Advances in Materials and Processing Technologies, Available online 16 April 2026
DOI: 10.1080/2374068x.2026.2630731

Advancements in Fused Deposition Modeling (FDM): A Comparison of Advanced Composite Materials, Optimization Strategies, and AI/ML Integration

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Abstract

Fused deposition modeling (FDM) is a modern manufacturing technique that simplifies the manufacturing process by removing complexities with traditional methods, allowing the designer to design complex and customized parts with greater efficiency and flexibility. In this review, different composite and biodegradable filaments used in FDM are compared based on their mechanical strengths to understand the effect of different material reinforcements. The paper also compares different methods of optimizing the FDM 3D printing process, including RSM, Taguchi, and AI/ML techniques, to improve the quality, strength, and accuracy of 3D-printed parts. Among the reviewed biodegradable filament materials, it was concluded that while the choice of FDM filament depends on specific requirements and application, PETG composites demonstrated a more versatile performance, offering superior mechanical strength and thermal resistance. In addition to that, using bio-fillers and recycled materials in the PETG matrix enhances sustainability without sacrificing functionality. Moreover, the analysis revealed that integrating artificial intelligence (AI) and machine learning (ML) techniques into the FDM process, such as for property prediction, defect detection, and topology optimization, can enhance the accuracy of outcomes, provided that the appropriate AI/ML model is selected for each specific task. This review establishes a solid base for researchers and practitioners considering the adoption of AI/ML in FDM while also outlining potential directions for future work in this evolving field. FDM 3D printing proved to have a strong potential in biomedical/healthcare, microelectronics, aerospace, and automotive industries, indicating a great future scope while maintaining biodegradability, sustainability, and biocompatibility.

Keywords:

Additive Manufacturing, Optimization, Process Parameters, Artificial Intelligence, Machine Learning, Fused Deposition Modeling.

1. Introduction

Additive manufacturing (AM) or 3D printing is a modern approach used to produce industrial products, allowing for the creation of lighter and stronger parts. AM originated in 1980, incorporating FDM as one of the most commonly used techniques. In 1989, S. Scott Crump, co-founder of Stratasys, developed the FDM technique in which the part is built layer by layer, directly from a digital 3D model, utilizing thermoplastic filaments as base materials. FDM has gained significant popularity in industrial sectors due to its affordability, simplicity, and accurate fabrication of complex parts. A comprehensive overview of the AM process from the CAD model to the final product is illustrated in Figure 1.

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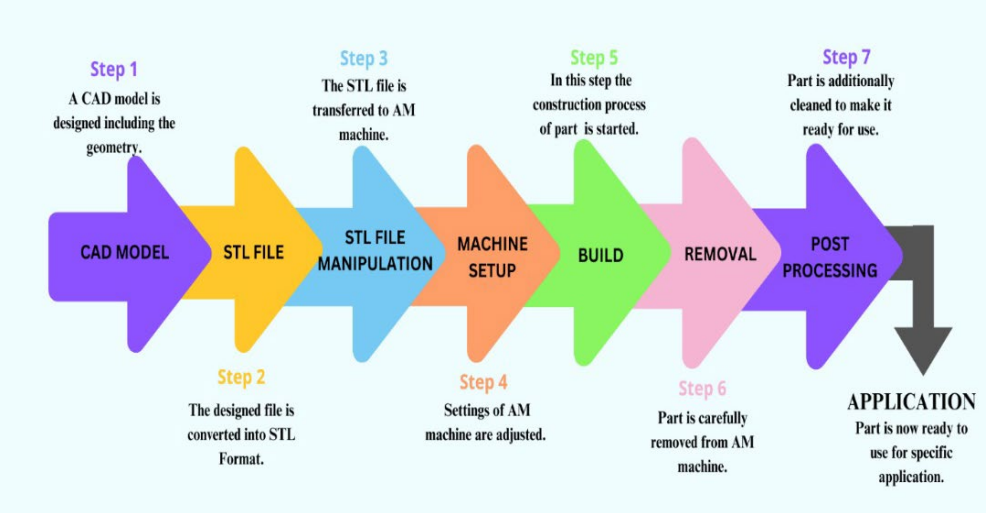


Figure 1.Overview of AM Process.

In the beginning, AM technology was used to produce models of different component designs. However, with technological advancements, its applications have also increased. Now, it can be easily used to produce fully functional and geometrically stable finished products [1, 2]. It was predicted that the global AM market will grow 17% annually between 2021-2023 [3]. According to another report published in 2023, the annual growth reached 20-25%, which is 5-10% more than the predicted growth. Now it is predicted that the global AM market will grow at 23.3% Compounded Annual Growth Rate (CAGR) from 2023-2030 [4]. This indicates that AM has a promising future scope, which is a good indicator for related industries. The CAGR of various production sectors between 2020 and 2024 has been presented in Figure 2.

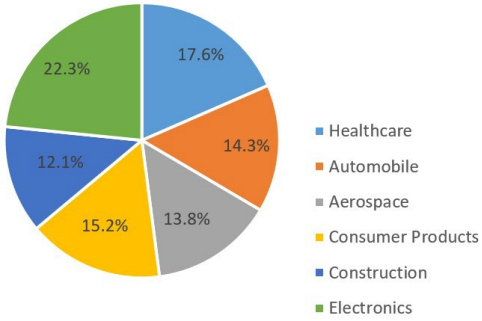


Figure 2. CAGR of 3D printing between 2020 and 2024 across various industries [5].

An industry must maintain a positive reputation among its customers so that the demands of society can be met timely and efficient manner while maintaining the quality of the finished product. Such industries often use Subtractive Manufacturing (SM) but have disadvantages like waste production, design limitations, tool wear, energy consumption, and surface integrity. AM is usually recommended due to less waste, design freedom and complexity, cost efficiency, material diversity, and sustainability [5]. CNC is a type of subtractive approach in which there is a compulsion that the material used must be at least as long and as wide as the part you are about to produce. Parts produced through AM sometimes show anisotropic characteristics because of errors in adjustments of processing parameters, but parts produced through CNC mostly possess homogeneous surface properties [1, 6]. Moreover, hybrid manufacturing, a combination of AM and SM, is also a powerful evolving technology involving the proficiencies of both methods to effectively optimize the manufacturing process [7].

ABS and PLA are the two commonly used matrix materials for FDM. Researchers are trying to enhance the mechanical properties of printed specimens by incorporating different filament materials into ABS and PLA [8-11]. Coconut wood [12], calcium peroxide [13], aluminum (Al) [9], bronze [11], anchovy fish powder [14], biogenic hydroxyapatite and graphene nanoplatelets [10], nano-clay [15], polyurethane [16, 17], biochar [18], lignin [19], carbon fiber [20], and many other materials have been used as reinforcing agents. Various tests and analyses have revealed that the mechanical, thermal, and chemical properties of printed specimens are greatly improved by the incorporation of these reinforcing agents. Considerable increments in tensile strengths, compressive strengths, elastic modulus, flexural modulus, and impact strengths were observed [9-19, 21, 22].

While fabricating a part using FDM, certain controllable variables or parameters need to be optimized in such a way as to achieve the desired mechanical properties of the part. There are three main classifications of these parameters i.e. process parameters (layer thickness, infill pattern, infill density, raster angle, build orientation), environmental parameters (ambient temperature, build chamber temperature, humidity, air quality, vibrations), and print parameters (print velocity, layer height, fan speed, laser power, print orientation) [23]. Many experimental studies have been conducted to investigate different process parameters and their influence on the mechanical properties of the part. Most of the output parameters selected by researchers include tensile strength [24-29], surface roughness [24, 30, 31], elastic modulus [24, 27, 32], elongation at break [27, 29], and flexural strength [9].

Several techniques exist that can be utilized to optimize and predict these input parameters and output variables accurately and efficiently. The most renowned techniques are Response Surface Methodology (RSM) and Taguchi. RSM is a mathematical or statistical approach utilized to investigate the relationship between various independent and dependent variables (actual responses). The main goal of this technique is to optimize the responses in such a way as to maximize or minimize them. The main working steps include selecting variables, designing an experiment, collecting data, building a model, analysing the results, and then optimizing them.

The Taguchi method is an effective statistical approach, developed by a Japanese engineer named Genichi Taguchi, to optimize the process parameters and product quality. This method emphasizes the Design of Experiments (DOE) to identify and optimize various factors that significantly impact product performance. Based on the Taguchi method, the Signal-to-Noise (S/N) ratio and Analysis of Variance (ANOVA) are used to evaluate performance characteristics.

AI is increasingly influencing various aspects of life today. It has become a crucial technology for optimizing parameters and forecasting the performance of 3D-printed structures, leading to enhancements in the quality and effectiveness of the final products [8, 9, 33]. Incorporating AI into AM aids in predicting and optimizing mechanical properties while enhancing process control and enabling real-time adjustments during printing [34, 35]. AI models, like artificial neural networks (ANNs), have shown high accuracy in predicting mechanical properties, demonstrating AI's potential to transform AM processes [31, 33, 36-38]. However, advanced and complex applications of AI in AM still face challenges, requiring extensive research and development across various industries [37-39]. The digital transformation of Industry 4.0 has triggered the need for smart AM solutions that are automated and data-driven. Additionally, innovations in AI technology to reduce materials and energy use for construction are required due to the increased focus on sustainability and efficiency.

This review aims to compare conventional optimization techniques and the integration of AI/ML into conventional AM methods to assess their suitability in terms of accuracy, cost, computational efficiency, and real-world applicability. Additionally, different materials used in FDM 3D printing were studied from a sustainability point of view, and their mechanical properties were investigated to check which materials performed well. This study is novel as no study has yet focused on these aspects in a single paper. For example, Batu et al. [40] investigated the techniques of FDM process parameters optimization, such as RSM, Taguchi, AI, and ML, and their effectiveness and applications were discussed. The study did not focus on comparing the experimental (RSM and Taguchi) and computational methods (Genetic Algorithms (GA) and Artificial Neural Networks) with each other, and their limitations were also not discussed. In addition, the use of different filament materials and their effect on mechanical properties was also not analyzed. Another review by Suniya et al. [41] also highlights various optimization techniques such as RSM, Taguchi, ANN, and GA to enhance part quality. Still, it does not discuss the best-performing method and the limitations of these methods. Additionally, different FDM filament materials such as ABS, PLA, nylon, and PET have

also been analyzed to assess their suitability in FDM, but their sustainability and biodegradability aspects have not been discussed.

Ciccone et al. [42] highlighted the role of AI in AM to solve challenges like defect detection, process parameter optimization, and simulation accuracy using ML techniques such as Deep Learning (DL), ANN, Convolutional Neural Network (CNN), and generative adversarial networks (GANs). The paper suggests that there is a need to increase AI model accuracy by selecting and implementing the most suitable models according to specific applications. Mohsin et al. [43] analyzed the influence of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) technologies on the designs in Additive Manufacturing (AM). The study describes several significant outcomes in this area but does not delve into the transparency and interpretability of AI-driven design optimization, the quality and standardization of data used for training ML models, the computational cost and scalability of deep learning models, the adaptability of defect identification using predictive models, and the integration of AI in multi-material 3D printing. Hassan et al. [44] focused on a holistic approach by discussing key areas of 3D printing process, including material selection, process efficiency, design optimization, and quality control. This review discussed predictive modeling without going into the detail that which AI methods (i.e. machine learning, deep learning, or reinforcement learning) are most suitable within certain stages of the 3D printing process and how those methods can be integrated into existing workflows.

