Artificial Intelligence for Optimizing 3D Printing Quality, Time, and Material Use

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Abstract

Additive manufacturing (AM) has evolved from a prototyping tool into a key production technology across aerospace, healthcare, and automotive sectors, yet persistent issues in dimensional accuracy, surface quality, material waste, and print time still limit its wider adoption. This research investigates how artificial intelligence (AI)-driven optimization can improve the accuracy, efficiency, and quality of 3D-printed parts by jointly optimizing build orientation and support structures. Building on an extensive review of the main AM technologies (FDM, SLA, SLS) and recent advances in AI for manufacturing, the study synthesizes evidence on how machine learning, deep learning, and reinforcement learning can be used to predict print defects, select near-optimal orientations, and design minimal yet stable support topologies. The analysis highlights that AI-based predictive models can reduce trial-and-error in parameter selection, enhance dimensional fidelity, and mitigate common defects such as warping, poor layer adhesion, and surface roughness. Furthermore, AI-optimized support generation can significantly decrease material consumption, post-processing effort, energy use, and overall printing time, thereby improving both economic performance and environmental sustainability. The research consolidates these insights into a conceptual framework for AI-augmented 3D printing, outlining data requirements, learning workflows, and feedback-control loops needed for closed-loop, self-optimizing print systems. Finally, it discusses current barriers to industrial deployment, including data scarcity, computational cost, and the limited accessibility of advanced AI tools for small and medium-sized enterprises, and identifies promising research directions such as user-friendly AI interfaces, technology-specific models, and sustainability-oriented optimization objectives. Overall, the work demonstrates that integrating AI with additive manufacturing offers a viable pathway towards more accurate, efficient, and sustainable 3D printing processes. The proposed framework serves as a roadmap for researchers and practitioners aiming to design robust, autonomous, and resource-efficient AM workflows.

Keywords: Additive manufacturing; 3D printing; Artificial intelligence; Machine learning; Build orientation optimization; Support structure optimization; Sustainable manufacturing

1. Introduction

3D printing is the manufacturing method through which, a physical object is created based on an initial digital model with three dimensions and typically involves a series of thin layers of materials and material deposition successively, layer by layer (Rezaei et al., 2023). The additive manufacturing process is defined by the successive layering of materials (Lim et al., 2016). Originally, 3D printing was developed as a prototyping method. However, during the last few decades, this field has undergone massive development and has now become a technologically practical method to create functional components in aerospace, healthcare, automotive, or consumer goods fields. Due to the potential to create complex shapes that would either be too expensive or difficult to manufacture through other processes, it has been beneficial in the aerospace, automotive, medical, and consumer items fields (Gardan, 2015).

The primary impetus for the adoption of additive manufacturing technology lies in its capacity to produce geometries unattainable by conventional manufacturing methods. This capability facilitates the reduction of weight in structural components and allows for the integration of functional elements, enabling the design of bespoke products tailored to specific requirements (Zeynivand et al., 2021). The advantages of 3D printing encompass design flexibility, material efficiency, and the customization of particular components. Nonetheless, there exist several challenges that warrant examination, including issues related to precision, processing duration, and the necessity for post-production treatment (Lim et al., 2016).

The advantages of 3D printing include high design flexibility, reduced material waste, and the capability to produce complex shapes without the need for specialized tooling, molds, or subtractive manufacturing methods like milling or cutting (Tuleshev and Fatahi Valilai, 2026). This makes 3D printing particularly appropriate for rapid prototyping, low-volume production, and the manufacturing of parts with features that would be difficult to produce and create using traditional approaches (Attaran, 2016). Unlike subtractive manufacturing, where material is taken away to form an object, additive manufacturing makes use of material only which is necessary, henceforth, reducing waste significantly.

It also makes on-demand production possible, which translates into significant cost savings on inventory and speeds up the time-to-market for new products (Delaram et al., 2023, 2021).

The initial applications of 3D printing were primarily on rapid prototyping which helped the engineers and designers to come up with a prototype of their designs. Such early applications were relatively restricted in their potential, and this was mostly due to the costly nature of 3D printers and the restricted variety of materials that could be used (Thompson et al., 2016). The further development of more complicated 3D printing technologies enabled the creation of working parts and components for such a huge number of industries and businesses, that the use of the technology became relevant to much more than just prototyping. Fused Deposition Modelling (FDM), Stereolithography (SLA), and Selective Laser Sintering (SLS) are just some of the few of the modern printing techniques that have boosted the precision and resolution of printed things while also expanding the range of possible materials usable (Albarnawi and Bashir, 2017, Mohammadian et al., 2024). However, some blanks still need to be filled, which will be mainly touching on the topics of print quality, material consumption, and production efficiency. These problems are exaggerated by the fact that the objects being produced in the current complex 3D printing applications have to be of complex shapes and high-performance standards.

Together, the use of computers and 3D printing technology can simplify many printing processes, via automation and optimization. Machine learning algorithms can analyze previous prints to determine the best build orientations, allowing for lower support structures while optimizing the printed objects'' mechanical abilities (Yang et al., 2017). AI can optimize printing parameters such as layer thickness, layer height, temperature, and speed while building the part using feedback control (Rojek et al., 2020). Moreover, techniques like neural networks and genetic algorithms can be applied to AI in order to determine optimum support structures with good stability, material efficiency, and removal ease (Shah et al., 2023).

AI based technologies are capable to anticipate the entire printing process that will take place even before its start, thus assisting in preventing situations that could lead to warping or poor lamination of layers that might bring in, printing defects. Therefore, printing faults never arise. (Sani, Zolfagharian, & Kouzani, 2024). As AI and 3D printers improve, AI will become a major player in the additive manufacturing industry where AI will be seamlessly incorporated into 3D printers increasing productivity and enhancing the quality of the prints. The data-driven processes of AI, along with the characteristics of 3D printing will cause almost a revolution in modern manufacturing and its applicability to many other industries. This development will facilitate the implementation of innovative mechanisms to advance nascent production systems, such as Cloud Manufacturing, which are designed to provide service-oriented support for 3D printing technologies (Niari et al., 2022; Rezapour Niari et al., 2023).

1.2 Purpose of this research

The purpose of this research is to primarily answer the research question; How can AI-driven optimization techniques improve accuracy, efficiency, and quality of 3D printed objects by optimizing their orientation and support structures? This research will discuss the integration of AI-driven optimization techniques within the 3D printing process that enhances accuracy, efficiency, and quality. This research, which focuses on the strategic optimization of print orientation and support structures, aims to develop an approach to additive manufacturing that is more automated and efficient. This will help not only to concentrate on factors that make the productivity of 3D printing better, but also target important challenges such as material waste and post-processing requirements.

The first sub-objective deals with understanding how AI can, in principle, analyze all factors in order to determine systematically the best print orientations and support structures. This will be used to demonstrate the potential for automation to realize substantial improvements in print quality and operational efficiency, opening up 3D printing to mass production in a wider range of industries.

The second sub-objective is to analyze the impact of AI-driven optimization on the additive manufacturing landscape as a whole. This includes an assessment of how these technologies can enhance additive manufacturing throughout the printing process. By highlighting the benefits of including AI into traditional practices of 3D printing, this research aims to provide significant insights that will increase the implementation and acceptance of additive production in business situations thus supporting its importance in present-day manufacturing.

This research will be performed in multiple stages, commencing with a comprehensive literature review, which will discuss the current methods that are being utilized in the field of additive manufacturing and 3D printing; three in particular, namely, Fused Deposition Modelling (FDM), Stereolithography (SLA), and Selective Laser Sintering (SLS). Then comes the evaluation of the gaps and challenges being faced currently in the mentioned printing processes. Technologically, this research will evaluate how AI will bridge these gaps and improve the 3D printing process for more efficient, customized, and sustainable production. And lastly, this research will focus on identifying the most suitable options for successful integration of AI into 3D printing, as well as the challenges that may arise in leveraging these technologies to achieve wider adoption for industrial and modern production processes. This research will also look into the future trend that can be predicted for the use of AI in 3D printing, focusing on its potential to shape the manufacturing process.

2. Literature Review

2.1 Additive Manufacturing (3D Printing)

AM, also referred to as the “the third industrial revolution” in recently published articles, is a manufacturing process that fabricates a 3D object by adding materials layer by layer. Construction of homes, intricate mechanical components, medical implants, and even food are examples of applications. In general, the eight phases in an AM process can be used to make 3D-printed objects. First, users use a CAD software to produce a 3D model. This 3D model is then converted into a stereolithography (STL) file. Slices of the digital mock-up are created once the user enters the parameters and the STL file into the AM system, and then they are transferred into the build sequence. The part is then constructed by the machine, layer by layer. After the part is finished, the user will take it off the substrate and do any postprocessing required to make it a working prototype or product. Most importantly, to facilitate easy assembly and serve its purpose, it is necessary that these printed parts satisfy the three Fs—form, fit, and function.

3D printing, an inventive approach of additive manufacturing, has revolutionized production environments by presenting innovative methods of production, improved material choices, and unique design opportunities. Since its introduction, this technology has demonstrated significant potential across multiple industries owing to its distinctive attributes, such as customization, adaptability, and resource efficiency (Lu, Li, & Tian, 2015). Additive manufacturing, as compared to conventional manufacturing methods like subtractive and equivalent manufacturing, originated in the late 20th century. Conventional techniques including metallic casting and forging have origins that extend over a thousand years. Nonetheless, the emergence of stereolithography in 1980s indicated the beginning of the present-day 3D printing technology (Wohlers, 2015). The main difference lies in the layer-by-layer construction technique used in 3D printing, which differs from subtractive techniques that necessitate intensive tooling and waste materials control. 3D printing facilitates the construction of complex shapes through incremental object assembly, which would be tough or impractical to do with conventional manufacturing techniques (Lu, Li, & Tian, 2015).

