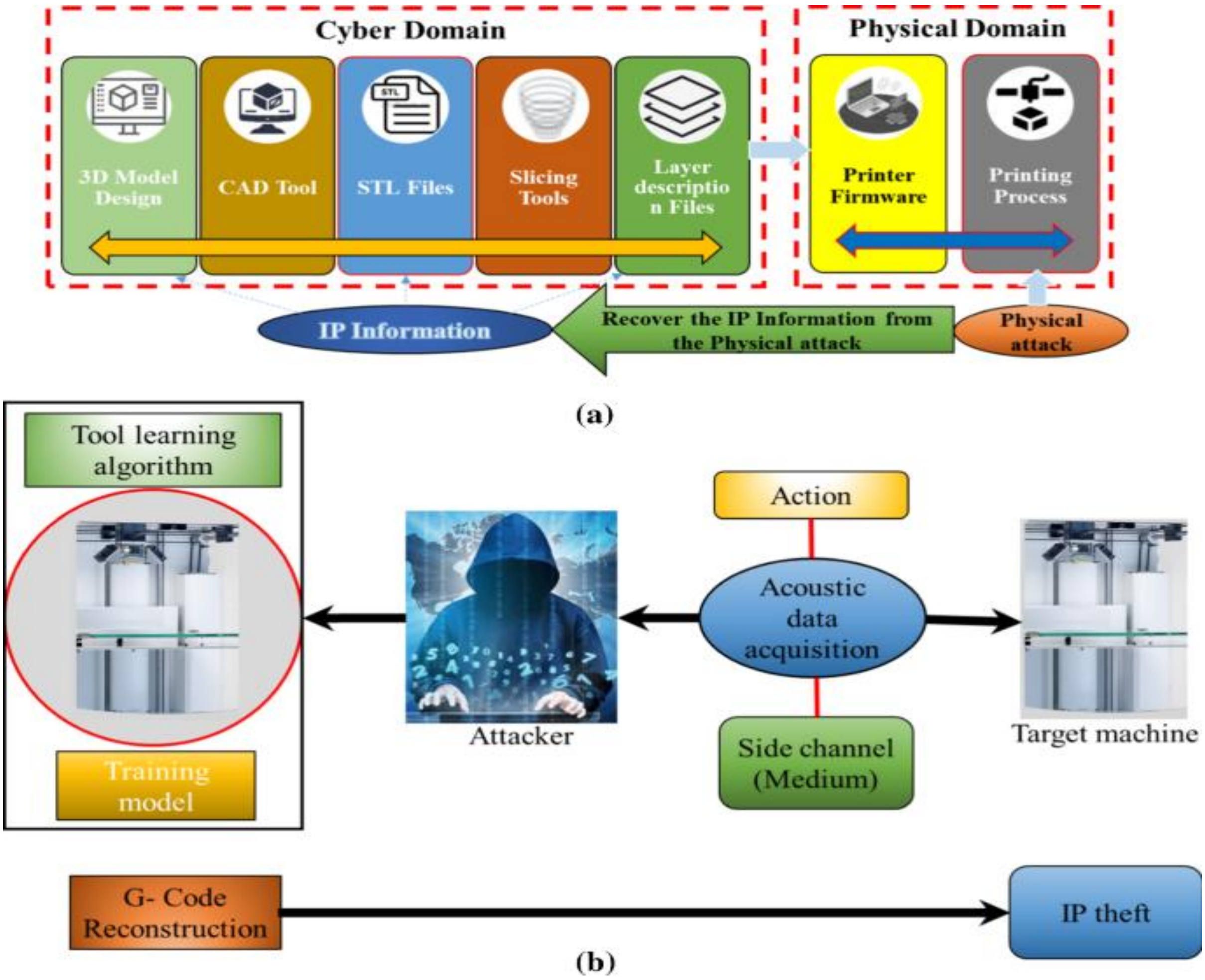

Figure 12. (a) A Cyber And Physical Attack Model In The AM System Development Process. (b) Side Channel Acoustic Model Attack (Al Faruque et al., 2016; Wang et al., 2020)

EMERGING TECHNOLOGIES IN ADDITIVE MANUFACTURING AND MACHINE LEARNING

Generative design (GD)

Generative design is an emerging approach that utilises computational algorithms and Machine Learning to explore a large design space and generate a large number of innovative solutions that meet specific performance criteria. In the context of additive manufacturing, Generative design is very powerful as it can create highly complex, organic shapes that are difficult or impossible to produce using traditional methods. By integrating generative design with machine learning, researchers can further enhance the design process by training ML models to recognise patterns in successful designs and guide generative algorithms towards optimal solutions.