From above studies there is a clear research gap in previous reviews. Previously, conventional statistical optimization techniques like RSM and the Taguchi have been extensively used for parameter optimization in FDM but there are lack of comparative studies to analyze their precision, reliability, robustness and limitations. The literature covers the use of various FDM filament materials, but there is limited focus on sustainability and biodegradability which are the key aspects for the future of manufacturing due to increase in environmental impact by plastic waste. Even though AI based techniques such as Artificial Neural Networks (ANN), Genetic Algorithms (GA), and other Machine Learning models are emerging for process optimization, there is a dire need for comparison in their effectiveness, adaptability, and scalability in FDM processes.

This review investigated the current and future prospects of FDM in AM by analyzing the various studies on process parameter optimization using RSM, Taguchi, and other techniques. Various filament materials utilized in AM and the effect of their composition on different mechanical properties were also studied. In addition, the impact of integrating AI or ML-based techniques was also examined so that the prediction and optimization of process parameters can be done more accurately. The performance of these techniques was compared and gaps were identified based on which the future directions were provided. This review article can prove beneficial for future researchers in deciding which FDM parameters will be more significant for targeting the specific output mechanical property and which AI or ML technique should be chosen to get the desired results with minimum error. Some terminologies and abbreviations used in this review are given in Table 1.

Table 1. Terminologies used

Abbreviation	Meaning	Abbreviation	Meaning
ANN	Artificial Neural Network	**UV**	Ultraviolet
RSM	Response Surface Methodology	**PE**	Polyethylene
FDM	Fused Deposition Modelling	**CF**	Carbon Fiber
ABS	Acrylonitrile Butadiene Styrene	**ANOVA**	Analysis of Variance
UTS	Ultimate Tensile Strength	**ID**	Infill Density
LT	Layer Thickness	**DOE**	Design of Experiment
IP	Infill Percentage	**ID**	Inner Diameter

ASTM	American Society for Testing and Materials	**PS**	Polystyrene
ML	Machine Learning	**LH**	Layer Height
DL	Deep Learning	**WT**	Wall Thickness
AM	Additive Manufacturing	**ROC**	Receiver Operating Characteristic
CNN	Convolutional Neural Network	**Cu**	Copper
CAD	Computer-Aided Design	**TiO_2**	Titanium Dioxide
PLA	Polylactic Acid	**PA6**	Polyamide 6
G code	Geometric code	**ZnO**	Zinc Oxide
UTM	Universal Testing Machine	**PC-ABS**	Polycarbonate Acrylonitrile Butadiene Styrene
Al	Aluminum	**Fe**	Ferrous (Iron)
FFF	Fused Filament Fabrication	**MgO**	Magnesium Oxide
UFS	Ultimate Flexural Strength	**Al_2O_3**	Aluminum Oxide
SP	Strength at Peak	**PTFE**	Polytetrafluoroethylene
SB	Strength at Break	**$CaCO_3$**	Calcium Carbonate
XRD	X-ray Diffraction	**PEI**	Polyetherimide
SEM	Scanning Electron Microscope	**PSU**	Polysulfone
MSE	Mean Squared Error	**PVA**	Polyvinyl Alcohol
RMSE	Root Mean Squared Error	**STL**	Stereo Lithography
GA	Genetic Algorithm	**FIS**	Fuzzy Inference System
DT	Decision Tree	**FL**	Fuzzy Logic
RF	Random Forest	**CCD**	Central Composite Design
SGD	Stochastic Gradient Descent	**PETG**	Polyethylene Terephthalate Glycol
DNN	Deep Neural Network	**DE**	Differential Evolution
GANN	Generative Adversarial Neural Network	**PET**	Polyethylene Terephthalate
AUC	Area Under the Curve	**DFM**	Design for Manufacturing
FS	Flexural Strength	**DSD**	Definitive Screening Design
TS	Tensile Strength	**DIC**	Digital Image Correlation
DfAM	Design for Additive Manufacturing	**SME**	Shape Memory Effect
GRA	Grey Relational Analysis	**FDAM**	Fused Deposition Additive Manufacturing
MSD	Mean Squared Deviation	**GBR**	Gradient Boosting Regression
S/N	Signal-to-noise ratio	**MAE**	Mean Absolute Error
BO	Build Orientation	**CNC**	Computer Numerical Control

RW	Raster Width	**AgNP**	Silver Nanoparticles
CMM	Coordinate Measuring Machine	**KNN**	K-Nearest Neighbor
TPU	Thermoplastic Polyurethane	**AI**	Artificial Intelligence
PC	Polycarbonate	**MATLAB**	Matrix Laboratory
PLGA	Poly-Lactic-co-Glycolic Acid	**FEA**	Finite Element Analysis
PCA	Polycaprolactone	**NT**	Nozzle Temperature

2. Methods:

This systematic review was conducted following the guidelines provided by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The literature search was performed in Google Scholar with a publication date filter to include the last 7 years (2019-2025). The results for the following keywords were searched in Google Scholar: ("3D printing" OR "Additive Manufacturing" OR "rapid prototyping") AND ("AI/ML in SLA/DLP" OR "SLS/SLM/EBM" OR "Binder Jetting" OR "Material Jetting") AND ("Applications of AM" OR "3D Printed Industrial Products") AND ("PLA and ABS Composite Filaments in FDM" OR "Thermoplastic Materials in FDM" OR "Biodegradable Filaments/Bio composites used in FDM") OR ("AI/ML Based Optimization in FDM" OR "ANN Based Predictions in FDM"). Two authors (HA and SA) independently performed this search on the database, while the senior authors (AA and SW) resolved the controversies. All titles and abstracts were screened to remove irrelevant or duplicate research. To minimize methodological bias, case reports and smaller case series, containing five or fewer tests, were excluded so the analysis could concentrate on validated techniques. All the papers that were not originally published in English were excluded. Studies were included if they: (i) were published within the last 7 years, (ii) reported quantifiable results such as accuracy and success rates. (iii) included all major AM technologies (e.g., FDM, SLA, SLS, Material Jetting) integrated with AI and ML. (iv) addressed 3D printing applications. (iv) covered both conventional and biocompatible/specialized materials. (v) Used RSM and Taguchi for parameter optimization in FDM (vi) integrated AI/ML in FDM for process optimization.

1.1 Data Extraction:

The selected papers were assessed independently by three authors (HA, SA, and SW). The senior authors (AA and SW), prepared a list of key points to be addressed in this review. Each research paper was then evaluated if the required data is available. The papers were then divided according to those points and the necessary data was rigorously assessed and summarized in a Word file. Only the headings related to abstract, methodology, and results from research papers were summarized, and the data were extracted according to the need of a specific point. In the data extraction process, no automation tools were used. If data were incomplete or unclear, cross-referencing was conducted with similar studies to verify the findings. The following points were considered as key aspects and outcomes:

i. Comparison of conventional optimization techniques (RSM and Taguchi)
ii. Comparison of AI/ML-based optimization techniques.
iii. How AI/ML can aid future research in AM, especially in FDM.
iv. Various composite and thermoplastic filaments used in FDM.
v. Biodegradable and biocompatible composite filaments.

3. Results:

1.2 Study Selection

The initial search identified a total of 1034 articles. After taking out 320 duplicate entries, 714 papers were evaluated through their titles and abstracts. Out of these, 472 articles were filtered out because they did not meet the inclusion

criteria. The remaining 242 articles went through full-text review for eligibility assessment. After further exclusions due to non-English language (n = 7), review documents (n = 15), subjects not related to AI or FDM (n = 44), case or concept without empirical data (n = 25), and incomplete or non-extractable data (n = 18), 22 studies were included in this systematic review (Figure 1). Out of the remaining 133 papers, 79 were experimental studies, 10 were review papers to identify the gaps, 9 papers related to AM types other than FDM, and 20 papers were application-based studies of FDM. All studies that focused on parameter optimization, material property characterization, and model prediction with FDM were included in this review.

4. AM Types

There are seven major AM process categories defined by ISO/ASTM 52900, including material extrusion, vat photopolymerization, powder bed fusion (PBF), binder jetting, material jetting, sheet lamination, and direct energy deposition. Vat photopolymerization and PBF are further divided into "Stereolithography (SLA) and Digital Light Processing (DLP)" and "Selective Laser Sintering (SLS), Selective Laser Melting (SLM) and Electron Beam Melting (EBM)" respectively. The focus of this review is limited to the first five AM categories because they are widely adopted in both industrial applications and academic research. Integration of AI/ML in these AM methods has proved beneficial as it enhances precision, reduces defects, accelerates production, and minimizes waste through predictive modelling, real-time monitoring, and adaptive process control.

Table 2.Challenges, AI/ML solutions and trade-off comparison of AM methods.

AM Methods	Optimization Challenges	AI and ML-Based Solutions	Trade-offs Vs Other Methods	References
Vat photopolymerization (SLA/DLP)	Support removal, thermal accumulation, curing inaccuracies, and dimensional accuracy	CNN-based support minimization, LSTM-based prediction, and RL for exposure control	High accuracy than FDM, but raw materials are costly and limited	[45], [46]
PBF (SLS/SLM/EBM)	thermal deformation, porosity, surface quality	CNN, SVR algorithm,	Significant energy consumption and lengthy process but superior density.	[47], [48], [49]
Binder Jetting	Shrinkage effect, binder saturation.	Random Forests for droplet control, GANs for sintering simulation	Mechanical strength is lower but the process is fast.	[50], [51]
Material Jetting	Multi-material bonding, droplet errors.	Computer Vision for droplet inspection, CNN, LSTM based viscosity prediction.	Different materials in single part, high resolution but material wastage.	[52], [53]

4.1. SLA/DLP: Precision at the Cost of Material Limitations

SLA is mainly concerned with producing detailed prototypes by converting liquid resin into solidified plastic [54] while DLP is a light-based 3D printing method that uses a Digital Micromirror Device (DMD) to solidify the whole layer of powdered monomer [55]. SLA and DLP are known for their precise production of parts with complex geometries, excellent resolution (up to 25µm), and smooth texture [54]. The schematic diagrams of SLA and DLP methods are shown in Figure 3 and Figure 4, respectively. Recent progress shows that machine learning algorithms like CNNs are enabling greater optimization of support structures in SLA, minimizing post-processing activities by 40% [45]. The accuracy is further enhanced by LSTM networks through the prediction of resin curing processes, reducing dimensional inaccuracies [46].

The strength of these methods is enhanced surface finish and dimensional accuracy, but they have tradeoffs like high costs of resins and limited material options as compared to filament-based methods. Machine learning algorithms improve material efficiency by using optimized support structures, which partially reduces the costs.

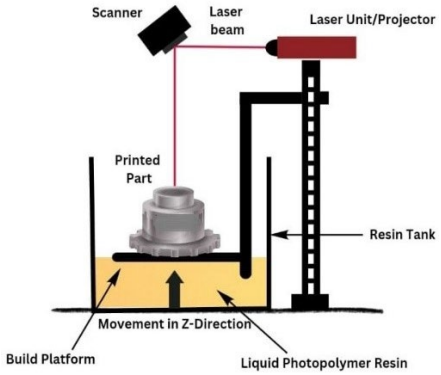


Figure 3. Pictorial Representation of the SLA.

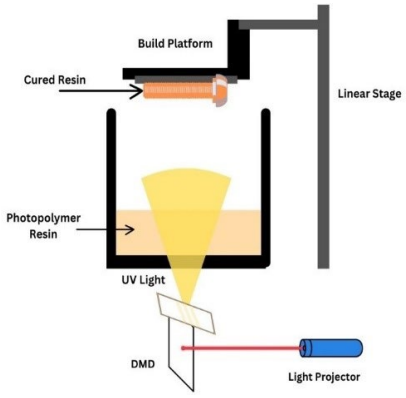


Figure 4. Pictorial Representation of the DLP.