An important advantage of 3D printing is its adaptability, summarized by researchers as the "five any's": the capacity to manufacture any material, into any component, at any site, in any volume, and for any sector (Lu, Li, & Tian, 2015). This has enabled industries such as aerospace and healthcare make use of 3D printing for specialized requirements, including low-volume, high-complexity components. In aerospace, 3D printing has enabled the manufacture of lightweight, load-bearing components and structurally intricate designs, hence minimizing material waste and assembly duration (Bullis, 2013; Hoyt, 2013).

The healthcare industry has significantly benefited from the customization potential of 3D printing, especially in prostheses and implants. 3D printing facilitates the production of patient-specific medical equipment, enhancing physical compatibility and functionality (Sutradhar, Park, & Carrau, 2014). This customization corresponds with the growing desire for personalized healthcare solutions and has made substantial progress in bioengineering, particularly with the advancement of biocompatible materials appropriate for medical purposes (Hoyt, 2013).

The advancement of innovative materials has led to the expansion of 3D printing, emphasizing high-performance alloys and multi-material configurations engineered for endurance and toughness. NASA has led research on high-temperature alloys appropriate for 3D-printed rocket components that endure extreme temperatures (NASA, 2013). Likewise, multi-material printing has facilitated the creation of functionally graded materials, wherein diverse qualities are integrated within a singular structure to enhance performance attributes such as weight, flexibility, and strength (Lu, Li, & Tian, 2015). These material innovations enable engineers to create components that satisfy certain application criteria, expanding the possibility of 3D printing in industries with high material performance standards (Bullis, 2013).

As 3D printing evolves, researchers are progressively integrating intelligent systems and technology such as the Internet functionalities to improve the process's accuracy and adaptability. Advanced 3D printing systems, integrated with sensors and real-time data processing capabilities, allow for dynamic modifications in printing parameters, leading to enhanced consistency in quality throughout production cycles (Lu, Li, & Tian, 2015). The integration of 3D printing with Internet indicates a future of distributed manufacturing networks, enabling on-demand local creation, hence minimizing logistics expenses and lead times. This advancement is especially encouraging for distant or inhospitable areas. In circumstances where conventional manufacturing infrastructure is lacking or unfeasible, 3D printing provides an appealing option for on-site production, including potential applications in space, as researchers explore the feasibility of producing structures directly on extraterrestrial surfaces (Cesaretti, Dini, & De Kestelier, 2014).

Although 3D printing provides distinct benefits, it does not ultimately replace conventional manufacturing. Hybrid manufacturing procedures are evolving, incorporating additive, subtractive, and similar methods into a single manufacturing chain. This combined approach facilitates the production of intricate, high-precision components, minimizing the production steps and allowing innovative design methodologies that capitalize on the advantages of each technique (Alec, 2014). For example, DMG's creation of a hybrid machine that combines laser-based additive manufacturing with milling facilitates the production of components featuring complex interior geometries while preserving external precision (DMG MORI, 2024).

The evolution of 3D printing technology demonstrates its revolutionary effect on modern day production. Initially a prototyping tool, 3D printing has evolved to serve critical industries through advancements in material science, automated production, and hybrid processing. With ongoing research, 3D printing is set to assume a pivotal role in a diverse manufacturing environment, complementing conventional manufacturing techniques and facilitating unparalleled customization, flexibility, and efficiency. 3D printing, a revolutionary method of layer production, has impacted manufacturing processes by offering innovative manufacturing procedures, improved material options, and unique design possibilities (Lu, Li, and Tian, 2015).

2.2 Types of 3D Printing

Selective Laser Sintering (SLS), Stereolithography (SLA), and Fused Deposition Modeling (FDM) are the three most common 3D printing technologies currently are being used in today's manufacturing processes. FDM is ideal for creating models, parts, and prototypes using materials such as PLA and ABS because it works by extruding thermoplastic filament layer by layer. Quick production and low-cost production are two of the main reasons to use this technology (Vaezi et al., 2013). SLA produces detailed, high-quality prints by pouring liquid resin in layers, and curing it with a laser. It is widely used in industries that require precision, such as dentistry and jewelry (Chua et al., 2010). SLS can create complex parts using laser-cut materials such as nylon without the need for reinforcement. In industries that require prototypes which offer multiple functions, such as aerospace and automotive, this approach is more suitable for producing durable, long-lasting parts (Frazier, 2014). Since each technology offers different advantages, they can be used in many industries.

2.2.1 Selective Laser Sintering (SLS)

Selective Laser Sintering (SLS) is a large-scale manufacturing technique that uses a powerful laser to fuse powdered materials into a solid state. This technology, which was first identified in the late 1900s (Thompson et al., 2016), is capable of processing numerous materials, such as ceramics, metals and polymers. SLS provides considerable flexibility in terms of design, allowing products to be manufactured from 3D CAD models instead of relying on traditional manufacturing methods. As a growing number of businesses adopt additive manufacturing, SLS has emerged as crucial instrument for rapid, robust production and product design. This literature review examines the advantages of SLS, its applications across various industries, its limitations and future advancements. Although SLS offers many benefits, it is important to consider challenges as well.

SLS presents numerous advantages which make it a favorable option for various manufacturing sectors. The primary benefit lies in its capacity to generate intricate and detailed designs; a feature that traditional techniques often struggle to achieve. The layer-by-layer methodology facilitates the production of fully integrated components with sophisticated internal architectures; this is particularly beneficial for complex applications within the aerospace and engineering domains (Gardan, 2017). Furthermore, a significant advantage is the diverse array of materials available through SLS. It can process a broad spectrum of materials (including thermoplastics, metals and composites) thereby allowing manufacturers to select the most suitable material for their specific requirements (Frazier, 2014). This capability encompasses the potential for utilizing recycled materials, which, in turn, contributes to the promotion of sustainable practices within the manufacturing sector (Jiménez et al., 2019).

SLS is additionally known for its efficiency in producing operational and mechanical parts. It varies from other additive manufacturing processes due to the fact that it reduces the need for process support since the surrounding powder acts as a support throughout the printing process. This decreases material waste and processing time (Vaezi et al. 2013). One of the most significant advantages is the quickness of construction; SLS can produce several components in a single run, making it a good choice for small to medium-sized manufacturing businesses (Gokhare, Raut, & Shinde, 2017). Because of its unique properties, several firms have adopted SLS technology.

SLS is widely used in the aerospace industry to produce lightweight materials capable of improving fuel efficiency and machine performance. Engineers are designing complex materials to improve aerodynamics, which in turn improves airplanes performance (Bullis, 2013). SLS has transformed medical device production and interaction. Orthopedic items can be created and built to fit certain physical models. This enhances patient results as well as productivity (Shahrubudin et al., 2019). Furthermore, SLS strives to build surgical standards that allow for accuracy in treatments such as dental implants (Rojek et al., 2020). The automobile sector uses SLS for quick prototyping and small-scale manufacturing.

SLS enables the manufacturing of prototype models that can be tested to their limitations by vehicle makers in order to efficiently work on their designs. Using SLS to incorporate several functions into a single part reduces assembly time and improves automotive part reliability (Grosious & Lakshmaiya, 2024). SLS is used in the production of customized consumer products including as clothing, accessories, and gadgets. The technology's capacity to quickly and cost-effectively create unique designs that match the needs of custom items (Lim et al., 2016).

Regardless of its numerous advantages, SLS has some problems that limit its widespread use. Firstly, SLS is extremely expensive, particularly in terms of equipment and raw materials. The initial cost of procuring SLS equipment is exceedingly high for small and medium enterprises (Yang et al., 2017). Furthermore, the cost of raw materials, particularly fine powder, has a significant impact on the price of the finished product. The other problem is post-processing. Although SLS eliminates the need for post-processing, it still requires the removal of surplus powder and the finishing of the surface, which takes time and may raise overhead costs (Frazier, 2014).

The material characteristics of SLS-produced parts can vary depending on the processing technique. As a result, it involves extensive evaluation and verification in order to ensure validity and consistency (Yehia et al., 2024). Furthermore, the lack of options compared to traditional operating systems is an issue. Although SLS can process a wide range of materials, the available powders are not as varied as traditional manufacturing processes. This may limit choices in design for specific reasons (Thompson et al., 2016).

Hence, overall, it can be said that SLS has emerged as an important technology in the additive manufacturing business, providing numerous benefits which include scalability, adaptation, and flexibility. Its applications in consumer goods, automobiles health care, and aerospace industries demonstrate its ability to handle the present industry. To fully grasp SLS's potential, concerns such as cost, the post-production requirements, and challenges must be solved. SLS is going to assume a much larger role in industry as technical improvements drive innovation and long-term development in a variety of industries.

2.2.2 Stereolithography (SLA)

Chuck Hull developed stereolithography (SLA) in 1986, one of the earliest and most popular additive manufacturing methods. This method uses a focused ultraviolet (UV) laser to cure a photopolymer resin, building up the solid layer by layer based on a 3D computer model. SLA has a reputation for producing products with high resolution and excellent surface finishes, making it a popular material in manufacturing and prototypes across a variety of industries.