For example, a study by Umetani and Schmidt combined generative design and deep learning to create structures optimised for additive manufacturing. The researchers developed a convolutional neural network (CNN) trained on a dataset of successful and unsuccessful 3D printed structures. The trained CNN was then integrated into the generative design workflow and provided real-time feedback on the printability of the generated designs. This allowed generative algorithms to explore a wider design space and enabled the generated structures to be manufacturable using AM. The resulting designs exhibited complex and organic shapes with improved mechanical performance compared to conventional designs. This case study highlights the synergistic potential of generative design and machine learning for what can be achieved in additive manufacturing.

Explainable artificial intelligence (XAI)

As machine learning is more widely adopted in additive manufacturing, there is a growing need for AI models that are transparent, interpretable, and allow users to understand the logic behind the model's predictions and decisions. This concept, known as Explainable Artificial Intelligence (XAI), is particularly important in regulated industries such as aviation and healthcare, where decisions made by AI systems can have significant consequences.

In the AM context, XAI will help build confidence in machine learning algorithms by providing insights into the factors that influence the model's predictions. For example, in the case of predicting part defects during the AM process, an XAI model will be able to identify the specific process parameters or material properties that contribute most to the probability of a defect occurring. This information will help AM operators make informed decisions about process adjustments and enable more effective troubleshooting.

Furthermore, XAI will facilitate regulatory compliance by providing a transparent audit trail of decisions made by AI systems throughout the AM process. This is especially important in industries with stringent quality standards to demonstrate the reliability and safety of AM parts. By incorporating XAI into AM workflows, manufacturers will improve their ability to meet regulatory requirements and build confidence in the use of Machine Learning technologies in additive manufacturing.

REGULATORY CONSIDERATIONS AND ETHICAL IMPLICATIONS

Data privacy and security

As machine learning becomes more prevalent in additive manufacturing, the collection and use of large amounts of data raises concerns about data privacy and security. AM processes generate vast amounts of data, including part designs, process parameters, and sensor data, which can be sensitive and proprietary. Ensuring the protection of this data is vital to maintaining competitive advantage and preventing the theft of intellectual property.

Regulatory frameworks, such as the General Data Protection Regulation (GDPR) in the European Union, have been established to protect personal data and ensure its responsible use. While these regulations primarily focus on personal data, they emphasise the importance of data privacy and security in the digital age. In the AM context, similar principles should be applied to protect sensitive production data and ensure its ethical use.

Measures such as data anonymisation, access control, and secure data storage can help mitigate risks associated with data collection and use in AM processes. In addition, establishing clear data management policies and training employees on data privacy best practices will help foster a culture of responsible data management in AM organisations. By prioritising data privacy and data security, AM companies will be able to build trust with their customers, business partners and regulators and ensure the responsible use of machine learning technologies in their production processes.

Protection of intellectual property

The integration of Machine Learning and additive manufacturing poses new challenges in intellectual property protection. As AM technologies enable the rapid production of complex parts, they also increase the risk of unauthorised copying and distribution of designs. Moreover, the use of ML algorithms in the AM process can lead to the creation of new designs or modifications to existing designs, blurring the boundaries of ownership and ownership.

To overcome these challenges, AM companies and researchers need to adopt a multi-pronged approach to intellectual property protection. Legal frameworks such as patents, copyrights and trade secrets can provide a basis for the protection of AM-related intellectual property. However, in the face of rapidly evolving technologies and new business models, these traditional methods will not be sufficient. Technological solutions such as digital watermarking, blockchain and secure data storage can help trace the origin of AM designs and prevent unauthorised access or modification. AM companies can also experiment with new business models that prioritise IP protection, such as design licensing, subscription-based services and collaborative design platforms.

By proactively addressing IP protection challenges, AM stakeholders can foster innovation, collaborations, and ensure the sustainable growth of the additive manufacturing sector in the era of AI-driven manufacturing.

SECTOR ADOPTION AND FUTURE TRENDS

Barriers to Implementation: Despite the promising potential of machine learning in additive manufacturing, several obstacles prevent its widespread adoption. One of the main challenges is the quality and availability of data needed to train effective machine learning models. AM processes generate vast amounts of data, but much of it is unstructured, incomplete, or of low quality. Addressing these data quality issues requires significant investment in data cleaning, pre-processing and optimisation.

Another barrier is the skills gap between AM professionals in terms of machine learning expertise. Bridging this gap requires targeted training programmes, collaboration with academic institutions and the development of user-friendly machine-learning tools specifically designed for AM applications.

Infrastructure limitations such as insufficient computing power, storage capacity and network bandwidth can also hinder the application of ML in AM. Upgrading hardware and software infrastructure, leveraging cloud computing resources and optimising data processing workflows can help overcome these limitations.