4.2. SLS/SLM/EBM: Density vs. Energy Efficiency

PBF method of AM uses a thermal source like a laser or electron beam, which selectively fuses powdered material layer by layer to form parts [56]. PBF methods (SLS/SLM/EBM) create components with improved mechanical strength (density>99%), which is vital for automotive [57], aerospace [58], tooling and manufacturing [59], and medical implants [60]. The overview of SLS, SLM, and EBM processes is shown in Figure 5, Figure 6, and Figure 7, respectively. Physics-guided ML techniques like CNNs have demonstrated a significant reduction of porosity by 15% while maintaining thermal distortion [47, 48]. Surface quality is also improved by Support Vector Regression (SVR) models using real-time parameter adjustments [49].

These methods can produce parts with outstanding mechanical properties, which is ideal for load-bearing tasks, but with tradeoffs like excessive energy use (up to 10 times FDM) and slower build rates (5-20 mm^3/s) [53]. AI algorithms like CNNs, SVR, and digital twin applications are beneficial for energy waste reduction through intelligent process control.

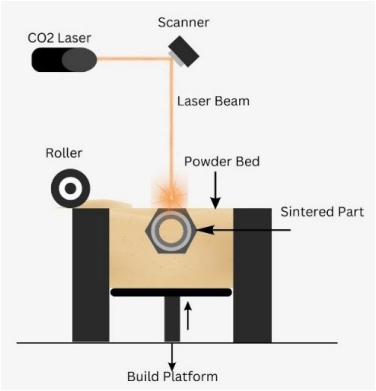


Figure 5.Pictorial Representation of the SLS

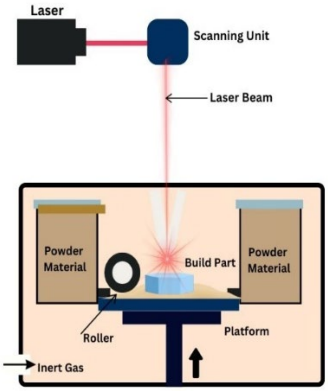


Figure 6.Pictorial Representation of the SLM

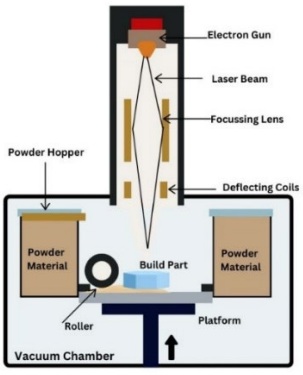


Figure 7.Pictorial Representation of the EBM.

4.3. Binder Jetting: The Speed-Strength Compromise

Binder Jetting is another powder-based type of AM process used for large-scale production. In the first step, the powder is spread onto the build platform, after which the powder is bonded by selective deposition of binder using an inkjet printer [61] . Binder jetting is the fastest AM method (up to 10,000 cm^3/hr), highly suitable for rapid prototyping

and sand casting [62]. The schematic diagram for the binder jetting method is shown in Figure 8 . With the help of the Random Forest algorithm, dimensional accuracy has improved through optimizing binder saturation parameters which reduced shrinkage by 30% [54]. Process reliability is further improved with virtual sintering simulations done by Generative Adversarial Networks (GANs) [55].

Enhanced production speeds for large batches are one of the advantages of this method, but with limited functional performance due to reduced mechanical strength (50-100 MPa). Through machine learning-assisted sintering protocols, the strength of parts manufactured through this method can be enhanced.

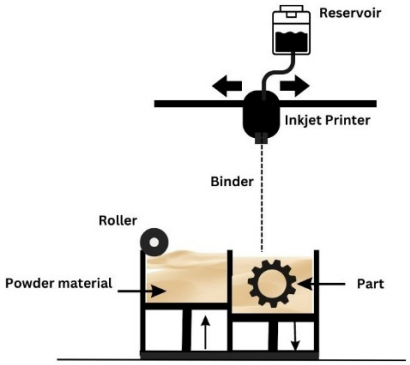


Figure 8. Pictorial representation of binder jetting process.

4.4. Material Jetting: Multi-Material Flexibility with Waste Challenges

Material Jetting is a modern AM technology that fabricates components by step-by-step layering of material droplets onto the build platform. It uses multiple jet polymer print heads to deposit the material onto the platform, where a UV light is used to solidify the layers [63]. Simultaneous depositing of multiple materials in material jetting unlocks new possibilities in the manufacturing of soft robotics and electronics because it can manufacture parts with different colors and materials, as shown in Figure 9. ML-assisted computer vision has improved accuracy in droplet placement up to 40% of the target [52], and ML algorithms like LSTM networks control the printing of materials with varying viscosity [53]. All these innovations continue to strengthen the demand for functionally graded materials.

Material jetting can provide exceptional multi-material features and enhanced resolution, but the cost is usually high due to significant material wastage in support structures, unused photopolymer resin, and failed droplets or misprints. Predictive algorithms minimize the material expenditure by optimizing the support structures and deposition patterns.

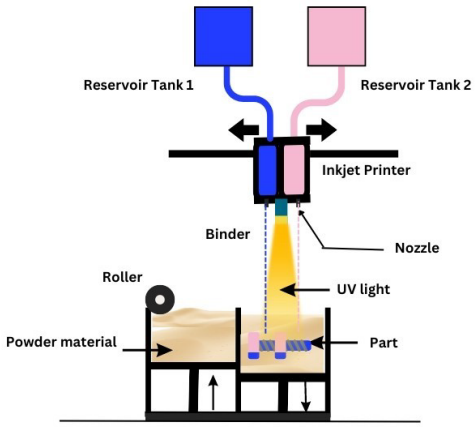


Figure 9. Pictorial representation of material jetting process.

5. Applications of AM

Each of the AM techniques discussed in the previous section has its distinct and unique processes, properties, and material applicability. These technologies are being used in a range of industries, including aerospace, automotive, healthcare, and consumer goods, leading to advancements in innovation and productivity.

5.1. Biomedical/Healthcare

AM has numerous biomedical applications providing personalization, precision, strength, and efficiency to medical devices. AM is used to fabricate titanium implant surfaces using appropriate porosity and size, increasing bone implant stability. A new lattice-type implant is introduced, which is designed to enhance the bonding strength of bone implants and facilitate the ingrowth of bone. With 65% porosity and 750 μm average pore size, this implant features a 3D spherical lattice structure which assists in the growth of bone cells with many corners for cell clustering and smoothens the transport of fluid and nutrients [64].

Reinforced composite filaments offer a promising option for AM technologies, especially in meeting the requirements for bone-related applications. The optimal hydroxyapatite/graphene nanoplatelets (HA/GNP) ratio was identified which is necessary for producing printable composite filaments suitable for biomedical applications [10].

Sugar glass has proven to be an exciting sacrificial and 3D printable material that is used to improve the transfer of mass within cell-laden matrices. For cellular biology, tissue engineering, and other biomedical applications, optimization methods for improving sacrificial inks can facilitate the manufacture of functional cell structures [65].

A shortage of PPE during the pandemic of COVID-19 gave rise to the use of AM face masks. This emphasized the significance of filter material quality and frame design for the increased effectiveness of AM face masks during any pandemic [66]. Additionally, to create instruments like forceps and hemostats, a material called bio-polymer was used for manufacturing customized surgical instruments quickly and cheaply using the FDM technique [28].

The physical blend of Poly-lactic-co-glycolic acid (PLGA) and Silver Nanoparticles (AgNP) for 3D printing a new material has promising applications in advanced manufacturing, particularly for developing biodegradable implant interventional medical devices [67]. 3D printed carbon-reinforced PLA composites have shown significant advancements in improving the efficiency of FDM for producing complex, high-performance biomaterial applications and represent a major potential step forward in additive manufacturing [29].

The integration of nano-clay into PLA is used to create composite filaments using the FDM technique which proved to have potential applications in the pharmaceutical industry [15]. FDM 3D printers have a wide range of applications in the pharmaceutical and biomedical sectors. The new biomaterial reinforcing calcium peroxide (CPO) in PLA has a great capability of contributing to industrial demands [13]. A new composite filament of polybutylene succinate (PBS) and lignin was developed that is expected to possess huge potential for utilization in biomedical applications [19].

5.2. Aerospace

AM has proved a beneficial technology for aerospace sectors because it manufactures lightweight and thermally stable parts. Suppressing airplane engines' sound is nowadays a challenge for the aerospace industry. A wide range of noise absorption from 643 Hz to 1160 Hz has been obtained by a combination of five AM Helmholtz resonators with rounded and narrow channels, which exceeds the normal honeycomb core panels in both acoustic and mechanical performance. Metal extrusion additive manufacturing (MEAM) techniques were used to manufacture these panels with intricate shapes [68].

AM can be used for prototyping and fabricating by implementing various optimization methods while designing a part, such as structural optimization, support layout optimization, and selecting part arrangement and part integration. By optimizing its design, AM can minimize the fabrication costs of intricate parts like a jet engine air manifold. Nowadays AM technology is being adopted by various aerospace companies, either by using internal AM service providers or qualified aerospace suppliers equipped with AM capabilities [69].

The carbon fiber (CF) composites formed from the blend of polyether ether ketone (PEEK) and polyetherimide [64] utilized in manufacturing filaments using the FFF AM process proved to have very strong potential for aerospace applications even for operating temperatures of more than 120 ^{0}C [70].

5.3. Automotive

AM has provided substantial opportunities for the automotive sector due to its cost-effectiveness, ease of use, and improved product quality. It assists in decreasing the weight of vehicles and improving efficiency through parts integration, customizing material properties, facilitating multifunctional parts, and making the manufacturing processes simple and less time-consuming. Direct manufacturing of vehicle metal parts using AM is highly feasible in automotive applications, particularly by combining the binder jetting method with generative design [71].

The goal of developing polypropylene (PP)-based composites for FFF is to use it for fully automatic robotic repair applications for polymeric components in the automotive industry. In automotive applications, a primary challenge in fixing and bonding polyolefins is understanding the interaction of microstructural attributes with the joining process to attain fully functional repaired parts [72].

5.4. MEMS and NEMS

Microelectromechanical systems (MEMS) and nanoelectromechanical systems (NEMS) are transforming AM by facilitating the fabrication of complex, highly intricate, and micro-scaled parts. The size of MEMS typically ranges from micrometers to millimeters while NEMS on the other hand operates at the nanoscale. Integrating MEMS and NEMS in 3D printing improves AM technology's functionality and expands creativity opportunities in various fields such as environmental monitoring and telecommunications.

A profound reduction in the size of NEMS resonators paves the way for achieving improved resolution in high-performance mass sensing. A 3D-printing technique called two-photon polymerization (TPP) is employed to fabricate rigid NEMS resonators with high-quality factors. This rapid prototyping technique proved an effective substitute for semiconductor resonators, allowing it to be used for highly sensitive mass and force sensors [73].

A functional MEMS accelerometer can also be fabricated utilizing the TPP method by settling a strain gauge transducer through metal evaporation. The 3D printing of MEMS devices is a feasible technique that allows the efficient manufacturing of various custom-designed MEMS devices. This approach unveils new application ranges that conventional MEMS fabricating strategies strive to accommodate [74].

An SLA technique is used to fabricate a micro-cantilever that incorporates an open channel of fluid and a reservoir, to enhance the surface functionalization of already available silicon MEMS drop deposition tools. This 3D-printed technique can recreate the functionality of traditional silicon-based tools but with reduced costs, high intricacy, and less time [75].

Ultrasonic sensors are fabricated by using piezoelectric composites as a core material. Conventional manufacturing techniques such as mold mixing, forming, and dicing-filling are utilized to prepare these piezoelectric composite structures. However, these conventional methods are not suitable for fabricating complex parts or structures. Barium titanate-based piezoelectric composite ceramics with honeycomb microstructure can be manufactured utilizing a 3D printing method, namely, mask-image-projection-based SLA (MIP-SL). After integrating these ceramic composites into an ultrasonic device, they displayed great performance and enhanced output power characteristics for ultrasound sensing. Employing this 3D printing technique has great potential to fabricate MEMS-based ultrasonic devices [76].