SLA has several advantages that contribute to its widespread use in additive manufacturing. The high level of detail and accuracy you can get is one of its biggest advantages. Layer depths in SLA are up to 25 microns, allowing complex designs and fine details to be accurately reproduced (Pandzic, A., 2021). Attention to detail is particularly useful in applications that require high precision, such as gold and dentistry (Sculpteo, 2020). Another important advantage of SLA is improved surface finish compared to other build-up manufacturing methods.

According to Formlabs, parts printed with SLA have a smooth glossy surface, which reduces the need for long post-processing. This gives the printed material an added aesthetic value while reducing the cost and time of the finish process. SLA accommodates a wide variety of photopolymer resins, allowing for the manufacturing of parts with variable mechanical properties and colors. Such resins can be formulated with particular properties, such as flexibility, weight, or heat resistance, to enable the application of SLA in diverse fields (Husna et al., 2024). The flexibility of SLA materials allows them to fit into various industries for manufacturing customized components that can cater to specific needs.

SLA technology is applied in all fields to utilize their resources and to fulfill specific production needs. SLA is highly adopted in the healthcare sector for preparing patient-specific models, surgical guides, and dentures. Preparation of accurate anatomical models can enhance preoperative planning and improve surgical results (Aimar, Palermo, & Innocenti, 2019). SLA is used to make biological implants, where precision and surface finish are important for effective integration with biological tissue (Kurowiak et al., 2023). SLA is used in the aerospace and automotive sectors for rapid prototyping and production of functional components. Engineers use SLA to produce composite designs that improve aerodynamic efficiency and reduce weight (Alami et al., 2023). Technology facilitates design iteration, thereby speeding up development cycles and reducing time to market for new products (Bullinger, Warschat, & Fischer, 2000). The consumer goods industry has adopted SLAs to produce customized products such as toys, homewares, and fashion accessories. This technology encourages the rapid creation of different designs based on individual customer preferences, reflecting the increased personalization of consumer goods (Kudus, Campbell, & Bibb, 2016). SLA’s ability to produce complex components allows designers to explore new shapes and forms that would be difficult to achieve using conventional manufacturing methods.

SLA has many advantages, but it faces some challenges that may limit its wider use. Material and equipment cost is a major concern. High-quality SLA printers and photopolymer resins are typically expensive and can be a barrier to entry for small and medium-sized enterprises (SMEs) (Formlabs). The limited-service life of photopolymer resins, combined with their sensitivity to UV light, can lead to product waste and increased repair costs. A major challenge is the post-printing post-processing required. SLA produces the highest quality products; however, to obtain a good and beautiful treatment, cleaning and treatment are often required (Kantaros et al., 2024). Such additional steps can raise the overall production time and complexity, which can cause some time to be used up, that was saved during the printing process.

The devices compatible with SLA are diverse; however, the field of use is still small compared to other production methods. The mechanical properties of products produced with SLA can differ depending on the material type, and detailed and practical knowledge is required to ensure reliability (Husna et al., 2024). Stereolithography (SLA) is a significant improvement in manufacturing technology, with benefits such as high precision, great surface quality, and a diverse variety of applications. Uses in the health-related, automotive, aerospace, and consumer industries indicate its capacity to live up to the standards of modern manufacturing requirements. Achieving SLA results requires tackling expenditure, reliability, and product limitations. As technology advances, SLA is expected to play a critical role in developing complementary solutions that encourage innovation and acceptance across multiple sectors.

2.2.3 Fused Deposition Modelling (FDM)

Fused Deposition Modeling is one of the predominant additive manufacturing technologies discovered in the late 1980s by Scott Crump. It is an activity of layering level by level, heated material pressed into the mold to create 3D objects from a digital model (Crump, 1992). Because the production process of FDM is simple and produces parts at low cost within less time, it has wide uses in various industries.

FDM has numerous advantages that make it the encouraged additive manufacturing method. The most major advantage is cost. FDM systems are typically less expensive to purchase and operate than other additive printing technologies, making them accessible to both enthusiasts and professionals (Shahrubuddin et al., 2019). FDM materials, particularly thermoplastics such as polylactic acid (PLA) and acrylonitrile butadiene styrene (ABS), are economical and readily available, lowering production costs (Agocs, Hanon, and Zsidai, 2024). FDM has several significant advantages, including its simplicity of usage and versatility. FDM machines are meant to be user-friendly, allowing operators to quickly set up and create parts. This is important for rapid prototyping, enabling faster design decisions and minimal downtime (Zivanovic et al., 2020).

By using different thermoplastic materials, it is easy to produce parts with different mechanical properties, such as durability, adaptability, and heat resistance, so FDM is regarded as suitable for numerous applications (Murariu, 2022). In addition, FDM also draws more attention due to its sustainability features. This technology enables recycling of thermoplastic materials and the inclusion of bio-based fibers like PLA, matching with the increasing emphasis on sustainability in manufacturing (Hasan, 2024). With industries looking at making less of an environmental footprint, the emphasis on sustainability is crucial.

Because of its distinct advantages, FDM technology is in use in several industries. Fused Deposition Modelling (FDM) is a technique used in the aerospace sector to create basic parts that meet high performance specifications. Additive manufacturing allows engineers to create complicated designs that improve fuel economy and reduce weight, which is a vital necessity for applications in aerospace (Alami, 2023). Furthermore, aerospace businesses use FDM for rapid prototyping to validate and develop ideas, speeding up their manufacturing cycles.

FDM is widely used in the automotive sector to produce prototypes, components, and finished products. Automotive manufacturers employ FDM to generate functioning component prototypes, which enhances dependability and the testing processes (Alami, 2023). Furthermore, FDM is increasingly being utilized to create specialized parts, such as tools and housings, in cases when standard manufacturing processes have proven unsuccessful or expensive (Ngo, 2018). It enables the insertion of sophisticated parts and design, hence improving the vehicle's performance.

FDM has been used in numerous applications, including customized production, dental care, and the human body. The capacity of FDM to generate patient-specific solutions enhances the ease of use and efficiency of medical equipment, ultimately improving the health of patients (Bozkurt & Karayel, 2021). This technology enables the development of surgical and prosthetics treatments that are matched to the unique characteristics of the individual body, hence improving personalized medicine and surgical precision.

Although FDM offers several benefits, it has a number of difficulties that may restrict its general use. The biggest issue is the scarcity of materials. Fused Deposition Modelling (FDM) is appropriate for most thermoplastics; nevertheless, the mechanical characteristics of printed products may not fulfil the needs of some applications, particularly in high-volume settings (Rouf, 2022). Asymmetry in FDM printed parts can cause variances in durability and strength between designs, making it difficult to maintain consistency.

One of the significant challenges has been the surface finish and accuracy of FDM. Even when design and control are successful, many FDM parts have uneven lines and surfaces and need post-processing to exhibit a good aesthetic appearance. This performance is difficult over time, especially for those designs that need further development and validation (Kantaros et.al., 2024). The speed of FDM printing may become a limitation, especially in terms of large parts. Even though FDM allows rapid prototyping, the process of layering may result in higher lead times compared to industrial processes used to generate large-scale products (Cano-Vicent et al., 2021). This limitation may not suit some companies, that may even prevent them from making full use of FDM for large-scale applications.

FDM is one of the flexible and efficient methods of additive manufacturing. It provides many benefits like versatile devices, user-friendliness, and security. The applications in the aerospace, automotive, and healthcare industries show that FDM can accommodate the industries of today. Material issues, space availability, and manufacturing speed are to be resolved for the best use of FDM. With further advancements in technology, FDM will become a significant player in the additive manufacturing industry in the years to come.

2.3 Gaps in the Literature Review

A common issue with FDM, SLA, and SLS in 3D printing is obtaining high precision and a quality surface finish. All three techniques fail to maintain proper standards due to issues such as layering and material deposition, thermal stress, and, in some circumstances, polymer breakdown or changes during curing or cooling. There is currently a gap in the literature covering the continuous issues involved with developing 3D printing processes in order to reduce material waste, increase the quality of prints, and achieve efficient manufacturing. Current solutions frequently include manual modifications and established plans, which are insufficient to address the complicated needs caused by numerous materials, complicated frameworks, and quick reactions in the printing process.

This gap allows artificial intelligence to employ machine learning models that read historical print data to predict potential problems and auto-correct parameters on the fly. AI-driven processes will be able to remove most of the key limiting factors of 3D printing, such as waste generation and dimensional irregularities, thereby making the process of additive manufacturing more productive, cost-effective, and sustainable.

3. Integration of Artificial Intelligence in 3D Printing

3.1 Artificial Intelligence and its applications

The term "artificial intelligence" (AI) refers to a rapidly developing field that consists of a wide range of technologies that are meant to replicate human intelligence in computer systems. In its most general form, AI seeks to allow computers and other systems to carry out activities that usually require the intelligence of an actual person. These activities include learning, solving problems, pattern recognition, and making decisions. As the technology has progressed, applications of artificial intelligence have become significantly integrated into a variety of industries. This has resulted in major breakthroughs and automation in a variety of fields, ranging from data processing to autonomous systems (Russell & Norvig, 2016). The use of AI is outperforming traditional computer applications, creating significant implications not just for everyday life but also for advanced industries such as healthcare, aerospace, and the automotive sector.