To overcome these barriers, AM companies and research institutions must take a holistic approach combining targeted investments, skills development and collaborative efforts. By working together to overcome these challenges, the AM industry will be able to unlock the full potential of machine learning and drive the next generation of smart manufacturing.

Future Developments: As machine learning and additive manufacturing continue to evolve, many exciting developments are on the horizon that could shape the future of smart manufacturing. One potential trend is the integration of ML with emerging AM technologies such as multi-material printing, in-situ monitoring and closed-loop control systems. By leveraging ML algorithms to optimise these advanced AM processes, manufacturers will be able to achieve unprecedented levels of precision, efficiency and flexibility in part production.

Another promising area is the development of self-learning and adaptive AM systems that can autonomously adjust process parameters based on real-time feedback from on-site sensors and machine learning algorithms. These intelligent systems will revolutionise the way we think about manufacturing by enabling highly complex, customised parts to be produced with minimal human intervention.

The convergence of machine learning and additive manufacturing is also expected to drive the development of new materials and material systems tailored for specific AM processes and applications. Researchers using machine learning to analyse the relationships between material composition, microstructure and performance will be able to accelerate the discovery and optimisation of new materials for AM, opening up new possibilities in aerospace, biomedical, energy, etc.
As these developments unfold, the integration of machine learning and additive manufacturing will continue to push the boundaries of what is possible in smart manufacturing. By embracing these emerging technologies and fostering a culture of innovation, the AM industry will lead the transition to Industry 4.0 and create a more sustainable, efficient and personalised manufacturing ecosystem.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In today's data-rich environment, vast amounts of data are generated every day from a variety of sources, including planning statistics, sensor readings, financial records, Additive Manufacturing (AM) data, medical information and mobility data. Extracting meaningful insights from this extensive and interconnected data environment is crucial. Machine Learning (ML) algorithms are effective in leveraging existing knowledge to explore new research areas by analysing heterogeneous data. In the context of smart manufacturing, the synergy between AM and ML, as emphasised by Kang et al. (2016), points to significant progress leading to Industry 4.0, known as the fourth industrial revolution.

This study investigated the effectiveness of ML techniques and their application in basic AM processes. Machine learning has demonstrated its effectiveness in improving the quality of 3D structures in AM, improving printer productivity, discovering new materials and establishing important feature-structure relationships. While current ML applications in manufacturing focus primarily on processing-related procedures such as process parameter optimisation, there is an urgent need to develop more streamlined and efficient approaches. The future direction of ML in AM is expected to be towards new materials, optimised manufacturing strategies and automated in-process feedback systems to further develop intelligent AM applications.

Despite the transformative potential and increasing value of ML in the AM, many ML solutions in the AM field have yet to undergo real-world testing. Future efforts should focus on increasing the applicability of these tools to tackle concrete industrial challenges and providing concrete industrial examples that will increase confidence in their effectiveness.

Investigating the optimisation of machine variables based on raw material constraints, process settings and past machining results, as exemplified by Weiss et al. (2014), has the potential to pave the way to achieving high-quality standards. This optimisation paradigm can be extended from part-specific stages to machine- and plant-specific stages. This would increase overall productivity while taking into account resource efficiency, energy savings and operational constraints.

Another promising research topic will be to simplify equipment and extend the limits of raw material constraints. Machine learning-driven optimisation strategies can meet the increasing demands of processing stages, guaranteeing consistent quality while reducing machine and raw material costs.

The integration of Machine Learning into Additive manufacturing processes has enormous potential to revolutionise the industry, improve efficiency and drive innovation. Future research should focus on improving ML applications, addressing real-world challenges and optimising AM processes to unlock the full capabilities of smart manufacturing in the Industry 4.0 era.

REFERENCES

Ahlers, D., Wasserfall, F., Hendrich, N., & Zhang, J. (2019). 3D printing of nonplanar layers for smooth surface generation. IEEE International Conference Automative Science Enginerring. https://doi.org/10.1109/COASE.2019.8843116

Al Faruque, M. A., Chhetri, S. R., Canedo, A., & Wan, J. (2016). Acoustic Side-Channel Attacks on Additive Manufacturing Systems. 2016 ACM/IEEE 7th Int Conf Cyber-Physical Syst ICCPS 2016-Proceedings 2016. https://doi.org/10.1109/ICCPS.2016.7479068

Alabi, M. O. (2018). Big data, 3D printing technology, and industry of the future. International Journal of Big Data and Anal Healthcare, 2, 1–20. https://doi.org/10.4018/ijbdah.2017070101

Aoyagi, K., Wang, H., Sudo, H., & Chiba, A. (2019). Simple method to construct process maps for additive manufacturing using a support vector machine. Additive Manufacturing, 27, 353–362. https://doi.org/10.1016/J.ADDMA.2019.03.013