A capacitive force sensor with a detailed suspended beam plate structure can be 3D-printed in a single step by utilizing a triple-extruder 3D. This integrative 3D printing approach needs no additional metallurgical coating, filament loading, replacing, orientation, or assembly steps. This 3D-printed force sensor can monitor human blood pulse due to its great dynamic performance. This new 3D-printing method possesses great potential for fabricating MEMS devices that can be designed for personalized applications [77].

6. FDM-based Filament Materials

Various filament materials used in the FDM process have unique characteristics, making them suitable for many applications. The selection of filament material significantly affects the mechanical properties, surface texture, and suitability of various applications of printed objects. It is crucial to understand the properties and applications of these materials to optimize the FDM process to meet the desired performance and quality of printed parts.

6.1. Composite Filaments

Thermoplastics are versatile polymers that soften on heating and harden upon cooling, facilitating easy reshaping and recycling. Composites contain thermoplastics as a base material with some reinforced materials like bronze, carbon fiber, or other metals to improve the strength and durability of the part.

6.1.1. PLA

Many studies have focused on developing novel PLA composites due to their cost-effectiveness, availability, and ease of printing. For example, a survey by Bochnia et al. [11] analyzed the effect on the mechanical properties of thin-walled specimens printed using the FDM technique by integrating 80% bronze into PLA. Figure 10 (a) indicates that elastic modulus values for PLA specimens with bronze fillings under different conditions or variations range from approximately 277 MPa to 713 MPa, indicating a significant variability in stiffness or rigidity among the specimens tested. Figure 10 (b) illustrates that a high concentration of bronze powder in the composite material led to a significant reduction in the tensile strength of specimens printed in the Z direction. In contrast, Soms et al. [78] conducted research in which they integrated 10 wt% % brass in PLA fabricated through FDM to analyze its effect on key mechanical properties such as tensile strength, flexural strength, and impact strength. A significant increase in tensile strength of 85%, flexural strength by 107%, and impact strength by 83% was observed by incorporation of brass within the PLA matrix. This means the addition of bronze in the PLA matrix reduces the tensile strength, while the addition of brass leads to an increase in the tensile strength.

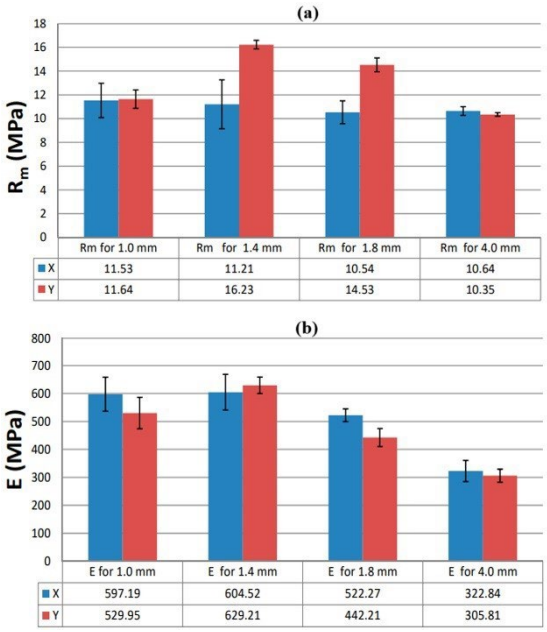


Figure 10. (a) Tensile strength (Rm) of PLA/bronze samples based on thickness and print direction (b). Elastic Modulus (E) of PLA/bronze samples based on thickness and print direction [11].

Furthermore, Doungkeaw et al. [79] incorporated iron (Fe) into PLA and studied the effect of incorporation on printability and mechanical properties. The percentage incorporation of Fe has not been mentioned in the paper. The results were also compared with another composite of PLA/Stainless Steel (SS). Authors concluded that PLA/Fe exhibited superior mechanical properties and printability (at 280 ^{0}C) as compared to PLA/SS, which exhibited 1.2 times greater elongation and 1.5 times increased maximum stress. A similar study by Memiş et al. [80] produced PLA-

based filament with 5% incorporation of Fe powder and studied the effect on tensile strength and hardness. The results were compared with pure PLA which revealed 21.5% increase in hardness, 49.60% increase in tensile strength and 4 times increase in surface roughness. The mechanical properties of PLA in both these studies were significantly increased by incorporating Fe but with disadvantage of reduced surface quality due to increased surface roughness.

6.1.2. ABS

ABS is another petroleum based filament and is well known for its high impact strength, temperature endurance and low cost as compared to PLA [81]. To further enhance its strength, Mogan et al. [81] developed ABS/SS composite filament with different compositions of SS powder (5 and 10 wt. %) and compared its mechanical properties and thermal conductivity with pure ABS. Adding SS powder decreased the UTS by 10.25% for the 5 wt% SS and 17.91% for the 10 wt% SS. In contrast, elongation increased by 34.26% for 5 wt% SS and 84.41% for the 10 wt% SS. Moreover, there was a significant improvement in thermal conductivity showing a 43.95 % increase for 10 wt% SS. A subsequent research by Ranjan et al. [9] analyzed the effect of incorporating aluminum (Al) in ABS matrix. Acrylic mist spray was used for the reinforcement process in which Al particles were sprayed between the ABS layers. Approximately 65 mg of Al was deposited on each layer to ensure consistency in amount of Al particles. This resulted in significant improvement (up to 50%) in flexural strength and crystallinity while decrease in ductility (up to 20 %).

6.1.3. PBS

Polybutylene succinate (PBS) filament has recently gained popularity among researchers because it is easy to print as compared to PLA and ABS and has enhanced mechanical and thermal properties [82]. For this reason, a study by Zhou et al. [82] blended PBS with talc (5, 10, 20, 30, and 40 wt.%)to increase the melting strength of pure PBS. In addition to that, mechanical, rheological, and morphological properties were also investigated to evaluate the strength and durability of the newly developed composite. Authors reported a 14.75% increase in crystallization temperatures, a 68.45% increase in flexural strength, while tensile strength was not much affected by 5 wt. % incorporation of talc. However, incorporation of talc greater than 40 wt. % showed a significant decrease in tensile strength values. On the other hand, Abdullah et al. [19] incorporated lignin into polybutylene succinate (PBS) to obtain enhanced printability and antimicrobial properties. The methodology involved coating of printed filaments with Silver/Zinc Oxide (Ag/ZnO) having 2.5 and 3.5 wt. % of lignin coated by Ag/ZnO nanoparticles, utilization of Ampicillin for assessing antimicrobial performance. This study showed that printing quality, dynamic moduli, and antioxidant performance of the composites can be enhanced by adding lignin. The composites with 2.5% lignin addition showed the best properties, while composites with 3.5 wt. % of lignin coated by Ag/ZnO showed a clear inhibition zone against all studied microorganisms. Nano-coating with Ag/ZnO at a thickness of 100 nm enhanced the antimicrobial activity of the 3D-printed composite grafts. This shows that above mentioned studies of PBS can provide a good balance between strength, thermal resistance, and antimicrobial performance, which is a crucial aspect from a medical point of view.

6.1.4. PETG

Many studies also reported PETG as a high-strength and thermally stable material for FDM printing. For example, a study by Zmuda et al. [83] focused on developing 3D printable filaments with a metal-like finish by adding micrometric steel powder in pure PETG. Steel powder was added in 3-13 wt. % of the total mixture and its effect was analyzed on mechanical performance, thermal properties, and physicochemical properties such as roughness and moisture absorption. The addition of steel filler with 13 wt. % improved the thermal stability by 4.48 % and compressive strength by 62%, while the highest increase in tensile strength (20%) was achieved with 3 wt. % of steel powder in PETG. Faidallah et al. [84] compared the tensile and compressive strengths of pure PLA and PETG filament with PLA and PETG reinforced with 10% carbon fiber and fabricated through FDM. Results of this study revealed that CF-PLA demonstrated a 27% increase in tensile strength as compared to CF-PETG, while PLA outperformed all the filaments, CF-PLA, PETG, and CF-PETG in compressive strength by 23.7%, 53%, and 67%, respectively. This clearly shows that reinforcement of CF increased the tensile strength but reduced the compressive strength.

6.1.5. TPU

Jayswal and Adanur [16] analyzed the effect of integrating thermoplastic polyurethane (TPU) into PLA and observed composite filaments' thermal behavior, mechanical properties, compatibility, and printability. The feasibility and suitability of the newly developed composite filaments were assessed for their potential use in FDM specifically in

producing elastic structures. Their study concluded that by increasing the contents of TPU fillers, a decrease in tensile strength and stiffness was particularly due to the elastomeric properties, which have been inhibited by TPU. The addition of TPU increased flexibility and ductility, ultimately increasing the percentage elongation at the break of each filament. A similar study by Olalla et al. [85] also investigated the effect of a 40:60 blend of PLA and TPU composite and analyzed the effect on its morphological, thermal, mechanical, and thermoresponsive cyclic shape memory behavior. In contrast with the results of Jayswal and Adanur [16], the UTS and elongation at break were significantly improved by 258% and 2730%, respectively, as compared to pure PLA. PLA/TPU 60:40 blend was found to have a remarkable set of characteristics, which include flexibility, strength, and shape memory capabilities, due to the impact of TPU alignment, impact resistance, and elasticity in the printing direction.

Table 3. Effect of different compositions on mechanical properties of filaments.

References	Base Polymer	Filler/Modifier	Filler (wt)	Features
Bochnia et al. [11]	PLA	Bronze	80%	High tensile strength but Low Young's modulus
Soms et al. [78]	PLA	Brass	10%	High tensile strength, flexural strength, and impact strength.
Doungkeaw et al. [79]	PLA	Fe	Not given	High tensile strength and hardness, but reduced surface finish
Mogan et al. [81]	ABS	Stainless Steel	5 and 10 %	High elongation and thermal conductivity but low UTS.
Ranjan et al. [9]	ABS	Al	65 mg per layer	High flexural strength but poor ductility
Zhou et al. [82]	PBS	Talc	5, 10, 20, 30, and 40 %	High flexural strength and temperature resistance, but no effect on tensile strength
Abdullah et al. [19]	PBS	Lignin	2.5 and 3.5 %	Easy printing, antimicrobial, antioxidant
Zmuda et al. [83]	PETG	Steel powder	3-13 %	High tensile strength (with 3 wt. %), High compressive strength and thermal stability (with 13 wt. %)

Faidallah et al. [84]	PETG	CF	10 %	High tensile strength but low compressive strength
Jayswal and Adanur [16]	TPU	PLA	50:50	Highly flexible and ductile but low tensile strength.
Olalla et al. [85]	TPU	PLA	50:60	High flexibility, elasticity and impact strength

From Table 3**,** it can be observed that despite PLA composites' low flexibility, it has high tensile strength, which is perfect for structural components of functional prototypes, even though the surface finish may be compromised. Thermoplastic ABS composites have a remarkable thermal conductivity, which allows them to withstand great heat, but are not ductile, making them ideal for enclosures, heat spreaders, and primary mechanical components. PBS's easy printability and antimicrobial properties, tensile and thermal stability stand out, making the filament perfect for use in medical tools and kitchen accessories, and even in the aerospace sector. Composites based on PETG offers high tensile strength with good thermal resistance, but lower compressive strength and high tensile strength, making it a great option for flexible electronics components and structural parts. Outstanding impact strength, elasticity, and flexibility make TPU perfect for use in soft robotics, shock-absorbing sports gear, and even in ergonomic wearables. Overall, the choice of FDM filament depends on specific requirements and application.