The origins of artificial intelligence may be dated back to the middle of the 20th century, with leading scholars like as Alan Turing making significant contributions. Turing's conceptual "Turing Test" was crucial in defining machine intelligence. In the 1950s and 1960s, researchers developed techniques to facilitate thinking, reasoning, and decision-making. These algorithms lay the foundation for artificial intelligence and are sometimes called “Good Old-Fashioned AI” (GOFAI) (Reyneke, 2023). In the 1980s, there was a revolution in machine learning, with artificial intelligence focusing more on statistical methods and data-driven models. Deep learning refers to the field of machine learning that uses neural networks to model complex human behavior (Janiesch, Zschech, & Heinrich, 2021). Developments in processing power and data availability were studied in depth during the 2000s. According to LeCun, Bengio, and Hinton (2015), this approach is a game changer in the field of artificial intelligence because of its ability to create highly accurate models for image recognition, programming languages, and other applications.

Since then, artificial intelligence has evolved to include more intelligent algorithms, such as deep neural networks and reinforcement learning models. At the same time, AI systems can learn and grow by using data on their own, adapting to new things and improving their skills over time. A completely different approach was discovered called reinforcement learning. This method uses feedback from the product to improve performance. For example, Silver et al. (2017) confirmed the promise of promoting learning by developing AlphaGo, an artificial intelligence model capable of defeating high-level players playing complex games such as Go. This self-learning process is at the forefront of many aspects of artificial intelligence, from robotics to simply tracking movement (Sutton & Barto, 2018). Jordan and Mitchell (2015) believe that the development of artificial intelligence is marked by the continuous development and progress of machine learning. These advances have created an environment where artificial intelligence can analyze and respond to data with increasing accuracy and sophistication.

Artificial intelligence has revolutionized many important industries, including aerospace, medical and automotive. In the aviation industry, artificial intelligence algorithms play an important role in managing the safety, navigation and maintenance of aircraft. For example, using artificial intelligence systems, the National Aeronautics and Space Administration (NASA) can monitor and predict equipment failures and help develop improvement plans to reduce delays and all costs (Shukla, Fan, and Jennions, 2020). Additionally, artificial intelligence will help drive the development of autonomous drones and autonomous aircraft, bringing new opportunities for access and data collection (Oche, Ewa, & Ibekwe, 2021). These innovations powered by artificial intelligence will help address the complexity and safety requirements of space missions, which is important because they require instant decision-making and strategic planning.

Much of the progress in autonomous driving technology is being driven by artificial intelligence in the automotive industry. AI algorithms are being used by companies like Tesla to develop driverless cars. These companies use deep learning models to process large amounts of sensor data to ensure safe navigation (Soori, Arezoo, & Dastres, 2023). For example, in Tesla’s case, the automation system includes real-time data processing, allowing the vehicle to automatically respond to traffic, driving conditions, and pedestrian movements (Bathla et al., 2022). The goal of these developments is not only to improve safety, but also to make transportation simpler and more efficient, and potentially reduce the environmental impact of traditional cars.

Another industry that could benefit greatly from the application of AI is healthcare, particularly in the areas of diagnostics, personalized healthcare and medical imaging (Shahab et al., 2025, 2022; Sharifisari et al., 2025). Artificial intelligence models such as Convolutional Neural Networks (CNNs) are commonly used in the field of image diagnostics. This type helps in detecting diseases such as cancer with high accuracy through X-ray analysis, MRI and other examinations (Abdou, 2022). DeepMind Health, a subsidiary of Google, for example, has worked with medical centers to build artificial intelligence diagnostic tools that allow healthcare professionals to diagnose eye problems and diseases more accurately and at an earlier stage (Vincent, 2018). In addition, artificial intelligence models enable the creation of personalized treatment plans by analyzing patient data to predict individual responses to treatment. The result is healthcare solutions that are more efficient and tailored to individual needs (Alowais et al., 2023).

Overall, AI has emerged as an innovative and emerging technology that has the potential to drive innovation across various industries while improving decision-making processes, efficiency, and safety. The uses and benefits of AI are expected to continue to expand as modern industry advances, integrates, and transforms. Therefore, from here, we can see how AI has provided various benefits to industries where 3D printing has made significant contributions in various areas such as healthcare and automotive. Therefore, the application of AI in 3D printing has the potential to provide better results not only for certain industries but also for various other industries.

3.2 AI-Driven Optimization for the Improvement of 3D Printing Quality

The purpose of this study is to conduct an in-depth examination into the implementation of artificial intelligence-based optimization techniques in the fields of additive manufacturing and three-dimensional printing. The combination of Artificial intelligence (AI) with additive manufacturing (AM), which is one of the alternate terms for 3D printing, is causing a revolutionary change to take place in the manufacturing sector.

As a result, production efficiency, cost efficiency and product quality are improved. In the world of 3D printing, artificial intelligence enables manufacturers to better utilize the various components involved in the process. These issues include materials planning, support system design, and efficient utilization of materials. Some AI technologies used to automate and improve the 3D printing decision-making process include model prediction, on-the-fly analysis, and adaptive learning. Both methods are examples of artificial intelligence. Machine learning (ML), deep learning, and reinforcement learning are some of the methods that fall into this category. According to research by Russell and Norvig (2016) and Yang, Chen, Huang, and Li (2017), productivity is increasing in various industries such as the aerospace industry, health industry, automobile industry, and consumer goods production, and these industries place a high emphasis on accuracy and quality. Due to its flexibility and adaptability, AI has the ability to handle the complex parameters required by these industries.

As stated by LeCun, Bengio, and Hinton (2015), deep learning has made great progress in recent years. These advances allow artificial intelligence to further develop its capabilities. As a result, processing and analysis of complex data related to 3D printing has become possible, resulting in increased accuracy and speed. Because these models understand relationships and patterns within printed values, one can grasp the concepts of processing direction and supporting structures. Machine learning has been at the core of the development of artificial intelligence, giving systems the opportunity to improve themselves based on available data, which is important for producing high-quality products (Jordan & Mitchell, 2015). Machine learning has always been at the core of the development of artificial intelligence. Machine learning is increasingly helping processes that have historically relied heavily on human expertise to perform (Jarrahi, 2018), which is the most common trend in business. One example of this development is the role artificial intelligence plays in improving and automating the 3D printing process.

The use of artificial intelligence in the field of additive manufacturing can help improve the accuracy and efficiency of printed parts, especially by improving the methods and support structures of the manufacturing process. The aesthetic quality, structural integrity and edge accuracy of the final product are directly affected by this factor. As part of the comprehensive review, every component of the additive manufacturing process will be examined in detail. Additionally, the study will examine how improvements in artificial intelligence impact each sector.

Achieving the highest level of dimensional accuracy through process optimization is one of the most important tasks to be accomplished. Third-party printing requires orientation modification to achieve very high dimensional precision. According to Tan et al. (2017), it was found that the spatial location of a particular part on the print bed has an effect on a variety of factors, including quality, material distribution, and structural stability. As a result, these qualities will influence the whole structural reliability of the print material. In some sectors, such as healthcare equipment, aerospace parts, and automobile parts, where even minor variations in measured values can cause product failure or represent a safety risk. Such sectors are examples of businesses that have greatly benefited from accurate dimensions and measurements.

The science of machine learning, based on artificial intelligence, is used to select the proper path with the goal of minimizing measurement errors. This is accomplished via an optimization procedure, to examine data on geometry, quality of material, and printing settings. Sani, Zolfagharian, and Kouzani (2024) explain how to employ reinforcement models to gradually improve guideline options based on immediate input. For example, they show how this can be done throughout the printing process. When picking approaches to reduce typical printing flaws such as distortion and incorrect alignment, these closed methods allow the AI model to gather information from past results, progressively improving its predictive ability (Kumar et al., 2023).

Optimization of orientation relies on predictive models, a form of machine learning. From this, Wei et al. (2019) described how algorithms developed based on past data can predict the optimal paths for the various formats and devices, reducing the amount of trial and error needed and making the model more accurate in applying it to complex geometries. Another example is Yang et al. (2017), which describes the use of neural networks in the process of orientation selection. The model, in this case, can provide predictions concerning the orientation by considering the material and the required structure.

According to Russell and Norvig (2016), this enables the model to find a balance between providing accurate results and achieving high performance.

With the use of advanced predictive techniques, artificial intelligence can solve orientation-related problems. This technology allows artificial intelligence to be adapted to different printing conditions, such as temperature change and material defects. High-risk industries such as aerospace and healthcare require AI models to adjust the direction of printing using predictive analysis so that the accuracy of parts is maintained throughout the manufacturing process.

Minimizing the support structures is one of the most important tasks and achieving a high level of optimization efficiency. Support structures are used in 3D printing to stabilize the overhangs or complexity of the objects as well as the details while they are printed. These support structures also increase material usage, time required to print, and post-processing. Traditional methods for producing support structures result in the over-production of support, which generally leads to more material being wasted and longer production times. As stated by Ciccone, Bacciaglia, and Ceruti (2023), using AI optimization can improve efficiency in terms of materials as well as products because this optimization only focuses on needed areas to reduce unnecessary support volumes as well as production time.

Rojek et al. (2020) explain this in their research, which describes artificial intelligence strategies for optimizing support structures in the field of medical applications. These techniques are especially relevant when using resources in such a situation where proper and cost-effective use of resources would be important. Neural network and deep learning models create different support structures to measure the effectiveness of the system while simulating the generation of a sustainable configuration requiring the least resources. This opens up an opportunity for sustainable design development. Ciccone et al (2023) have found that, these algorithms can analyze the physical structure of parts and provide information on crucial areas which will require supports. Thus, this eliminates the repeating structure and results in no wastes (Jiang et al., 2018).