Banga, S., Gehani, H., & Bhilare, S. (2018). 3D topology optimization using convolutional neural networks. ArxivOrg. https://doi.org/10.48550/arXiv.1808.07440

Bendsoe, M. (1999). Material interpolation schemes in topology optimization. Amsterdam: Springer. https://doi.org/10.1007/s004190050248

Bennett, J., Dudas, R., Jian Cao, J. and Ehmann, K. (2016). “Control of heating and cooling for direct laser deposition repair of cast iron components.” Northwestern University, Evanston, IL uluslararası esnek otomasyon sempozyumu (ISFA) , IEEE (2016). https://doi.org/10.1109/ISFA.2016.7790166

Caggiano, A., Zhang, J., Alfieri, V., Caiazzo, F., Gao, R., & Teti, R. (2019). Machine learning-based image processing for on-line defect recognition in additive manufacturing. CIRP Annals, 68, 451–454. https://doi.org/10.1016/J.CIRP.2019.03.021

Caiazzo, F., & Caggiano, A. (2018). Laser Direct metal deposition of 2024 al alloy: Trace geometry prediction via machine learning. Materials, 11, 444. https://doi.org/10.3390/MA11030444

Chan, S., & Lu, Y. (2018). Data-driven cost estimation for additive manufacturing in cybermanufacturing. Amsterdam: Elsevier. https://doi.org/10.1016/j.jmsy.2017.12.001

Charalampous, P., Kostavelis, I., Kontodina, T., & Tzovaras, D. (2021). Learning-based error modeling in FDM 3D printing process. Rapid Prototyping Journal, 27, 507–517. https://doi.org/10.1108/RPJ-03-2020-0046

Chen, C., Chen, G.X., Yu, Z.H. and Wang, Z.H. (2014). “A new method for reproducing oil paintings based on 3D printing.” Appl. Mech. Mater. Pages 644–650, pp. 2386–2389. https://doi.org/10.3390/polym12112536

Chen, Q., Guillemot, G., Gandin, C.A. and Bellet, M. (2017). “Three-dimensional finite element thermomechanical modeling of additive manufacturing by selective laser melting for ceramic materials.” Addit. Manuf. 2017, 16, pp. 124–137. https://doi.org/10.1016/j.addma.2017.02.005

Chowdhury, S., Mhapsekar, K., & Anand, S. (2018). Part build orientation optimization and neural network-based geometry compensation for additive manufacturing process. Journal of Manufacturing Science and Engineering, 1, 140. https://doi.org/10.1115/1.4038293

Ding, N., Benoit, C., Foggia, G. Bésanger, Y. & Wurtz, F. (2016). Neural Network-Based Model Design for Short-Term Load Forecast in Distribution Systems. IEEE Transactions on Power Systems, Volume: 31, Issue: 1, Page(s): 72 – 81. https://doi.org/10.1109/TPWRS.2015.2390132

Dowling, L., Kennedy, J., O’Shaughnessy, S., & Trimble, D. (2020). A review of critical repeatability and reproducibility issues in powder bed fusion. Materials and Design, 186, 108346. https://doi.org/10.1016/j.matdes.2019.108346

Dumais, S. T. (2004). Latent semantic analysis. Annual Review of Information Science and Technology, 38, 188–230. https://doi.org/10.1002/aris.1440380105

Everton, S.K., Hirsch, M., Stavroulakis, P.I., Leach, R.K. & Clare, A.T. Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing Mater. Des., 95 (2016), pp. 431-445. https://doi.org/10.1016/j.matdes.2016.01.099

Francis, J., & Letters, L.B.-M. (2019). Deep learning for distortion prediction in laser-based additive manufacturing using big data. Amsterdam: Elsevier. https://doi.org/10.1016/j.mfglet.2019.02.001

Frazier, W. E. (2014). Metal additive manufacturing: A review. Journal of Materials Engineering and Performance, 23, 1917–1928. https://doi.org/10.1007/S11665-014-0958-Z/FIGURES/9

Fu, F., Zhang, Y. Chang, G. and Dai, J. (2016). “Analysis on the physical mechanism of laser cladding crack and its influence factors.” Optik Volume 127, Issue 1, January 2016, pp. 200-202. https://doi.org/10.1016/j.ijleo.2015.10.043

Gobert, C., Reutzel, E. W., Petrich, J., Nassar, A. R., & Phoha, S. (2018). Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Additive Manufacturing, 21, 517–528. https://doi.org/10.1016/J.ADDMA.2018.04.005

Gorunov, A. (2018) “Complex refurbishment of titanium turbine blades by applying heat-resistant coatings by direct metal deposition.” Eng Fail Anal, 86 (2018), pp. 115-130. https://doi.org/10.1016/j.engfailanal.2018.01.001