6.1.6. Biodegradable Composite Filaments:

PLA

In AM, various biodegradable and biocompatible filament materials are used to advance the efforts toward environmental sustainability, enabling the production of eco-friendly products. Many studies have been done focusing on PLA-based bio-filaments to support sustainable practices. For example, Mihankhah et al. [15] introduced nano-clay into PLA, Scaffaro et al. [14] made a composite filament by integrating EE and MB within PLA, Kananathan et al. [12] reinforced coconut wood into PLA, Mocanu et al. [10] integrated HA and GNP into the PLA matrix, and Mohammed et al. [13] utilized CPO-reinforced PLA composite. Tests reported by Jha et al. [86] show that PLA-based bio-composites are fully biodegradable and environmentally friendly, which leads to enhanced bioactivity while preserving PLA's compostability. The addition of plant-based fillers enhanced biodegradability by up to 7.6% compared to pure PLA, indicating enhanced microbial degradation [87]. These composites, however, are generally considered mechanically recyclable under carefully controlled conditions, but are typically less recyclable due to thermal degradation and natural fiber incompatibility [86]. According to Bhat et al. [88], natural PLA fiber composites exhibit low toxicity because there are no heavy metals or synthetic substances added to them.

PBAT

The growing interest in sustainable, high-performance materials is exhibited by the latest developments in biodegradable filaments for Fused Deposition Modeling (FDM). One such advancement by Sciancalepore et al. [89] was the reinforcement of PBAT with zein–titanium dioxide (TiO_2) ZTC complexes to increase thermo-mechanical and interfacial bonding while maintaining printability and biocompatibility. Moreover, Jubinville et al. [90] blended PBAT and polylactic acid (PLA) with hemp hurd microparticles and successfully increased toughness and compostability; however, the 3D-printed versions still required optimization to match the mechanical strength of injection-molded parts. Da Silva Fortes et al. [91] in their study incorporated peanut and soya bean shells into PBAT, which significantly affected their mechanical properties and dimensions, while maintaining good processability and thermal stability for 3D printing. The results of Tselana et al. [92] showed that PBAT achieved approximately 68.65% biodegradation during the exponential phase after 70 days. This indicates that PBAT undergoes significant biodegradation under composting conditions. All these studies show a balance of PBAT composites in terms of mechanical and thermal properties while maintaining biodegradability.

PETG

Pure PETG filaments exhibit limited biodegradability, with degradation rates not exceeding 30% [93], but the use of waste leaf carbon fillers or natural fibers as fillers and additives can improve the biodegradability of PETG composites, increasing the sustainability of the materials. For example, in a study by Garwacki et al. [94], multilayered PET-based foil waste was recycled with PETG and chain extenders, and elastomeric copolymers were added, which showed potential for FDM filament production, although unmodified versions proved to be brittle. Kumar et al. [95] incorporated pineapple fiber (PALF-P) particulates in PETG to enhance its mechanical integrity, with alkali-treated fibers demonstrating better bonding and tensile strength at 5 wt.%. Moreover, research by Balou et al. [96] demonstrated that sustainable composites of PETG and activated carbon from waste leaves have outstanding improvement in mechanical strength and thermal stability, as well as successful FDM fabrication of functional objects like anatomical models. While Balou et al. [96] showed the benefits of blending PETG with activated carbon from waste leaves in improving the biodegradability of PETG, Garwacki et al. [94] focused on the recycling aspect by using PET foil waste and blending it with PETG and some chain extenders. It showed some degree of recyclability, although there was increased brittleness with the unmodified blends. Balou et al. [96] also showed that blending waste leaf carbon with PETG enables greater waste valorization and circular material possibilities.

PU Based

Larraza et al. [97] conducted a study on Polyurethane (PU)-based nanocomposites modified with graphene and cellulose nanofibers, which proved promising for thermal and mechanical properties of FDM printed parts, owing to their flexibility, biocompatibility, and shape retention, making them ideal for biomedical applications. Graphene oxide enhances the mechanical properties; however, depending on the level of concentration and exposure, nanocarbon materials exhibit cytotoxicity. Rahman et al. [98] concluded that bio-based thermoplastic polyurethanes (TPU) (TPU synthesized from Polytrimethylene Ether Glycol (PO3G), 1,5-Pentamethylene Diisocyanate (PDI), and 1,4-Butanediol (BDO)) made from 100% renewable monomers demonstrated high modulus, hardness, and remarkable cell viability, presenting a sustainable option for 3D-printed parts, which enhanced the biodegradability of otherwise non-biodegradable thermoplastics. Bio-based TPU exhibited biodegradation rates up to 42% in 60 days, suggesting that the incorporation of bio-based components can enhance the biodegradability of TPU [99].TPU composites may involve the synthesis of volatile solvents, due to which the evaluation of human and environmental safety is important in the case of TPU solvents [99].

Collectively, these studies show the potential of using bio-fillers and recycled materials in FDM filaments to enhance sustainability without sacrificing functionality. Table 4 presents an overview of biocompatible materials recently developed. Compared to other filament materials, the strength of PLA is low due to which researchers are trying to enhance its mechanical properties using different fillers. Among all the composites, the highest improvement in tensile strength (15.3%) was seen in PLA reinforced with 4% nano clay. Conversely, TPU with cellulose nanofibers exhibited lower mechanical performance after the printing process because of material damage due to FDM. Composites of TPU with Graphene were not the strongest, but their printability, morphology, and flexibility are better than PLA composites, making them more appropriate for biomedical applications.

Composites based on PBAT were found to have less mechanical strength as compared to PLA and TPU, but outperform in biodegradability and flexibility, thus making them suitable for sustainable and flexible packaging or scaffold materials for medicine. However, their poor printability remains a challenge.

In comparison, PETG composites have lower biodegradability and biocompatibility when compared to PLA and TPU-based materials, but show higher mechanical strength and thermal endurance, making them suitable for high-load applications.

While all previously discussed materials are tailored for particular applications like strength, flexibility, biodegradability, or printability, they also offer unique disadvantages. For example, PLA's brittleness, TPU's sensitivity to heat, PBAT's weak mechanical properties, and PETG's limited biodegradability highlight the need to balance functionality with sustainability depending on the intended end-use.

521 Table 4. Effect of different compositions on mechanical properties and sustainability.

References	Base Polymer	Filler/Modifier	Filler (wt)	Key Findings	Merits
Mihankhah et al. [15]	PLA	Nano clay	2 % and 4 %	4.6% and 15.3% increase in tensile strength of PLA for both percentage fillers	Biodegradable, nontoxic, enhanced mechanical properties
Scaffaro et al. [14]	PLA MB (a co-polyester)	EE	10 %	Flexural modulus increased by 23% for PLA and 32% for MB; MB elongation at break increased by 364%	Antimicrobial, enhanced mechanical properties, renewable, cost effective
Kananathan et al. [12]	PLA	Coconut Wood	40%	Reduction in mechanical properties: tensile strength, compressive strength, Young modulus	Thermal resistive, corrosion resistive, bio-compatible
Mocanu et al. [10]	PLA	HA and GNP	HA: 0-50% GNP: 0-5%	6.67 % and 14.12 % increase in compressive strength and elastic modulus, respectively.	Improved wettability, no internal porosity, enhanced mechanical properties
Mohammed et al. [13]	PLA	CPO	3-24 %	Tensile strength decreased except for 6% CPO content, and viscosity increased.	Good printability, improved ductility, stable rheology, and biocompatible
Sciancalepore et al. [89]	PBAT	ZTC	5-40 %	Storage modulus and creep resistance increased by 194% and 252% at 20^{o}C respectively.	Significant mechanical improvement, biocompatible, good printability
Jubinville et al. [90]	PLA:PBAT 50:50	Hemp hurd	10-40%	Tensile strength and Young modulus have increased by 30.8% and 130% respectively.	Compostable, enhanced thermal stability, low cost, and ecofriendly.
Da Silva Fortes et al. [91]	PBAT	Peanut and soybean shells	2.5 and 5%	Soybean shell composites have the highest elastic modulus. Peanut shell composites exhibited the highest tensile strength.	Good processability, agro-waste valorization, and dimensional stability

Garwacki et al. [94]	PETG	Chain extender (CE), PET foil waste	40-69 %	Elongation at break increased by 50% and impact strength by 296%	Scalability, waste valorization, biocompatible
Kumar et al. [95]	PETG	PALF-P	1.5%, 2.5%, 5%, and 7.5%	Tensile strength was increased by 24.6% with 5% filler content while Young modulus almost remains same.	Lightweight, cost-effective, bio compatible and easy to print
Balou et al. [96]	PETG	(waste leaves)-derived activated carbon	30% and 50%	Tensile strength and Young's modulus was increased by 30% with 30% incorporation of filler.	Enhanced mechanical properties, waste reduction, thermally stable, Hydrophilicity
Larraza et al. [97]	PU	Cellulose nanofibers and Graphene	3%	Young's modulus and stress at break were increased by 383% and 68% for cellulose nanofibers and 369% and 422% for graphene respectively.	Improved Printability with graphene, enhanced mechanical properties, biocompatible, more flexible
Rahman et al. [98]	Bio-based TPU (TPU synthesized from PO3G, PDI, and BDO)	No filler specified	N/A	Young's modulus shore A hardness was increased by 302.5% and 2.17% respectively.	100% bio based, good mechanical properties (high strain and modulus), thermal stability, improved cell adhesion

7. Optimization of FDM Process Parameters

7.1. Parameters Optimization using RSM

RSM is a mathematical or statistical approach by which complicated processes and systems can be optimized by investigating the relationship between input and output variables [100]. The structural layout of RSM can be conceptualized in Figure 11. The two commonly used experimental designs in RSM are Box Behenken Design (BBD) and Central Composite Design (CCD), however, with advancements in the design process, some other designs, including Face Central Composite Design (FCCD) and Central Composite Rotatable Design (CCRD) are also very popular [101]. In various recent studies, RSM proved to be an effective approach to improving product quality and efficiency in various industries [102].

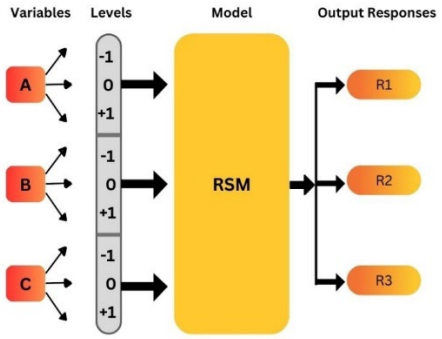


Figure 11. Structural Layout of RSM Model.

The BBD requires small number of experimental runs and does not require extreme settings for factors, making it more efficient and practical for optimizing FDM parameters [103]. For example, Rahmatabadi et al. [103] used BBD to optimize the 3D printing parameters of the FDM technique by investigating the relationship between input variables and performance parameters. Shell thickness, infill density, and nozzle temperature were the parameters that were investigated and their effects were observed on key properties such as recovery stress, loading stress, shape fixity, and shape recovery ratio. ANOVA results have shown that infill density was the most significant factor affecting SME properties, while nozzle temperature was the least significant. This study indicates how well RSM can capture non-linear behavior as shape memory ratio did not changed linearly with changes in infill density, shell count and temperature. A similar study by Tura et al. [25] observed different process parameters, namely raster angle, printing orientation, air gap, raster width, layer height, and their effect on tensile strength using FDM. 46 experimental trials were generated utilizing a BBD RSM technique. Results have shown that raster angle, air gap, and raster width were the most significant parameters affecting the tensile strength. This study used more experimental runs to analyze the more complex relationships effectively but it was also much time consuming and costly because higher number of runs need more testing iterations.

Afshari et al. [104] also utilized RSM in combination with a BBD to optimize FDM 3D printing parameters such as stacking angle, infill extrusion width, layer thickness, and bed temperature and analyzed their effect on part fractures, tensile strength, impact energy, and flexural strength. The study also estimates the effectiveness of RSM in modeling intricate multi-parameter response systems by contrasting predicted and validated conditions (e.g., stacking angle of 13.5°, infill width of 145%) against proposed values derived using the desirability function technique which confirms RSM's systematic refinement of part attributes. These results highlights RSM's superiority in capturing multi-factor interactions compared to simpler methods like Taguchi.