The models of artificial intelligence using reinforcement learning are mainly beneficial for optimizing the process of support construction. According to Sarker (2021), this model adjusts the amount of support added by taking knowledge from previous occurrences in determining the minimum without sacrificing stability. This reduces resources and saves time involved in post-processing. Since there is less support that has to be removed after printing, less time is spent on post-processing. According to Paraskevoudis, Karayannis, and Koumoulos (2020), benefits of reducing support through AI optimization include cost savings and environmental benefits. According to Sani et al. (2024), the use of artificial intelligence optimization to reduce support structures may lead to substantial material usage reductions, especially for parts with complex designs.

The next step forward would be surface quality plus more accurate design and appearance. For 3D printing, the surface quality must be highly taken into account. Indicative of this are form-function combined industries such as healthcare, aerospace, and consumer electronics. Artificial intelligence-based optimization of layout and structures of supports can play significant roles in improving the overall quality of the surface. This is because improper orientation can cause visible layer separation, which can affect both the aesthetics and functionalities of the part (Sani et al., 2024).

AI algorithms can reduce visual image distortions and offer a seamless solution on key surfaces by capturing several surface products in numerous directions at the same time (Batu, Lemu, & Shimels, 2023). This enables the program to identify configurations that eliminate issue surfaces. Artificial intelligence models, particularly the ones built around neural networks, optimize the layout to minimize support interactions and on display areas, hence lowering surface imperfections. Metal part manufacturing require such abilities because even the smallest surface fault has a substantial impact on the functionality of these parts, which frequently require additional post-processing.

Artificial intelligence models such as convolutional neural networks, are helpful in managing the areas of support and unsupported areas that may sink or distort. According to Valizadeh and Wolff (2022), this allows the model to handle this problem more effectively. Using machine learning models, the areas of support most likely to be compromised can be predicted to avoid any compromise on the quality of the surface. This allows for proper placement of supports to avoid structural compromise. Optimization in such applications that use polymers and composites has been found particularly useful and important for the integrity of the surface (Hassan, Misra, Taylor, & Mohanty, 2024). In addition, Habeeb et al. (2023) has talked about how artificial intelligence can bring in post-processing considerations into optimization, especially in the choice of methods that require less smoothing and secondary processing. It not only makes the final product look better but also helps save on costs and speed up the production cycle (Hassan et al., 2024). This is because it cuts down on the time and energy needed to have the object completed.

The next most important task would be the increase in the efficiency of resource use and energy efficiency in order to obtain the full accomplishment of sustainable development goals set. Artificial intelligence in optimizing 3D printing is contributing largely to the sustainable manufacturing principles because it reduces material wastage and labor. Any inefficient support and layout ends up consuming unnecessary and extra resources. This not only increases costs but also the environmental impact of production. Artificial intelligence can design small but structurally thorough supports as ways of developing manufacturing processes that are less harmful to the environment.

According to Rojek, Mikołajewski, Macko, Szczepański, and Dostatn (2021), AI-based improvements can significantly reduce waste, and strategies to eliminate all waste have been proposed. This can be done with additional support and orientation arrangements in 3D printed objects. In environments where size or cost are high, and where even small savings can add up over time, these reductions are significant because they save a lot of money. That is why these removals are important. The research, conducted by El Youbi El Idrissi et al. (2023) provides an example of how artificial intelligence models can improve orientations to reduce printing times. This reduces the total effort and energy even further by increasing the total time that is to be taken per print. Rojek et al., (2021) highlighted in their study that artificial intelligence has the potential to improve environmental performance by improving resource efficiency. When it comes to companies that prioritize reducing emissions and conserving data, this is significantly important. By using AI-based methods, manufacturing companies can improve their energy efficiency and reduce the carbon footprint associated with 3D printing. This is done by reducing the amount of heat entering each device.

The combination of artificial intelligence and additive manufacturing is predicted and expected to lead to the development of autonomous systems that are capable of managing changes in printed materials over time. These smart devices would use feedback from internal sensors to make real-time adjustments to the device's alignment, support placement and print speed. As a result, this greatly improves efficiency and reduces waste. When it comes to high performance demanding situations, Sani et al. (2024) predict AI-based systems that are autonomous and can modify printed text based on real-time data. This is likely to be very useful in the future. With the changes, a large amount of manual work can be eliminated, the quality of each print can be ensured to a high standard, and many errors would be reduced. Hassan et al. (2024) shows that automation would allow, with minimal supervision and/or human interaction, to create high-quality products, which are particularly useful in high performance demanding industries, such as aerospace and the automotive industry, and that this would become a feasible practice for everyone.

According to Paraskevoudis et al. (2017) and many other scholars, these types of artificial intelligence models have the ability to continuously learn, which allows them to react to environmental changes, resource changes, and other factors that affect production. This feature allows them to provide more accurate printing results. Artificial intelligence applications in 3D printing can achieve higher levels of flexibility, which is essential for 3D printing to move towards a more complete, efficient, and sustainable manufacturing process.

The application of artificial intelligence optimization strategies to realize its full potential for industrial use is a must for 3D printing. Ultimately, it eventually gives rise to success in sustainability projects with artificial intelligence as high-dimensional accuracy is combined with cost efficiency and material conservation. Refining orientation, reduction of support structures, and enhancing the surface quality are some of the ways through which this objective is achieved. These developments would give an green signal to further design completely automated 3D printing systems that would allow on-site optimization in real-time and could be implemented by numerous industries. These technologies are expected to enable previously unmatched degree of accuracy, adaptability, and resource efficiency. When it concerns the future of high-performance manufacturing, the inclusion of artificial intelligence technologies into additive manufacturing will surely result in more imaginative, autonomous, and environmentally responsible production processes.

3.3 Future Expectations

In the future, AI-powered 3D printing could revolutionize manufacturing and customization. AI is expected to improve 3D printing by optimizing parameters relating to product position, thickness of layers, and temperature over time. For example, machine learning algorithms can use past data to forecast good printing instructions, reduce product waste, and increase print quality (Yang et al., 2017). Furthermore, AI-based models can be used to evaluate the printing process and detect problems such as warping or poor adhesion, enhancing accuracy and lowering failure rates (Sani, Zolfagarian, & Kouzani, 2024). Such innovations not only improve the accuracy of 3D printing but also speed up the manufacturing process, allowing for large-scale alterations and faster development.

However, it must be integrated with a supporting environment that accommodates the actual production processes of 3D printing, and promotes environmentally friendly processes. AI helps reduce wastes and costs involved in making things since it optimizes both material usage and the entire support system (Ciccone, Bacciaglia, & Ceruti, 2023). For example, a neural network model can modify the support structure so that the product is stable and efficient by reducing the environmental impact of the manufacturing process (Jiang, Xu, & Stringer, 2018). Such innovations are especially critical in aerospace and medical industries where material usage and robust designs play an important role. As AI advances further, in the field of 3D printing, it will provide extremely efficient and effective, flexible, and environmentally friendly manufacturing systems to various industries in the future, available for all to use, regardless of size.

4. Conclusion

This research examines the applicability of AI to 3D printing and its impacts, in terms of accuracy, efficiency, and quality within the manufacturing process. The analysis demonstrates that AI-based optimization reduces most shortcomings present in traditional processes in 3D printing, by addressing key factors, such as design printing, material utilization, and orientation. AI can use predictive analytics, real-time data analytics, and machine learning algorithms to modify the printing process during production. The display improves the dimensional accuracy of the printed material, enhances its structural integrity, and makes it aesthetically appealing, thus reducing the amount of post-processing needed. High-performance industries including aerospace, healthcare, and automotive are likely to benefit from AI, increase efficiency, and encourage the production of complex custom parts with assurance of safety and quality standards. Additionally, AI-based 3D printing encourage sustainable and productive practice by managing materials and minimizing waste. This implies that the combination of AI with additive manufacturing can be critical in understanding the future of demand, quality, and environmental efficiency in various industries.

In order to enhance crucial aspects of additive manufacturing, including printing design, handling of materials, and support design, this study shows how AI can apply the findings of literature and research. The objectives of this research are accomplished by examining how AI-based 3D printing is optimized to increase accuracy, efficiency, and quality. Regarding time-constrained prediction and optimization, machine learning models are essential for dealing with issues like waste, partial errors, and surface flaws. The study shows how adaptive AI algorithms may preserve sustainable manufacturing processes while reducing processing demands and energy consumption. These characteristics enable the study to not only address the research objectives but also offer practical suggestions to industries that want to use 3D printing technology.

This research has implications that go beyond the improvement of quality, accuracy and efficiency, highlighting the chances for a completely automated and adaptable manufacturing system, that will be supported by AI. Artificial Intelligence is able to meet the demands of flexible and precise manufacturing in complex manufacturing environments thanks to its ability to learn from each print job and then adjusting its position. The benefits of applying AI-enabled 3D printing processes include reduced human interference, less chance of errors, and consistency in quality. This allows for the use of this technology in a competitive environment for any wide range of designs quickly. This research explores the evolving relationship between AI and 3D printing and demonstrates how their integration can transform manufacturing processes, reduce product-to-market time, and support advanced product design. This study shows how urgently manufacturing must harness AI-elevated 3D printing to serve as the only answer that transforms smart and sustainable processes for manufacturing based on dynamic, rapidly shifting consumers and their related environment constraints.