Grasso, M. and Colosimo, B.M. (2017). "Process defects and in situ monitoring methods in metal powder bed fusion." a review[J] Meas Sci Technol, 28 (4) (2017), Article 044005. https://doi.org/10.1088/1361-6501/aa5c4f

Grasso, M., Demir, A. G., Previtali, B., & Colosimo, B. M. (2018). In situ monitoring of selective laser melting of zinc powder via infrared imaging of the process plume. Robot Computer Integrating Manufacturing, 49, 229–239. https://doi.org/10.1016/J.RCIM.2017.07.001

Grasso, M., Laguzza, V., Semeraro, Q., & Colosimo, B. M. (2017). In-process monitoring of selective laser melting: spatial detection of defects via image data analysis. American Society Mechanical Engineering, 2017, 139(5). https://doi.org/10.1115/1.4034715

Grierson, D. R., & Quayle, S. D. (2021). Machine learning for additive manufacturing. Encyclopedia, 3, 1541–1556. https://doi.org/10.1016/j.matt.2020.08.023

Gu, G. X., Chen, C. T., Richmond, D. J., & Buehler, M. J. (2018). Bioinspired hierarchical composite design using machine learning: Simulation, additive manufacturing, and experiment. Material Horizons, 5, 939–945. https://doi.org/10.1039/C8MH00653A

Gunther, D., Pirehgalin, M. F., Weis, I., Vogel-Heuser, B. (2020). Condition monitoring for the Binder Jetting AM-process with machine learning approaches. Proceedings - 2020 IEEE Conference Industrial Cyberphysical Systems ICPS 2020 2020:417–20. https://doi.org/10.1109/ICPS48405.2020.9274716

Guo, N., & Leu, M. C. (2013). Additive manufacturing: Technology, applications and research needs. Frontiers of Mechanical Engineering, 8, 215–243. https://doi.org/10.1007/s11465-013-0248-8

Heralić, A., Christiansson, A.K. & Lennartson, B. (2012). "Height control of laser metal-wire deposition based on iterative learning control and 3D scanning". Optics and Lasers in Engineering. Volume 50, Issue 9, September 2012, Pages 1230-1241. https://doi.org/10.1016/j.optlaseng.2012.03.016

Hojjati, A., Adhikari, A., Struckmann, K., Chou, E. J., Ngoc, T., Nguyen, T., Madan, K., Winslett, M.S., Gunter, C.A., King, W.P., (2016). Leave Your Phone at the Door: Side Channels that Reveal Factory Floor Secrets. In: Proceedings of 2016 ACM SIGSAC Conference on Computer Communications Security. https://doi.org/10.1145/2976749

Jia, C. B., Liu, X. F., Zhang, G. K., Zhang, Y., Yu, C. H., & Wu, C. S. (2021). Penetration/keyhole status prediction and model visualization based on deep learning algorithm in plasma arc welding. International Journal of Advanced Manufacturing Technology, 117, 3577–3597. https://doi.org/10.1007/s00170-021-07903-9

Jin, Z., Zhang, Z., Demir, K., & Gu, G. X. (2020). Machine learning for advanced additive manufacturing. Matter, 3, 1541–1556. https://doi.org/10.1016/j.matt.2020.08.023

Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., et al. (2016). Smart manufacturing: Past research, present findings, and future directions. International Journal of Precision Engineering Manufacturing - Green Technology, 3, 111–128. https://doi.org/10.1007/s40684-016-0015-5

Khanzadeh, M., Rao, P., Jafari-Marandi, R., Smith, B. K., Tschopp, M. A., & Bian, L. (2018). Quantifying geometric accuracy with unsupervised machine learning: Using self-organizing map on fused filament fabrication additive manufacturing parts. Journal of Manufacturing Science and Engineering. https://doi.org/10.1115/1.4038598

Kulkarni, P., Marsan, A., & Dutta, D. (2000). Review of process planning techniques in layered manufacturing. Rapid Prototyp J, 6, 18–35. https://doi.org/10.1108/13552540010309859

Kumar, S. (2016). Ultrasonic assisted friction stir processing of 6063 aluminum alloy. Archives of Civil and Mechanical Engineering, 16, 473–484. https://doi.org/10.1016/j.acme.2016.03.002

Kumar, S., & Kar, A. (2021). A review of solid-state additive manufacturing processes. Transactions on Indian Natational Academic Engineering, 6, 955–973. https://doi.org/10.1007/S41403-021-00270-7

Kumar, S., & Kishor, B. (2021). Ultrasound added additive manufacturing for metals and composites: Process and control. Singapore: Springer. https://doi.org/10.1007/978-981-16-3184-9_3