CCD approach usually require higher number of runs due to which it can capture more detail as compared to BBD [26]. CCD approach can capture the curvature of model beyond the given ranges which can provide a better estimate of model [30]. Research conducted by Mushtaq et al. [26] utilized the RSM CCD approach to optimize the parameters for 3D printing using PLA to improve the efficiency and quality of printed objects. The optimal characteristics of the PLA objects were demonstrated at specific settings as infill density of 84%, print speed of 68.87 mm/s, and layer thickness of 0.26 mm with the following optimized values: flexural strength of 70.1 MPa, tensile strength of 39.2 MPa, minimum surface roughness of 7.8 μm, print time of 47 minutes, and print energy of 0.18 kWh. This study used only 20 number of runs for CCD design which might affect the accuracy of model for this level of complexity. Similarly, Dev & Srivastava [30] enhanced the FDM process for ABS parts using various shapes and optimizing five different variables using the RSM CCD approach. ANOVA results revealed that optimized parameters can significantly impact surface quality up to 18.43%, reducing manufacturing time by 11.11% and improving dimensional accuracy for producing high-quality FDM parts. The RSM-CCD design was proved to be beneficial for industries to enhance quality in producing products through FDM additive manufacturing.

A study was conducted in which Moradi et al. [24] focused on optimizing the FDM process for 3D printing PLA components, with a particular focus on fiber-reinforced composites. This research successfully enhanced the mechanical properties of materials by applying RSM and varying infill percentages and layer widths. Results have

shown a significant 91% reduction in surface roughness, 25.6% improvement in tensile strength, and 34.1% in elastic modulus which was considered a notable achievement. This study concluded that RSM is good to study complex relationships between input and output variables. In addition to that, model accuracy and linearity can be further improved by Box-Cox Transformation.

7.2. Parameters Optimization using Taguchi

The Taguchi method is also a statistical technique for the optimization of process parameters. It uses various orthogonal arrays to analyze the impact of multiple variables and find the best conditions efficiently. This method is often used by various industries due to its robust nature of optimization [105]. Recent research work has shown that the Taguchi method can be undoubtedly utilized to refine the manufacturing processes in various sectors including aerospace [106], automotive [105], and electronics [107]. These studies indicate the robustness of the Taguchi method to obtain the best outcomes and operational efficiency [108]. Vinay et al. [27] conducted research that focused on utilizing the Taguchi DOE method for the FDM process to figure out the different factors affecting the adhesion and strength of metal-polymer composites and the relationship between tensile properties and processing variables. This study used L9 orthogonal array requiring only 9 experiments which reduced the time and material costs compared to full factorial designs. The study tested only 3 levels per factor, potentially missing finer optima. For instance, the layer thickness was considered at 0.1 mm, 0.2 mm and 0.3 mm, but values such as 0.15 mm may be more suitable. Taguchi's orthogonal arrays consider factors as independent, although there could be interactions such as infill density x temperature. The study highlighted some non-linear interactions for example, ductility decreased with increasing aluminum content, which Taguchi alone could not be able to explain.

A similar study by Gorana et al. [109] focused on improving the accuracy of ABS parts manufactured by low-cost FDM printers. The Taguchi Method with L9 orthogonal array was used to optimize the length and diameter of a cuboid-shaped ABS part. Layer thickness, build orientation, raster angle, and raster width were considered as the four process parameters with three different levels. Build orientation has more and layer thickness has less contribution in affecting length while layer thickness was proved to be the most and raster angle to be the least important parameter in affecting diameter. From this study it can be concluded that this approach can be used in industries where rapid screening of parameters is needed.

A study conducted by Tayyab et al. [110] predicted and modeled the mechanical properties of ABS samples. Nozzle diameter, layer height, infill density, printing velocity, raster orientation, and infill pattern were the process parameters selected for this study and the L27 Taguchi array was employed to associate these process parameters. Optimal parameters were identified as a nozzle diameter of 0.6 mm, layer height of 0.1 mm, infill density of 64.63%, printing velocity of 29.54 mm/s, and raster orientation of 85.23°. These optimal parameters resulted in a maximum flexural strength of 2.674 GPa. Furthermore, Mangla et al. [32] investigated the effects of different process parameters such as infill density, infill pattern, and layer thickness on various properties of PLA-printed samples using FDM. Taguchi's L27 DOE method was used to conduct 27 experiments investigating the relationship between layer thickness, infill density, and infill pattern. The results show that the effect of layer thickness varies between different performance indicators. For example, at 75% infill density, grid and triangle patterns tend to produce better results, while at 25% infill density, the choice of infill pattern affects the results differently. Gyroid and triangular patterns are optimal for thinner layers (e.g. 100 μm), while the grid pattern is better for thicker layers (e.g. 200 μm). Both studies demonstrated the optimization capability of Taguchi's method with FDM processes as its orthogonal arrays (L27) greatly minimized the number of runs while capturing the interactions of multiple parameters simultaneously.

Another research carried out by Ranjan et al. [9] fabricated a final-use product through FFF in which Al metal spray is reinforced into an ABS matrix. Taguchi L-9 array is used to observe the best possible combination of input parameters to obtain optimized flexural strength properties. The effect of Al incorporation is studied by focusing on three main parameters which include infill pattern, infill density, and number of sprayed layers. In the same way, Hasanzadeh et al. [29] examined the impact of material and process parameters on the mechanical properties of parts produced using FFF. Taguchi method was used for experimental design and the S/N ratio for statistical optimization. From Figure 14 (a) and (b), it was observed that by using optimal conditions, a maximum tensile strength of 61.85 MPa and an elongation-at-break of 17.7% can be achieved). S/N analysis revealed that filament type has a greater

influence on tensile strength, meanwhile, print speed has a significant effect on elongation-at-break. Whereas Ranjan et al. [9] focused on process-driven optimization (infill, layers) for metal-reinforced ABS, Hasanzadeh et al. [29] revealed material-driven dominance (filament type > speed) through S/N ratios—highlighting Taguchi's ability to balance material versus process factors.

Figure 12. S/N Diagrams for (a) Tensile Strength, and (b) Elongation at Break [29]

Kumar & Singh [28] discussed the use of a material called bio-polymer for manufacturing customized surgical instruments quickly and cheaply. Using Ultimaker Cura 4.9.1 and Taguchi's DOE method, 11 process parameters were optimized with three levels each. Results have shown that tensile strength increases with an increase in layer height showing that it has been the most influential parameter in improved tensile strength while a layer height of 0.1 mm contributed to achieving the maximum elastic modulus. Portoacă et al. [111] studied the effect of various process parameters on the tribological properties of ABS and PLA using 3D printing. The DOE method was used in which infill percentage and layer thickness were the main process parameters. The results have shown that the optimal settings for minimizing wear and friction were, an infill percentage of 50% and layer thicknesses of 0.1 mm for ABS and 0.15 mm for PLA. These studies illustrate Taguchi's blind spot—optimal layer height varies sharply by material (0.1 mm for ABS vs. 0.15 mm for PLA in wear resistance), indicating the need for more specific DOE designs rather than one-size-fits-all arrays.

7.3. Comparison of RSM and Taguchi:

A comparison between the RSM and the Taguchi optimization methods is presented below, with a summarized overview provided in the accompanying Table 5.

1. The Taguchi method required few test runs (maximum 27 in discussed studies) due to its design of experiments, while RSM required more than 40 runs on average for even a few parameters. Therefore, the Taguchi method is more efficient than RSM in terms of the number of tests that need to be performed, even when interaction terms are considered. Due to the limitations of the orthogonal array used in the Taguchi method, it can only take a limited number of interactions besides the linear terms. On the other hand, RSM can include all interactions and quadratic terms, which enhances the accuracy of the mathematical model that better fits the observed data.
2. After comparison of both methods, it is clear that the Taguchi method does not generate predictive results in any of the above-discussed studies. Even though ANOVA identified significant parameters, there was no response surface contour or regression model available for estimating performance at midpoints or unseen parameter values. This is a limitation of Taguchi compared to RSM or AI models such as ANN.
3. Higher experimental costs and time-consuming process of RSM designs can be a challenge as compared to Taguchi orthogonal arrays, where the number of experimental runs is significantly lower.
4. Because RSM regression models are parametric, they are sensitive to experimental errors and outliers that impact the accuracy of the model unless significant preprocessing or cleaning is performed.
5. Implementation of RSM, especially with more than 3-4 factors, sometimes becomes more complex and requires advanced statistical and software knowledge, which raises accessibility concerns, especially for beginners or practitioners.

Table 5. Comparative analysis of RSM and Taguchi.

Aspect	RSM	Taguchi Method
Objective	Accurate optimization by modelling complex interactions	Identification of dominant factors and robust settings.
Experimental Designs	BBD, CCD	Orthogonal arrays (L9, L27) for factorial designs
Number of Runs	High (18-30 for 3-5 factors)	Low (9 runs for 4 factors)
Data Analysis	Regression equations (Linear and quadratic) and ANOVA.	S/N ratios. ANOVA for Percentage contribution.

	Contour plots and 3D surfaces for better visualization	S/N Curves.
Predictive Capability	It can predict output responses (e.g., Flexural strength 43.5 MPa at A, B, C parameters).	Discretized input parameters (e.g., infill density of 80%) No predictive ability.
Complexity	Statistical and software expertise required	Simple, easy to implement
Strengths	Highly accurate for complex systems. Visualization of data in the form of 3D plots for better understanding. Detailed process Optimization.	Cost-efficient and fast. Ideal for screening initial parameters. Industrial robustness testing
Weaknesses	Costly due to resource consumption (more experiments). Increased complexity for factors > 5.	Restricted to single-response optimization. Unable to predict

8. Current Trends in FDM Process

8.1. AI/ML-Based Techniques:

8.1.1. Property Prediction:

The use of AI/ML techniques is on the rise for enhancing FDM processes. The recent work shows the implementation of various AI methods to heuristically forecast the properties of the materials and increase the accuracy of the manufacturing operations. These studies illustrate the application of various ML models to solve important problems of the control and supervision system in the AM process. For doing so, Soms et al. [78] explored six AI techniques to estimate the mechanical characteristics of PLA/brass composites produced using FDM: Artificial Neural Networks (ANNs), Decision Trees, Random Forests (RF), AdaBoost, Gradient Boosting (GB), and Support Vector Machines (SVM). The study looks at three types of strength: tensile, flexural, and impact. AI model predictions were assessed with three indicators: R^2, MSE, and MAE. For tensile strength, ANN was the best model with $R^2 = 0.986$, MSE = 0.131, and MAE = 0.209. Gradient Boost came in second with $R^2 = 0.982$, MSE = 0.216, and MAE = 0.223. AdaBoost was the worst with $R^2 = 0.843$, MSE= 1.496, and MAE= 0.812. For Flexural strength, ANN again dominated with $R^2=0.918$ and MSE=2.376, although Decision Trees outperformed all others on MAE=0.773. Gradient Boost had MSE=5.603, indicating greatly reduced predictive power. The study concludes that the most dependable AI-based model for predicting FDM-printed part properties is ANN, while Decision Trees, although more simplistic, yielded reasonable MAE results. While both Gradient Boost and SVM are feasible options, neither is highly efficient. Moreover, it would be sensible to avoid using AdaBoost for predicting mechanical properties.