Despite these promising results, AI-based optimization in 3D printing is still not extensively used because of several issues. AI-based 3D printing improvements are promising, but various limitations exist, which are major barriers to the extensive application of this approach. The main limitation lies in the dependency on high-quality and unique datasets for the functioning of AI algorithms in giving precise estimates and adjustments. Without specific information about the different printing tasks and shapes of materials, the AI models can appear nonflexible, and thus in different scenarios, they appear less reliable. Moreover, incorporating AI into 3D printing systems typically demands many resources with a high demand for advanced computer skills, which are not always feasible for small-scale businesses. This creates a gap between major companies that can afford infrastructure investment in AI and small-scale businesses with limited finances. The complexity of AI algorithms also carries usability and accessibility issues, requiring dedicated expertise to manage, interpret, and optimize these models.

Future studies will need to overcome these limitations by finding ways to enhance the integration of AI into 3D printing and expand its access to all sizes of businesses. This might be done by developing AI interfaces that are easy to use and do not require extensive technical knowledge so that operators can utilize AI-based optimization without needing a long training course. Future research could include AI models that can adapt and evolve itself over time, reducing the need for data entry and adjustments. Other research may include developing AI models specific to different 3D printing technologies and materials, which would increase the flexibility and applicability of algorithms across a wide range of manufacturing processes. Environmental impact from AI-powered 3D printing is emerging as an important area for future research. Future studies might consider how sustainable practices could be integrated into AI optimization, such as algorithms focused on energy efficiency and material conservation, allowing for environmental friendly manufacturing solutions. As autonomous manufacturing systems are adopted by businesses and industries as a whole, using AI capabilities to support autonomous operations and self-monitoring of print quality in real-time will be crucial. This would mean that in the future, AI-powered 3D printing systems will be self-leading, adjusting to environmental changes or material inconsistencies to achieve efficiency levels that can be met by today's manufacturing environment.

5. References

Abdou, M. A. (2022). Literature review: Efficient deep neural networks techniques for medical image analysis. *Neural Computing and Applications*, *34*(8), 5791-5812. Available at: https://doi.org/10.1007/s00521-022-06960-9

Agocs, C., Hanon, M. M., & Zsidai, L. A COMPREHENSIVE REVIEW OF FUSED DEPOSITION MODELING (FDM) METHOD USING PLA, ABS, AND PET-G POLYMERS. Available at: http://dx.doi.org/10.47833/2024.1.ENG.007

Aimar, A., Palermo, A., & Innocenti, B. (2019). The role of 3D printing in medical applications: a state of the art. *Journal of healthcare engineering*, *2019*(1), 5340616. Available at: https://doi.org/10.1155/2019/5340616

Alami, A. H., Mahmoud, M., Aljaghoub, H., Mdallal, A., Abdelkareem, M. A., Kamarudin, S. K., & Olabi, A. G. (2023). Progress in 3D printing in wind energy and its role in achieving sustainability. *International Journal of Thermofluids*, *20*, 100496. Available at: https://doi.org/10.1016/j.ijft.2023.100496

Alami, A. H., Olabi, A. G., Alashkar, A., Alasad, S., Aljaghoub, H., Rezk, H., & Abdelkareem, M. A. (2023). Additive manufacturing in the aerospace and automotive industries: Recent trends and role in achieving sustainable development goals. *Ain Shams Engineering Journal*, *14*(11), 102516. Available at: https://doi.org/10.1016/j.asej.2023.102516

Albarnawi, A.M. and Bashir, M.O. (2017). Additive Manufacturing: A New Industrial Revolution-A review. Available at:

https://www.researchgate.net/publication/315610680_Additive_Manufacturing_A_New_Industrial_Revolution-A_review

Alec. (2014). *GE 3D prints and test fires a fully functional miniature jet engine.* Available at: http://www.3ders.org/articles/20141112-ge-3d-prints-and-test-fires-a-fully-functional-miniature-jet-engine.html

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., ... & Albekairy, A. M. (2023). Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC medical education*, *23*(1), 689. Available at: https://doi.org/10.1186/s12909-023-04698-z

Attaran, M. (2017). The rise of 3-D printing: The advantages of additive manufacturing over traditional manufacturing. *Business horizons*, *60*(5), 677-688. Available at: https://doi.org/10.1016/j.bushor.2017.05.011

Bathla, G., Bhadane, K., Singh, R. K., Kumar, R., Aluvalu, R., Krishnamurthi, R., ... & Basheer, S. (2022). Autonomous vehicles and intelligent automation: Applications, challenges, and opportunities. *Mobile Information Systems*, *2022*(1), 7632892. Available at: https://doi.org/10.1155/2022/7632892

Batu, T., Lemu, H. G., & Shimels, H. (2023). Application of artificial intelligence for surface roughness prediction of additively manufactured components. *Materials*, *16*(18), 6266. Available at: https://doi.org/10.3390/ma16186266

Berman, B. (2012). 3-D printing: The new industrial revolution. *Business horizons*, *55*(2), 155-162. Available at: https://doi.org/10.1016/j.bushor.2011.11.003

Bozkurt, Y., & Karayel, E. (2021). 3D printing technology; methods, biomedical applications, future opportunities and trends. *Journal of Materials Research and Technology*, *14*, 1430-1450. Available at: https://doi.org/10.1016/j.jmrt.2021.07.050

Bullinger, H. J., Warschat, J., & Fischer, D. (2000). Rapid product development—an overview. *Computers in industry*, *42*(2-3), 99-108. Available at: https://doi.org/10.1016/S0166-3615(99)00064-0

Bullis, K. (2013, May 14). A more efficient jet engine is made from lighter parts, some 3D-printed. *MIT Technology Review.* Available at: https://www.technologyreview.com/2013/05/14/178451/a-more-efficient-jet-engine-is-made-from-lighter-parts-some-3-d-printed/

Cano-Vicent, A., Tambuwala, M. M., Hassan, S. S., Barh, D., Aljabali, A. A., Birkett, M., ... & Serrano-Aroca, Á. (2021). Fused deposition modelling: Current status, methodology, applications and future prospects. *Additive manufacturing*, *47*, 102378. Available at: https://doi.org/10.1016/j.addma.2021.102378

Cesaretti, G., Dini, E., De Kestelier, X., Colla, V., & Pambaguian, L. (2014). Building components for an outpost on the Lunar soil by means of a novel 3D printing technology. *Acta Astronautica, 93*, 430–450. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0094576513002889

Chua, C. K., Leong, K. F., & Lim, C. S. (2010). *Rapid prototyping: principles and applications*. World scientific. Available at: https://books.google.com.pk/books?hl=en&lr=&id=4OYcyiDUpsQC&oi=fnd&pg=PR7&dq=Chua,+C.+K.,+Leong,+K.+F.,+%26+Lim,+C.+S.+(2010).+Rapid+prototyping:+Principles+and+applications.+World+Scientific+Publishing+Co.+Pte.+Ltd.&ots=yROANoyGyE&sig=u_4UmedDbCeucocHQy2GflZ45ks&redir_esc=y#v=onepage&q=Chua%2C%20C.%20K.%2C%20Leong%2C%20K.%20F.%2C%20%26%20Lim%2C%20C.%20S.%20(2010).%20Rapid%20prototyping%3A%20Principles%20and%20applications.%20World%20Scientific%20Publishing%20Co.%20Pte.%20Ltd.&f=false

Ciccone, F., Bacciaglia, A., & Ceruti, A. (2023). Optimization with artificial intelligence in additive manufacturing: a systematic review. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *45*(6), 303. Available at: https://doi.org/10.1007/s40430-023-04200-2

Crump, S. R. (1992). Apparatus for production of three-dimensional objects by layered manufacturing. U.S. Patent 5,121,329. Google Patents. Available at: https://patentimages.storage.googleapis.com/21/01/d3/69165ba25d15e0/US5121329.pdf

Delaram, J., Houshamand, M., Ashtiani, F., Fatahi Valilai, O., (2023). Development of public cloud manufacturing markets: a mechanism design approach. International Journal of Systems Science: Operations & Logistics 10, 2079751. https://doi.org/10.1080/23302674.2022.2079751

DMG MORI. (2014, November 13). *LASER TEC 65 3D.* Available at: https://en.dmgmori.com/

Delaram, J., Houshamand, M., Ashtiani, F., Fatahi Valilai, O., (2021). A utility-based matching mechanism for stable and optimal resource allocation in cloud manufacturing platforms using deferred acceptance algorithm. Journal of Manufacturing Systems 60, 569–584. https://doi.org/10.1016/j.jmsy.2021.07.012

El youbi El idrissi, M. A., Laaouina, L., Jeghal, A., Tairi, H., & Zaki, M. (2023). Modeling of Energy Consumption and Print Time for FDM 3D Printing Using Multilayer Perceptron Network. *Journal of Manufacturing and Materials Processing*, *7*(4), 128. Available at: https://doi.org/10.3390/jmmp7040128

Formlabs. *The ultimate guide to stereolithography (SLA) 3D printing*. Formlabs. Available at: https://formlabs.com/asia/blog/ultimate-guide-to-stereolithography-sla-3d-printing/?srsltid=AfmBOoqDnpXWPRHWCqZSBpLpbYYS10mezgxqXSEooQ3txwwqkXsEIEQP

Frazier, W. E. (2014). Metal additive manufacturing: A review. *Journal of Materials Engineering and Performance*, 23(6), 1917-1928. Available at: https://link.springer.com/article/10.1007/s11665-014-0958-z

Gardan, J. (2017). Additive manufacturing technologies: state of the art and trends. *Additive Manufacturing Handbook*, 149-168. Available at: https://doi.org/10.1201/9781315119106