Kumar, S., & Wu, C. (2021a). Strengthening effects of tool-mounted ultrasonic vibrations during friction stir lap welding of Al and Mg alloys. Metallurgical and Materials Transactions a, Physical Metallurgy and Materials Science, 52, 2909–2925. https://doi.org/10.1007/s11661-021-06282-w

Kumar, S., & Wu, C. (2021b). Eliminating intermetallic compounds via Ni interlayer during friction stir welding of dissimilar Mg/Al alloys. Journal of Material Research and Technology, 15, 4353–4369. https://doi.org/10.1016/J.JMRT.2021.10.065

Kumar, S., & Wu, C. S. (2018). A novel technique to join Al and Mg alloys: Ultrasonic vibration assisted linear friction stir welding. Materials Today Proceedings, 5, 18142–18151. https://doi.org/10.1016/j.matpr.2018.06.150

Kumar, S., & Wu, C. S. (2020a). Suppression of intermetallic reaction layer by ultrasonic assistance during friction stir welding of Al and Mg based alloys. Journal of Alloys and Compounds, 827, 154343. https://doi.org/10.1016/j.jallcom.2020.154343

Kumar, S., Wu, C. S., & Shi, L. (2020b). Intermetallic diminution during friction stir welding of dissimilar Al/Mg alloys in lap configuration via ultrasonic assistance. Metallurgical and Materials Transactions a: Physical Metallurgy and Materials Science, 51, 5725–5742. https://doi.org/10.1007/s11661-020-05982-z

Kumar, S., Wu, C. S., & Song, G. (2020c). Process parametric dependency of axial downward force and macro- and microstructural morphologies in ultrasonically assisted friction stir welding of Al/Mg alloys. Metallurgical and Materials Transactions a: Physical Metallurgy and Materials Science, 51, 2863–2881. https://doi.org/10.1007/s11661-020-05716-1

Kumar, S., Wu, C. S., Padhy, G. K., & Ding, W. (2017). Application of ultrasonic vibrations in welding and metal processing: A status review. Journal of Manufacturing Processes, 26, 295–322. https://doi.org/10.1016/j.jmapro.2017.02.027

Kumar, S., Wu, C. S., Sun, Z., & Ding, W. (2019). Effect of ultrasonic vibration on welding load, macrostructure, and mechanical properties of Al/Mg alloy joints fabricated by friction stir lap welding. International Journal of Advanced Manufacturing Technology, 100, 1787–1799. https://doi.org/10.1007/s00170-018-2717-z

Kumar, S., Gopi, T., Harikeerthana, N., Gupta, M.K., Gaur, V., Krolczyk, G. & Wu, C.S. (2022). Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control. Journal of Intelligent Manufacturing, Volume 34, pages 21–55. https://doi.org/10.1007/s10845-022-02029-5

Kwon, O., Kim, H. G., Ham, M. J., Kim, W., Kim, G.-H., Cho, J.-H., et al. (2018). A deep neural network for classification of melt-pool images in metal additive manufacturing. Journal of Intelligence Manufacturing, 31, 375–386. https://doi.org/10.1007/S10845-018-1451-6

Meng, L., McWilliams, B., Jarosinski, W., Park, H. Y., Jung, Y. G., Lee, J., et al. (2020). Machine learning in additive manufacturing: a review. JOM Journal of the Minerals Metals and Materials Society, 72, 1. https://doi.org/10.1007/s11837-020-04155-y

Mozaffar, M., Paul, A., Al-Bahrani, R., Wolff, S., Choudhary, A., Agrawal, A., et al. (2018). Data-driven prediction of the high-dimensional thermal history in directed energy deposition processes via recurrent neural networks. Manufacturing Letters, 18, 35–39. https://doi.org/10.1016/J.MFGLET.2018.10.002

Noriega, A., Blanco, D., Alvarez, B. J., & Garcia, A. (2013). Dimensional accuracy improvement of FDM square cross-section parts using artificial neural networks and an optimization algorithm. International Journal of Advanced Manufacturing Technology, 69, 2301–2313. https://doi.org/10.1007/S00170-013-5196-2

Qi, X., Chen, G., Li, Y., Cheng, X., & Li, C. (2019). Applying neural-network-based machine learning to additive manufacturing: Current applications, challenges, and future perspectives. Engineering, 5, 721–729. https://doi.org/10.1016/J.ENG.2019.04.012

Rawat, S., & Shen, M. H. H. (2018). A novel topology design approach using an integrated deep learning network architecture. https://doi.org/10.48550/arXiv.1808.02334

Razvi, S. S., Feng, S., Narayanan, A., Lee, Y. T. T., & Witherell, P. (2019). A review of machine learning applications in additive manufacturing. Proceedings ASME Design Engineering Technical Conference. https://doi.org/10.1115/DETC2019-98415

Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Review, 65, 386–408. https://doi.org/10.1037/h0042519

Sames, W.J. and Pannala, S. (2016). "The metallurgy and processing science of metal additive manufacturing" [J] Int Mater Rev, 61 (5), pp. 315 – 360. https://doi.org/10.1080/09506608.2015.1116649

Scime, L., & Beuth, J. (2018a). Anomaly detection and classification in a laser powder bed additive manufacturing process using a trained computer vision algorithm. Additive Manufacturing, 19, 114–126. https://doi.org/10.1016/J.ADDMA.2017.11.009

Scime, L., & Beuth, J. (2018b). A multi-scale convolutional neural network for autonomous anomaly detection and classification in a laser powder bed fusion additive manufacturing process. Additive Manufacturing, 24, 273–286. https://doi.org/10.1016/J.ADDMA.2018.09.034

Scime, L., & Beuth, J. (2019). Using machine learning to identify in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process. Additive Manufacturing, 25, 151–165. https://doi.org/10.1016/J.ADDMA.2018.11.010

Shinde, P. P., & Shah, S. (2018). A Review of Machine Learning and Deep Learning Applications. In: Proceedings - 2018 4th International Conference Computer Communication Control Autom ICCUBEA 2018. https://doi.org/10.1109/ICCUBEA.2018.8697857

Singh, S., Ramakrishna, S., & Singh, R. (2017). Material issues in additive manufacturing: A review. Journal of Manufacturing Processes, 25, 185–200. https://doi.org/10.1016/j.jmapro.2016.11.006

Sterling , A.J., Torries, B., Shamsaei, N., Thompson, S.M. and W.Seely, D.W. (2016). "Fatigue behavior and failure mechanisms of direct laser deposited Ti–6Al–4V." Materials Science and Engineering: A Volume 655, 8 February 2016, pp. 100-112. https://doi.org/10.1016/j.msea.2015.12.026

Sutton, R. S., & Barto, A. G. (2015). Reinforcement Learning (2nd ed.). New York: The MIT Press.
Tapia, G., Elwany, A. H., & Sang, H. (2016). Prediction of porosity in metal-based additive manufacturing using spatial Gaussian process models. Additive Manufacturing, 12, 282–290. https://doi.org/10.1016/J.ADDMA.2016.05.009

Tapia, G., Khairallah, S., Matthews, M., King, W. E., & Elwany, A. (2017). Gaussian process-based surrogate modeling framework for process planning in laser powder-bed fusion additive manufacturing of 316L stainless steel. International Journal of Advanced Manufacturing Technology, 94, 3591–3603. https://doi.org/10.1007/S00170-017-1045-Z

Thompson, M. K., Moroni, G., Vaneker, T., Fadel, G., Campbell, R. I., Gibson, I., et al. (2016). Design for additive manufacturing: Trends, opportunities, considerations, and constraints. CIRP Annals - Manufacturing Technology, 65, 737–760. https://doi.org/10.1016/j.cirp.2016.05.004

Vaezi, M., Seitz, H. & Yang, S. (2013). A review on 3D micro-additive manufacturing technologies. The International Journal of Advanced Manufacturing Technology. Volume 67, pages 1721–1754. https://doi.org/10.1007/s00170-012-4605-2

Wang, C., Tan, X. P., Tor, S. B., & Lim, C. S. (2020). Machine learning in additive manufacturing: State-of-the-art and perspectives. Additive Manufacturing, 36, 101538. https://doi.org/10.1016/j.addma.2020.101538

Wang, C., Tan, X., Liu, E., & Tor, S. B. (2018b). Process parameter optimization and mechanical properties for additively manufactured stainless steel 316L parts by selective electron beam melting. Materials and Design, 147, 157–166. https://doi.org/10.1016/J.MATDES.2018.03.035

Wang, L., Törngren, M., & Onori, M. (2015). Current status and advancement of cyber-physical systems in manufacturing. Journal of Manufacturing Systems, 37, 517–527. https://doi.org/10.1016/J.JMSY.2015.04.008

Wang, T., Kwok, T. H., Zhou, C., & Vader, S. (2018a). In-situ droplet inspection and closed-loop control system using machine learning for liquid metal jet printing. Journal of Manufacturing Systems, 47, 83–92. https://doi.org/10.1016/J.JMSY.2018.04.003

Wang, Y. and Li, X. (2020). "An accurate finite element approach for programming 4D-printed self-morphing structures produced by fused deposition modeling." Mech. Mater. 2020, 151, pp. 103628. https://doi.org/10.1016/j.mechmat.2020.103628