The study by Deshmankar et al. [112] focuses on the application of different AI techniques in predicting the mechanical properties and identifying microstructures in Fused Deposition Modeling (FDM). The Supervised Learning Models included Artificial Neural Networks (ANNs) for estimating tensile strength, Young's modulus, and ductility, Support Vector Regression for process parameter optimization, Random Forest (RF) for hardness estimation, Gradient Boosting for estimating tensile strength, Lasso Regression for process parameter optimization, Deep Neural Networks (DNNs) for multi-property prediction, Long Short-Term Memory for time-dependent property prediction, Convolutional Neural Networks (CNNs) for microstructure to property relations, and Q-learning for process parameter optimization in a Reinforcement Learning Model. ANNs were the best for elastic modulus predictions with R2=0.968 and ductility R2=0.873. SVR was the best for small datasets where he achieved the highest R2=0.99. Followed by XGBoost and RF with R2 of 0.92 and 0.88 respectively. CNNs are the best for microstructure to property relations but they are very expensive in terms of computation. Q-learning was able to predict tensile strength with 0.66% error. In terms of Mechanical Properties, the most accurate for predicting tensile and elastic properties were ANNs and SVR.

The intersection of ANNs for accurate property estimation and parameter optimization via Desirability Analysis have been integrated effectively by Abdulridha et al. [113]. The main focus of analysis in this study was placed on predicting Ultimate Tensile Strength (UTS) and Ultimate Compressive Strength (UCS). The ANN model was successful in accomplishing the prediction of UTS and UCS with a high level of accuracy. During training, the model was found to have a regression coefficient of 0.99868, which implies a perfect correlation between the predicted and experimental values. The mean squared error (MSE) was observed to be 0.098 for UTS and 0.326 for UCS with minimal deviation, suggesting small differences between the measured values and the calculated values. The maximum percentage error recorded was 3.257% for UTS and 5.970% for UCS. The desirability analysis technique was applied to UTS and UCS to optimize multiple responses simultaneously. For the best parameter (after application of Desirability Analysis), a composite desirability value of 0.9454 was attained. Using the parameters deduced from Desirability Analysis and the parameters set, the optimal values given were UTS 66.5 MPa (predicted), 63MPa (experimental) and UCS 56.6 MPa (predicted), 60.5 MPa (experimental).

Grozav et al. [114] incorporated ANNs through the application of DNNs to anticipate the dimensional deviations and mechanical characteristics of parts produced by FDM. The research proved that DNNs could accurately forecast FDM part properties; however, the model architecture, dataset size, due to larger datasets allowing for more complex models, parameter choices, and other factors significantly affected the results. For linear deviations, the most effective architecture was 3x64, yielding a Mean Absolute Error of 0.05, while 3x32 was optimal for tensile strength, showcasing adequate predictive power alongside generalization.

A study by Yang et al. [115] applied a hybrid AI model integrating two major AI approaches, BP Neural Network (Backpropagation) and Genetic Algorithm (GA). The model aims to predict the dimensional errors in parts being printed with FDM technology from five process parameters. These parameters included: offset of cable width, layer thickness, filling speed, extrusion speed and fallback speed. The hidden layer contained ten neurons while the output layer contained three giving neurons relate to the outcomes to be predicted. Average Absolute Dimensional Errors along x, y and z directions were found to be 0.165 mm 0.149 mm and 0.072 mm respectively. For BP Neural Network, Mean Square Error was 4.65E–11 with 9 neurons, while for Genetic Algorithm it was 3.39E-11 with 10 neurons. The Genetic Algorithm model showed marked improvement over the BP neural network in predicting the dimensional errors of FDM printed parts. It offers superior prediction accuracy and fast convergence, which is ideal for complex systems with many parameters such as FDM.

The above studies show that ANN performs best out of all AI techniques in forecasting mechanical properties (tensile, flexural, and impact strength) of FDM-printed composites with the highest R^2 and MSE. Advertised benefits of ANNs are their non-linear modeling of process parameters (infill density, nozzle temperature) and material properties. For low MAE and better explainability, decision trees are satisfactory, but they cannot compete with the predictive power of ANNs. SVM and Gradient Boost offer fair accuracy, but AdaBoost always lags behind which indicates that it is not that much effective for this task. To predict microstructure- properties, CNNs are highly effective but costly in terms of computation, while SVR is favorable for small datasets. For multi-property optimization, hybrid models (ANN + Genetic Algorithm) are more accurate with minimal dimensional errors. ANNs are therefore the best option for highly accurate predictions.

8.1.2. Defect Detection:

In Fused Deposition Modeling (FDM), achieving the desired quality of a part is often challenging due to the defects like warping, stringing, under-extrusion, and layer misalignment. Inspections based on traditional quality control methods are often ineffective at providing up-to-date feedback due to the lengthy nature of the procedures used and limited real-time capabilities. In recent times, the use of Artificial Intelligence (AI) and Machine Learning (ML) has been increasingly explored for automated defect detection and prediction to mitigate these challenges. Image processing, as well as crucial data from sensors, can now be utilized alongside learning algorithms to enhance the speed and accuracy by which inspections are conducted – providing instantaneous monitoring of quality control. For this reason, a research by Kumar et al. [116] employed K-Nearest Neighbors (KNN), Decision Tree Classifier (DTC), Extra-Tree Classifier (ETC), Random Forest Classifier (RFC) and 1D Convolutional Neural Network (CNN) techniques to classify default in their printed products, as a result of changes in printing settings (temperature, speed and jerk). It included the defects due to changes in the printing parameters. Due to the CNN's ability to extract

complex features from multi-sensor data, CNN outperformed all models with the highest accuracy (92–94%) across all conditions. Ensemble methods like RFC and ETC performed well, predicting with an accuracy of (89–93%), which signifies their effectiveness in situations where a data loader was not available. The implemented KNN had the least accuracy of 68-74%. This is due to the algorithm's simplicity and weakness in multidimensional data processing. The research proved that Deep Learning (CNN) is the most efficient in classifying 3D printing faults while ensemble techniques (RFC, ETC) served as alternatives.

The major AI technique employed by Badour et al. [117] in their work for image processing tasks was CNN. The models various YOLO (You Look Only Once) frameworks considered in the study include YOLOv4 Tiny which is a lightweight version of YOLOv4 designed to be faster and more efficient in terms of memory consumption, YOLOv5 which strikes a good balance between speed and accuracy, making it a good candidate for real-time applications, YOLOv8 variant, followed by YOLOv10 which is the latest edition of the series in achieving better performance in defect detection. The study aimed the identification of 6 Defects in FDM; blobs (wasted material overlap on the very top surface of the print), cracks (breaks or fissures in the printed object), spaghetti (excess filament that resembles spaghetti often due to improper extrusion), stringing (thin strands of plastic that connect different parts of the print), under-extrusion (insufficient material being extruded, leading to weak prints) and warp (the print, as it cools, deforms, lifting from the print bed). It was discovered that YOLOv8 was the model with the best detection performance where its accuracy surpassed earlier models by 7%. Furthermore, it led to a 30% decrease in print errors which proves to its better efficiency in real-time defect identification.

Two primary AI techniques were used in another study by Li et al. [118] for defect detection in FDM printed parts. A Swin Transformer model was trained to classify any defects in the interlayer surface images. It uses transfer learning for better accuracy in image recognition tasks. 1D Convolutional Neural Network (1DCNN) focused on temporal sensing data with features, such as vibration signals and infrared temperature, for defect detection during the FDM process. The FDM process has 6 types of defects identified for this study rough, normal fill, regular pattern, underfill, warping & one normal condition (no defects). With Swin Transformer, the test set accuracy is around 89.9%. The model had good functionality but was not able to distinguish normal pattern defects from regular pattern defects, since they had many similar characteristics. The test set was trained at 1D CNN, which produced an accuracy of approximately 89.2%. For the normal printing class, it was able to classify more precisely than Swin Transformer, having a F1-score of 0.833 for the normal class. When both models were merged, the achieved model saw a boost in classification accuracy (97.9%). This was 8.9% higher than the Swin Transformer and 9.8% higher than the 1DCNN alone.

A similar study by Chen et al. [119] also employed 1D Convolutional Neural Network (1DCNN) model to analyze sensing data, specifically temperature and vibration signals during the printing process. The 1DCNN model demonstrated superior prediction accuracy compared to traditional models, achieving a higher macro F1-score and an AUC value that was 0.0036 better than the Random Forest (RF) model. The Random Forest (RF) algorithm was also applied to the sensing dataset for defect classification. While it provided reasonable results, the RF model's performance was outperformed by the 1DCNN model in terms of accuracy and robustness. The study combined predictions from both the 1DCNN and RF models to enhance classification accuracy. This fusion approach led to a significant improvement in defect detection, achieving an overall classification accuracy of approximately 97.9%. The 1DCNN model outperformed the RF model in terms of prediction accuracy and macro F1-score, indicating that the convolutional approach was more effective for the data types used in this study.

By critically analysing 6 AI models for defect detection in FDM, namely KNN, DTC, ETC, 1D-CNN, RFC, and Swin Transformer, it was concluded that 1D-CNN model outperformed all models in terms of accuracy (>95%) in the detection of following defects in FDM: rough, normal fill, regular pattern, underfill, warping, cracks, spaghetti, stringing, and under extrusion. Moreover, it was found that by integrating the Swin Transformer algorithm with 1D-CNN, the accuracy further increased by 9.8% as compared to incorporating 1D CNN alone.

8.1.3. Topology Optimization:

Topology optimization is a computational design approach used to find the most effective configuration of materials in a given design space, with a specific load and defined constraints. It greatly benefits the AM process by optimizing the production of custom parts that are lightweight and high-performance. Much research in this domain has been done because this is an important industry requirement to save material while not compromising on performance.

Huang et al. [120] used CNN for topology optimization in FDM while investigating key AI-driven methodologies, including Deep Learning (DL) for Generative Design, CNN for Topology Prediction, and a combination of SIMP (Solid Isotropic Material with Penalization) with CNN to accelerate optimization. Features Optimized in the study were Material Efficiency, Structural Integrity, and Production Time. Traditional methods explored only 20% of the design space, but CNN reflected a 75% improvement in design space exploration and explored 95% of the design space. Generative design with CNNs achieves 95% material efficiency, ensuring lightweight yet strong structures, while traditional methods could not achieve more than 70%. Structural Integrity, which was 80% with traditional methods, was increased to 95% with CNN-based optimization. Production time was 100 hours with traditional methods, while with CNN it was reduced to 20 hours. CNN also reduced iterative design cycles from 15 iterations in the case of traditional methods to just 3 iterations with deep learning. Material wastage was 30% in traditional methods but the CNN approach proved to be cost-effective with only 5% wastage of material.

In a related study, Rasulzade et al. [121] also used DL techniques to speed up topology optimization. The major AI methods employed in their study were 1D/2D/3D CNN, U-Net, and Res-U-Net. This study emphasized optimizing material distribution, which is a density-based topology optimization, structural compliance which is stiffness maximization under volume constraints, and physical parameters such as boundary defining, volume fraction, Von Mises stress, strain energy density, bound load vectors. U-Net's accuracy was 98.22% and Res-U-Net's was 99.55%. Thus, Res-U-Net had an accuracy gain of 1.3% over U-Net at 80 iterations. CNN's 3D accuracy was 93.22% and 2D reached 96.67%, outperforming the others. CNN's lightweight architecture was 96.67% accurate and suitable for real time topology optimization. The study proves that Res-U-Net and U-Net outperformed the others for acceleration in topology optimization, leveled by high iterations for Res-U-Net, also showing CNN balanced speed and precision for 2D/3D problems. The inclusion of physical features such as stress and loads improved models. Res-U-Net has 90% accuracy for boundary tested unseen conditions.