Gokhare, V. G., Raut, D. N., & Shinde, D. K. (2017). A review paper on 3D-printing aspects and various processes used in the 3D-printing. *Int. J. Eng. Res. Technol*, *6*(06), 953-958. Available at: https://d1wqtxts1xzle7.cloudfront.net/94059575/a-review-paper-on-3d-printing-aspects-and-various-processes-used-in-the-3d-printing-IJERTV6IS060409-libre.pdf?1668166204=&response-content-disposition=inline%3B+filename%3DA_Review_paper_on_3D_Printing_Aspects_an.pdf&Expires=1730069962&Signature=AYZUuD-

R4hbCohuTCFVNF3TRaHCwzFMuYYxA53wVJ-cF6gBejrxR8Byh5P1U74LI3OWTo8Y6LLWSZI1YLxgTB5-PW51Yg0EmCoD2eQ6qw2CM14AgJ-RnIt7v7c6he438ydWkuMNJfoSsWTPvIjAXBOTqSnngjkJFuWudYHMmfWrgTKB6zvuSF7fBwztkDo5A0sX1MuvvcoiVayDSLdP-tpK8J2b5F9AYrufxT6iQ2uKvFnVmCRbHBD25eRG7xawNFxdji0~ruTtAddkBucYdtsPE3-qJeQFs4RAGFUEI6ZekksoycwyDATvBQQuszzDAY4q1vJf50YGzpC~MjFIJ1g__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

Grosious, R. E., & Lakshmaiya, N. (2024, June). Advancements in automotive production: exploring the role of 3D printing and selective laser sintering. In *International Conference on Medical Imaging, Electronic Imaging, Information Technologies, and Sensors (MIEITS 2024)* (Vol. 13188, pp. 403-415). SPIE. Available at: https://doi.org/10.1117/12.3030833

Habeeb, H. A., Wahab, D. A., Azman, A. H., & Alkahari, M. R. (2023). Design optimization method based on artificial intelligence (hybrid method) for repair and restoration using additive manufacturing technology. *Metals*, *13*(3), 490. Available at: https://doi.org/10.3390/met13030490

Hasan, M. R., Davies, I. J., Pramanik, A., John, M., & Biswas, W. K. (2024). Potential of Recycled PLA in 3D Printing: A Review. *Sustainable Manufacturing and Service Economics*, 100020. Available at: https://doi.org/10.1016/j.smse.2024.100020

Hassan, M., Misra, M., Taylor, G. W., & Mohanty, A. K. (2024). A Review of AI for optimization of 3D Printing of Sustainable Polymers and Composites. *Composites Part C: Open Access*, 100513. Available at: https://doi.org/10.1016/j.jcomc.2024.100513

Hoyt, R. P. (2013). SpiderFab: An architecture for self-fabricating space systems. In *AIAA SPACE 2013 Conference and Exposition*, 1–17. Available at: https://doi.org/10.2514/6.2013-5509

Husna, A., Ashrafi, S., Tomal, A. A., Tuli, N. T., & Rashid, A. B. (2024). Recent Advancements in Stereolithography (SLA) and their Optimization of Process Parameters for Sustainable Manufacturing. *Hybrid Advances*, 100307. Available at: https://doi.org/10.1016/j.hybadv.2024.100307

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685-695. Available at: https://doi.org/10.1007/s12525-021-00475-2

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons*, *61*(4), 577-586. Available at: https://doi.org/10.1016/j.bushor.2018.03.007

Jiang, J., Xu, X., & Stringer, J. (2018). Support structures for additive manufacturing: a review. *Journal of Manufacturing and Materials Processing*, *2*(4), 64. Available at: https://doi.org/10.3390/jmmp2040064

Jiménez, M., Romero, L., Domínguez, I. A., Espinosa, M. D. M., & Domínguez, M. (2019). Additive manufacturing technologies: an overview about 3D printing methods and future prospects. *Complexity*, *2019*(1), 9656938. Available at: https://onlinelibrary.wiley.com/doi/full/10.1155/2019/9656938

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260. Available at: https://doi.org/10.1126/science.aaa8415

Kantaros, A., Ganetsos, T., Petrescu, F. I. T., Ungureanu, L. M., & Munteanu, I. S. (2024). Post-Production Finishing Processes Utilized in 3D Printing Technologies. *Processes*, *12*(3), 595. Available at: https://doi.org/10.3390/pr12030595

Khorram Niaki, M., & Nonino, F. (2017). Additive manufacturing management: a review and future research agenda. *International Journal of Production Research*, *55*(5), 1419-1439. Available at: https://doi.org/10.1080/00207543.2016.1229064

Kudus, S. I. A., Campbell, R. I., & Bibb, R. J. (2016). Assessing the value of 3D printed personalised products. Available at: https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Kudus%2C+S.+I.+A.%2C+Campbell%2C+R.+I.%2C+%26+Bibb%2C+R.+J.+%282016%29.+Assessing+the+value+of+3D+printed+personalised+products.&btnG=

Kumar, S., Gopi, T., Harikeerthana, N., Gupta, M. K., Gaur, V., Krolczyk, G. M., & Wu, C. (2023). Machine learning techniques in additive manufacturing: a state-of-the-art review on design, processes and production control. *Journal of Intelligent Manufacturing*, *34*(1), 21-55. Available at: https://doi.org/10.1007/s10845-022-02029-5

Kurowiak, J., Klekiel, T., & Będziński, R. (2023). Biodegradable Polymers in Biomedical Applications: A Review—Developments, Perspectives and Future Challenges. *International Journal of Molecular Sciences*, *24*(23), 16952. Available at: https://doi.org/10.3390/ijms242316952

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436-444. Available at: https://doi.org/10.1038/nature14539

Lim, C.W.J., Le, K.Q., Lu, Q. and Wong, C.H. (2016). An Overview of 3-D Printing in Manufacturing, Aerospace, and Automotive Industries. *IEEE Potentials*, 35(4), pp.18–22. Available at: https://doi.org/10.1109/MPOT.2016.2540098

Lu, B., Li, D., & Tian, X. (2015). Development trends in additive manufacturing and 3D printing. *Engineering*, *1*(1), 085-089. Available at: https://doi.org/10.15302/J-ENG-2015012

Murariu, A. C., Sîrbu, N. A., Cocard, M., & Duma, I. (2022). Influence of 3D printing parameters on mechanical properties of the PLA parts made by FDM additive manufacturing process. *Engineering Innovations*, *2*, 7-20. Available at: https://www.scientific.net/EI.2.7

Mohammadian, N., Silva, M.S.M., Basiladze, G., Valilai, O.F., 2024. Development of an AI Based Failure Predictor Model to Reduce Filament Waste for a Sustainable 3D Printing Process. International Journal of Advanced Computer Science and Applications (ijacsa) 15, 1–6. https://doi.org/10.14569/IJACSA.2024.0151001

Niari, M.R., Eshghi, K., Valilai, O.F., (2022). Adaptive capacity management in cloud manufacturing hyper-network platform: Case of COVID-19 equipment production. International Journal of Management Science and Engineering Management 17, 239–258.

NASA. (n.d.). *NASA tests limits of 3-D printing with powerful rocket engine check*. NASA. Available at: https://www.nasa.gov/technology/manufacturing-materials-3-d-printing/nasa-tests-limits-of-3-d-printing-with-powerful-rocket-engine-check/

Ngo, T. D., Kashani, A., Imbalzano, G., Nguyen, K. T., & Hui, D. (2018). Additive manufacturing (3D printing): A review of materials, methods, applications and challenges. *Composites Part B: Engineering*, *143*, 172-196. Available at: https://doi.org/10.1016/j.bushor.2011.11.003

Nilsson, N. J. (2014). *Principles of artificial intelligence*. Morgan Kaufmann. Available at: http://repo.darmajaya.ac.id/5328/1/Principles%20of%20Artificial%20Intelligence%20%28%20PDFDrive%20%29.pdf

Oche, P. A., Ewa, G. A., & Ibekwe, N. (2021). Applications and challenges of artificial intelligence in space missions. *IEEE Access*, *12*, 44481-44509. Available at: https://ieeexplore.ieee.org/abstract/document/9634015

Pandzic, A. (2021). INFLUENCE OF LAYER HEIGHT, BUILD ORIENTATION AND POST CURING ON TENSILE MECHANICAL PROPERTIES OF SLA 3D PRINTED MATERIAL. *Annals of DAAAM & Proceedings*. Available at: https://www.daaam.info/Downloads/Pdfs/proceedings/proceedings_2021/030.pdf

Paraskevoudis, K., Karayannis, P., & Koumoulos, E. P. (2020). Real-time 3D printing remote defect detection (stringing) with computer vision and artificial intelligence. *Processes*, *8*(11), 1464. Available at: https://doi.org/10.3390/pr8111464

Reyneke, J. A. (2023, October 24). *The history and foundations of artificial intelligence*. Medium. Available at: https://medium.com/@janelreyneke/the-history-and-foundations-of-artificial-intelligence-c6f44986e7f

Rezaei, M.R., Houshmand ,Mahmoud, and Fatahi Valilai, O., (2023). An autonomous intelligent framework for optimal orientation detection in 3D printing. International Journal of Computer Integrated Manufacturing 36, 908–946. https://doi.org/10.1080/0951192X.2022.2162587

Rojek, I., Mikołajewski, D., Dostatni, E., & Macko, M. (2020). AI-optimized technological aspects of the material used in 3D printing processes for selected medical applications. *Materials*, *13*(23), 5437. Available at: https://doi.org/10.3390/ma13235437