Weiss, S. M., Dhurandhar, A., Baseman, R. J., White, B. F., Logan, R., Winslow, J. K., et al. (2014). Continuous prediction of manufacturing performance throughout the production lifecycle. Journal of Intelligent Manufacturing, 27, 751–763. https://doi.org/10.1007/S10845-014-0911-X

Widrow, B., & Lehr, M. A. (1990). 30 years of adaptive neural networks: perceptron, madaline, and backpropagation. Proceedings of the IEEE, 78, 1415–1442. https://doi.org/10.1109/5.58323

Wu, D., Jennings, C., Terpenny, J., Gao, R. X., & Kumara, S. (2017). A comparative study on machine learning algorithms for smart manufacturing: Tool wear prediction using random forests. Journal of Manufacturing Science and Engineering Transactions on ASME, 2017, 139. https://doi.org/10.1115/1.4036350

Wu, D., Rosen, D. W., Wang, L., & Schaefer, D. (2015a). Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. Computer Design, 59, 1–14. https://doi.org/10.1016/J.CAD.2014.07.006

Wu, H., Wang, Y., & Yu, Z. (2015b). In situ monitoring of FDM machine condition via acoustic emission. International Journal of Advanced Manufacturing Technology, 84, 1483–1495. https://doi.org/10.1007/S00170-015-7809-4

Wu, H., Yu, Z., & Wang, Y. (2016a). Real-time FDM machine condition monitoring and diagnosis based on acoustic emission and hidden semi-Markov model. International Journal of Advanced Manufacturing Technology, 90, 2027–2036. https://doi.org/10.1007/S00170-016-9548-6

Wu, H., Yu, Z., et al. (2016b). A new approach for online monitoring of additive manufacturing based on acoustic emission. Asmedigitalcollection. https://doi.org/10.1115/MSEC2016-8551

Wu, M., Phoha, V. V., Moon, Y. B., & Belman, A. K. (2016). Detecting malicious defects in 3D printing process using machine learning and image classification. ASME International Mechanical Engineering & Congress and Exposition Proceedings. https://doi.org/10.1115/IMECE201667641

Wu, M., Song, Z., & Moon, Y. B. (2017). Detecting cyber-physical attacks in CyberManufacturing systems with machine learning methods. Journal of Intelligence and Manufacturing, 30, 1111–1123. https://doi.org/10.1007/S10845-017-1315-5

Wu, X., Xu, C., Zhang, Z. and Guo, C. (2020). "Modeling and visualization of layered curing conversion profile in ceramic mask projection stereolithography process." Ceram. Int. 2020, 46, pp. 25750–25757. https://doi.org/10.1016/j.ceramint.2020.07.053

Xing, C., Jia, C., Han, Y., Dong, S., Yang, J., & Wu, C. (2020). Numerical analysis of the metal transfer and welding arc behaviors in underwater flux-cored arc welding. International Journal of Heat and Mass Transfer, 153, 119570. https://doi.org/10.1016/J.IJHEATMASSTRANSFER.2020.119570

Yang, J., Li, F., Wang, Z. and Zeng, X. (2015). "Cracking behavior and control of Rene 104 superalloy produced by direct laser fabrication." Journal of Materials Processing Technology Volume 225, November 2015, Pages 229-239. https://doi.org/10.1016/j.jmatprotec.2015.06.002

Yao, X., Moon, S. K., & Bi, G. (2017). A hybrid machine learning approach for additive manufacturing design feature recommendation. Rapid Prototyping Journal, 23, 983–997. https://doi.org/10.1108/RPJ-03-2016-0041

Zhang, H.-C., & Huang, S. H. (1995). Applications of neural networks in manufacturing: A state-of-the-art survey. International Journal of Production Research, 33, 705–728. https://doi.org/10.1080/00207549508930175

Zhang, Y. and Chou, Y.K. (2006). "Three-dimensional finite element analysis simulations of the fused deposition modelling process." Proc. Inst. Mech. Eng. Part B J. Eng. Manuf., 220, pp. 1663–1671. https://doi.org/10.1243/09544054JEM572

Zhang, Y., Hong, G. S., Ye, D., Zhu, K., & Fuh, J. Y. H. (2018b). Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring. Materials and Design, 156, 458–469. https://doi.org/10.1016/J.MATDES.2018.07.002

Zhang, Y., Jarosinski, W., Jung, Y.G. and Zhang, J. (2018). "Additive manufacturing processes and equipment. In Additive Manufacturing: Materials, Processes, Quantifications and Applications." Elsevier: Amsterdam, The Netherlands. pp. 39–51. https://doi.org/10.1016/B978-0-12-812155-9.00002-5

Zhang, Z., Liu, Z., & Wu, D. (2021). Prediction of melt pool temperature in directed energy deposition using machine learning. Additive Manufacturing, 37, 101692. https://doi.org/10.1016/J.ADDMA.2020.101692