Rojek, I., Mikołajewski, D., Macko, M., Szczepański, Z., & Dostatni, E. (2021). Optimization of extrusion-based 3D printing process using neural networks for sustainable development. *Materials*, *14*(11), 2737. Available at: https://doi.org/10.3390/ma14112737

Rezapour Niari, M., Eshghi, K., Fatahi Valilai, O., (2023). Using cloud manufacturing to establish an ecosystem network for COVID-19 ventilator production. International Journal of Computer Integrated Manufacturing 36, 842–862. https://doi.org/10.1080/0951192X.2022.2162586

Rezapour Niari, M., Eshgi, K., Fatahi Valilai, O., (2021). Topology analysis of manufacturing service supply–demand hyper-network considering QoS properties in the cloud manufacturing system. Robotics and Computer-Integrated Manufacturing 72, 102205. https://doi.org/10.1016/j.rcim.2021.102205

Rouf, S., Raina, A., Haq, M. I. U., Naveed, N., Jeganmohan, S., & Kichloo, A. F. (2022). 3D printed parts and mechanical properties: Influencing parameters, sustainability aspects, global market scenario, challenges and applications. *Advanced Industrial and Engineering Polymer Research*, *5*(3), 143-158. Available at: https://doi.org/10.1016/j.aiepr.2022.02.001

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Pearson. Available at: https://people.engr.tamu.edu/guni/csce421/files/AI_Russell_Norvig.pdf

Sani, A. R., Zolfagharian, A., & Kouzani, A. Z. (2024). Artificial Intelligence-Augmented Additive Manufacturing: Insights on Closed-Loop 3D Printing. *Advanced Intelligent Systems*, 2400102. Available at: https://doi.org/10.1002/aisy.202400102

Sarker, I. H. (2021). *Machine learning: algorithms, real-world applications and research directions. SN Comput Sci 2: 160*. Available at: https://doi.org/10.1007/s42979-021-00592-x

Sculpteo. (2020). The advantages of SLA 3D printing. Available at: https://info.sculpteo.com/hubfs/downloads/The%20State%20of%203D%20Printing_2020%20edition.pdf

Shah, S.S., Pirayesh, A., Fatahi Valilai, O., (2023). Using Blockchain Technology for 3D Printing in Manufacturing of Dental Implants in Digital Dentistry, in: Kim, K.-Y., Monplaisir, L., Rickli, J. (Eds.), Flexible Automation and Intelligent Manufacturing: The Human-Data-Technology Nexus, Lecture Notes in Mechanical Engineering. Springer International Publishing, Cham, pp. 565–572. https://doi.org/10.1007/978-3-031-17629-6_59

Shahab, E., Kazemisaboor, A., Khaleghparast, S., Fatahi Valilai, O., (2022). A production bounce-back approach in the Cloud manufacturing network: case study of COVID-19 pandemic. International Journal of Management Science and Engineering Management 18, 305–317. https://doi.org/10.1080/17509653.2022.2112781

Sharifisari, A., Shahab, E., Valilai, O.F., (2025). Hybrid MTS/MTO production scheduling with cloud orders: a mathematical model based on an empirical study. International Journal of Management Science and Engineering Management 20, 400–416. https://doi.org/10.1080/17509653.2025.2475774

Shahrubudin, N., Lee, T. C., & Ramlan, R. J. P. M. (2019). An overview on 3D printing technology: Technological, materials, and applications. *Procedia manufacturing*, *35*, 1286-1296. Available at: https://doi.org/10.1016/j.promfg.2019.06.089

Shahab, E., Rabiee, M., Mobasseri, N., Valilai, O.F., (2025). A robust service composition for a resilient cloud manufacturing service network. International Journal of Computer Integrated Manufacturing. https://www.doi.org/10.1080/0951192X.2025.2504088

Shukla, B., Fan, I. S., & Jennions, I. (2020, July). Opportunities for explainable artificial intelligence in aerospace predictive maintenance. In *PHM Society European Conference* (Vol. 5, No. 1, pp. 11-11). Available at: https://www.researchgate.net/profile/Bibhudhendu-Shukla/publication/343362982_Opportunities_for_Explainable_Artificial_Intelligence_in_Aerospace_Predictive_Maintenance/links/5f25598192851cd302ceaaed/Opportunities-for-Explainable-Artificial-Intelligence-in-Aerospace-Predictive-Maintenance.pdf

Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., ... & Hassabis, D. (2017). Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv preprint arXiv:1712.01815*. Available at: https://doi.org/10.48550/arXiv.1712.01815

Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, *3*, 54-70. Available at: https://doi.org/10.1016/j.cogr.2023.04.001

Sutradhar, A., Park, J., Carrau, D., & Miller, M. J. (2014). Experimental validation of 3D printed patient-specific implants using digital image correlation and finite element analysis. *Computers in Biology and Medicine, 52*, 8–17. Available at: https://doi.org/10.1016/j.compbiomed.2014.06.002

Sutton, R. S. (2018). Reinforcement learning: An introduction. *A Bradford Book*. Available at: https://www.andrew.cmu.edu/course/10-703/textbook/BartoSutton.pdf

Taherdoost, H., & Ghofrani, A. (2024). AI and the Evolution of Personalized Medicine in Pharmacogenomics. *Intelligent Pharmacy*. Available at: https://doi.org/10.1016/j.ipha.2024.08.005

Talaat, F. M., & Hassan, E. (2021). Artificial intelligence in 3D printing. In *Enabling Machine Learning Applications in Data Science: Proceedings of Arab Conference for Emerging Technologies 2020* (pp. 77-88). Springer Singapore. Available at: https://doi.org/10.1007/978-981-33-6129-4_6

Tan, X. P., Tan, Y. J., Chow, C. S. L., Tor, S. B., & Yeong, W. Y. (2017). Metallic powder-bed based 3D printing of cellular scaffolds for orthopaedic implants: A state-of-the-art review on manufacturing, topological design, mechanical properties and biocompatibility. *Materials Science and Engineering: C*, *76*, 1328-1343. Available at: https://doi.org/10.1016/j.msec.2017.02.094

Thompson, M. K., Moroni, G., Vaneker, T., Fadel, G., Campbell, R. I., Gibson, I., ... & Martina, F. (2016). Design for Additive Manufacturing: Trends, opportunities, considerations, and constraints. *CIRP annals*, *65*(2), 737-760. Available at: https://doi.org/10.1016/j.cirp.2016.05.004

Tuleshev, K., Fatahi Valilai, O., 2026. Using the NFT Architecture to Protect Intellectual Property in 3D Printing Ecosystems, in: Arai, K. (Ed.), Proceedings of the Future Technologies Conference (FTC) 2025, Volume 2. Springer Nature Switzerland, Cham, pp. 590–599. https://doi.org/10.1007/978-3-032-07989-3_38

Vaezi, M., Seitz, H., & Yang, S. (2013). A review on 3D micro-additive manufacturing technologies. *The International Journal of Advanced Manufacturing Technology*, *67*, 1721-1754. Available at: https://link.springer.com/article/10.1007/S00170-012-4605-2

Valizadeh, M., & Wolff, S. J. (2022). Convolutional Neural Network applications in additive manufacturing: A review. *Advances in Industrial and Manufacturing Engineering*, *4*, 100072. Available at: https://doi.org/10.1016/j.aime.2022.100072

Vincent, J. (2018, August 13). *DeepMind's AI can detect over 50 eye diseases as accurately as a doctor*. The Verge. Available at: https://www.theverge.com/2018/8/13/17670156/deepmind-ai-eye-disease-doctor-moorfields

Wei, J., Chu, X., Sun, X. Y., Xu, K., Deng, H. X., Chen, J., ... & Lei, M. (2019). Machine learning in materials science. *InfoMat*, *1*(3), 338-358. Available at: https://doi.org/10.1002/inf2.12028

Wohlers, T. (2015). *Wohlers Report 2015: 3D printing and additive manufacturing state of the industry: Annual worldwide progress report.* Fort Collins, CO: Wohlers Associates, Inc. Available at: https://wohlersassociates.com/wp-content/uploads/2022/08/history2015.pdf

Yang, J., Chen, Y., Huang, W. and Li, Y. (2017). Survey on artificial intelligence for additive manufacturing. *2017 23rd International Conference on Automation and Computing (ICAC)*. Available at: https://doi.org/10.23919/IConAC.2017.8082053

Yehia, H. M., Hamada, A., Sebaey, T. A., & Abd-Elaziem, W. (2024). Selective Laser Sintering of Polymers: Process Parameters, Machine Learning Approaches, and Future Directions. *Journal of Manufacturing and Materials Processing*, *8*(5), 197. Available at: https://doi.org/10.3390/jmmp8050197

Zeynivand, M., Ranjbar, H., Radmanesh, S.-A., Fatahi Valilai, O., (2021). Alternative process routing and consolidated production-distribution planning with a destination oriented strategy in cloud manufacturing. International Journal of Computer Integrated Manufacturing 34, 1162–1176. https://doi.org/10.1080/0951192X.2021.1972459

Zivanovic, S. T., Popovic, M. D., Vorkapic, N. M., Pjevic, M. D., & Slavkovic, N. R. (2020). An Overview of Rapid Prototyping Technologies using Subtractive, Additive and Formative Processes. *Fme Transactions*, *48*(1). Available at: http://dx.doi.org/10.5937/fmet2001246Z