A comparable method was explored by Mohamed et al. [122] in which they used ANN alongside a second-order Definitive Screening Design (DSD) to optimize the accuracy of dimensions in cylindrical components produced by FDM. The optimization has been conducted based on the input parameters of slice thickness, raster-to-raster air gap, deposition angle, print direction, bead width, and count of perimeters while the output parameters were the percentage difference in length & percentage difference in diameter. For both output measures ANN was trained to achieve R^2=99.83% & R^2= 99.76% for length and diameter respectively, DSD produced R^2= 99.84% for length and R^2= 99.79% for diameter, while ANN achieved a slightly lower R^2= 98.91% for validation. DSD highlighted the most influential parameters and demonstrated that slice thickness, print direction, and deposition angle greatly influenced length, while bead width and air gap mostly affected diameter. Adopting the combined approach a decrease in experimental costs by 82% in comparison to conventional methods was observed. For screening parameters with the fewest experiments, DSD was the best choice. DSD provided data for the Artificial Neural Network (ANN) training. ANN outperformed in non-linear prediction with less than 0.5% error in dimension, which constructed an economical workflow for FDM optimization while maintaining high accuracy.

Another approach was taken by Qian et al. [123], utilizing Dual-Model ANN to accelerate gradient-based topology optimization for designs compatible with FDM. AI techniques implemented include Dual-Model ANN for forward sensitivity calculations and data augmentation strategies. The work addressed in the study comprised topology-optimized minimum compliance cantilever structures and metamaterials that exhibit negative Poisson's ratios. The time taken to compute the forward calculation is drastically reduced from 0.48s (FEM) to 0.0035s with ANN for 64 × 64 grids. The design accuracy with augmented data improves from 60% to 95%. Sensitivity errors reached 100% without data augmentation in some cases. With data augmentation, they were below 5%. In the case of metamaterials, the accuracy of predictions was increased through augmentation from 90% to 94%. Dual-Model ANNs have shown a great potential to optimize the time taken for topology optimization by 137x in forward calculation while sustaining 95% accuracy relative to FEM.

Upon comparative analysis, the most optimal AI model for topology optimization in FDM was found to be the Res-U-Net, which boasts an impressive accuracy of 99.55% in material distribution and compliance with structural design. For real-time applications, 2D/3D CNNs have exhibited great performance at 96.67% accuracy, while offering a balance of speed and precision. Additionally, Dual-Model ANNs accelerate gradient-based optimization (137x faster

than FEM) while maintaining 95% accuracy. For dimensional accuracy of FDM-produced parts, the ANN in conjunction with DSD achieves near-perfect prediction, with R^2 exceeding 99.7%, alongside a staggering 82% drop in experimental costs. In essence, for high-accuracy tasks, switch to Res-U-Net, Dual-Model ANNs for speed-critical applications, and ANN+DSD for parameter-sensitive FDM workflows.

8.2. CASE STUDIES:

While there is increasing literature on the application of AI and machine learning in the context of AM, its industrial use remains complex due to practical limitations. This section provides some industrial case studies of integrating AI/ML in AM processes. Each case study illustrates the primary milestones achieved, alongside the technical and organizational obstacles faced during implementation, including data availability, model abstraction, system integration, and system scalability. These findings highlight the practical value and relevance of advanced intelligent solutions within the context of AM technologies.

8.2.1. Siemens Quality Assurance Using AI:

Siemens Energy [124] has set up an AI-based quality control system for SLM manufacturing of the metal turbine components. The system in use features in-situ optical cameras mounted on Electro Optical Systems (EOS) printers, which take a snapshot after every recoating layer. A regression-based ML model, trained through supervised learning, analyzed these images for several defined common defects like missing powder, powder droppings, or any other defect that might cause a recoater crash or surface flaw. The print quality for every print was quantified based on deviation from an ideal recoating template and monitored on a per-layer and per-part basis. The system was trained using several hundred labelled images and tailored to recognize both new and known anomalies using a general anomaly detection framework. To guarantee scalability, the model normalizes images with its camera resolution, lighting, and lens distortion. Also, deployment across different machines is facilitated through printer-type specific models without needing retraining for every individual printer.

This system is applicable for both the prototyping and serial production phases. During prototyping, it detects problematic layers early, reducing trial-and-error cycles. In serial production, it allows time and material savings by automatically tracking the quality and early stopping of failed builds. Its versatility is shown in other adapted AM techniques such as binder jetting, demonstrating how easy it is to switch between different additive manufacturing techniques.

Overall, Siemens' AI-based monitoring has significantly reduced the prototyping time, lowered inspection overhead, and accelerated industrialization by offering a real-time, scalable, and interpretable quality assurance solution.

8.2.2. Intellegens AI-Based Parameters Optimization

In collaboration with the University of Sheffield Advanced Manufacturing Research Centre (AMRC), Intellegens [125] incorporated Alchemite™ machine learning software into AM processes, which accelerated the process parameter optimization with sparse and inconsistent historical data. This method improved efficiency by decreasing the time-consumption and reducing the expensive trial-and-error testing up to 90% relative to past tests. With the support of AMRC, Boeing, GE Additive, and Constellium, the project laser powder bed fusion (LPBF) showcased AI's capability of predicting optimal settings for new materials and machines. Phase 1 provided validation against nickel-base alloys. AI predictions were validated against experiments, showing a strong agreement. Phase 2 transitioned the technology to Constellium's Aheadd® CP1 powder processed on GE Additive's 400W M2 machine, where AI accurately predicted UTS after just one build, allowing rapid optimization without requiring expert statistical knowledge. The system also maintained institutional knowledge through the projects, enabling consistency throughout changes in materials, equipment, or personnel. With the assistance of graphical tools, critical parameter-property relationships were formed during the project, which demonstrated the capabilities of AI in managing various AM processes, machines, and powders. The application of AI in this project remarkably reduces developmental phases, allowing for AM processes to be integrated into industrial settings at a much faster pace.

8.2.3. Baker Huges-AM Workflow Optimization

Baker Hughes collaborated with Oqton to integrate an AI assisted AM workflow for the serial production of a Variable Resistance Trim (VRT) component [126]. This implementation aims at optimizing production workflow to ensure efficiency, quality, and sustainable traceability.

The workflow commences with systems integration in mind such as monitoring and control systems. So, a digital twin of the manufacturing environment is developed using Oqton's Manufacturing OS which can serve as interface with an enterprise-wide ecosystem. ML algorithms were used to analyze data from simulations and real-time monitoring, allowing for predictive adjustments to process parameters and early detection of anomalies.

Implementation of the above systems has resulted in decrease engineering active monitoring time by 98% saving around 136 engineering time hours per printer annually, 98% reduction in root cause analysis because of automatic reporting, and 18% decrease in costs related to scrap, attributed to real time alerts during actual parts production.

During the integration process, the team encountered several challenges, including the need to ensure smooth communication between AI models and existing manufacturing systems. They also had to address issues related to data quality, which is critical for training reliable machine learning models, and navigate complex industry regulations to maintain compliance throughout the workflow.

8.2.4. Xinix AI: AI-Assisted Manufacturing of Robot

A UK-based robotic start-up, Xinix AI, incorporated AI with polymer AM, specifically the SLS method, to design and produce an autonomous exploration robot aimed at conducting biodiversity research in tropical rainforests [127]. The project, carried out in partnership with Protolabs, illustrates the synergetic capabilities of AI-based design optimization and polymer 3D printing in addressing stringent performance and environmental specifications.

Using nylon-based polymers, Xinix employed selective laser sintering (SLS) to manufacture a robust and lightweight plate chassis that endures complex, unstructured terrain. AI was used to optimize the robot's geometry to lower its weight while maximizing impact resistance and thermal performance of the robot under jungle conditions. The SLS method made it possible to create complex internal structures and mechanical features that were impossible to build using traditional manufacturing methods

The incorporation of AI into the workflow processes not only accelerated development timelines but also enabled functional prototyping within rapid timeframes, critical for remote field location testing and deployment. However, the team still confronted some challenges with the alignment of simulation results with the performance of materials under real-world conditions, and ensuring the structural integrity of 3D printed polymer components during long-term field operation.

8.3. Performance Comparison of RSM and AI-based Techniques

Several studies have demonstrated the superior predictive performance of ANN and hybrid AI techniques over traditional optimization methods such as RSM and ANOVA in FDM applications. For example, Manoharan et al. [38] comparatively analyzed the predictions made by RSM, ANOVA, and ANN for the tensile strength of specimens produced through FDM. Results showed that the predictions made by ANN were most accurate compared to the predictions of ANOVA and RSM. ANN provided the lowest value of percentage deviation in error, which was 1.10%. The percentage deviation in error in the case of ANOVA and RSM was 2.18% and 2.13%, respectively.

In similar research by Dev and Srivastava [128] utilized RSM-GA and ANN-GA approaches to develop and optimize the mathematical models. In the case of RSM-GA-TOPSIS, the prediction error was 2.40% and 3.31% for storage and loss modulus, respectively. On the other hand, for ANN-GA-TOPSIS, the prediction error was 2.17% and 2.89% for storage and loss modulus, respectively. By comparing both models, ANN-GA-TOPSIS was recommended for optimization and prediction of storage and loss modulus with minimal error. This trend was supported by Malleswari et al. [129] in which they analyzed the following statistical variables to assess the performance of RSM and ANN: correlation coefficient (R), R^2, RMSE, mean average error, standard error of prediction, and absolute average deviation (AAD). Through comparison, it was observed that GA-ANN provided better performance compared to RSM in these variables. A higher value for R^2 and lower error metrics for ANN for predicting surface roughness indicate the superiority of this technique compared to RSM. Likewise, Bahrami et al. [36] compared the efficiency of RSM with GA-ANN, from which it was concluded that GA-ANN provided better performance compared to RSM with only a 0.25% margin of error, indicating better accuracy.

Furthermore, Tura et al. [25] used ANN and adaptive neuro-fuzzy techniques to predict the system's response. It was found that both ANN and adaptive neuro-fuzzy approach were accurate techniques for predicting tensile strengths

with an average percent error of 1.6437 and 0.0163%, respectively. The accuracy of the adaptive neuro-fuzzy inference system (ANFIS) model was between 1% to 2%, while the accuracy of the ANN model ranged from 1 to 5%. The robustness of the ANN model was further validated by Pazhamannil et al. [130] in which they predicted the tensile strength of FDM models using ANN and varying various process parameters. A correlation coefficient of 0.99982 was obtained by investigating regression plots using ANN. The UTS of the PLA specimen was estimated by conducting a set of confirmation experiments which seemed to have a good agreement well within 5% of that model.

Overall, the consistent performance of AI-based models across various studies emphasizes their robustness and reliability in predicting FDM process outcomes. These comparative results suggests that AI and hybrid techniques, especially ANN-based models, are becoming increasingly favored for their superior predictive precision and versatility as compared to RSM. The convergence of findings across multiple works reinforces the value of integrating AI and machine learning into FDM process optimization for enhanced performance and minimal prediction error.

9. Challenges, Limitations, Cost Implications

This review identified some gaps and limitations along with some proposed future research directions to practically implement them meaningfully and impactfully. The integration of AI and ML into AM processes poses several challenges and restrictions that can affect efficiency and reliability. From data quality issues to integration complexity, integration can significantly increase costs, particularly during the implementation and scaling phases of AI/ML in AM. The following are some limitations and challenges posed to AI/ML adoption:

1. Having inadequate data, which is needed to meet the demands of the management systems, will damage AI; thus, having powerful storage infrastructure becomes vital [131].
2. To develop and uphold advanced AI models, organizations require significant resources, including specialized personnel, constant modifications, and enhancements for precision and trustworthiness [132]. Integrating AI into ready AI systems for use in manufacturing processes is not straightforward and requires detailed strategizing and critical implementation [132].
3. When developing AI/ML solutions for manufacturing, it involves handling large datasets and performing intensive computations such as memory transfers and multi-dimensional matrix computations during model training [133]. These training cycles can take days or weeks, consuming significant energy and contributing to carbon emissions, especially when powered by non-renewable energy sources. Since 2012, the energy requirements needed to train AI models have escalated periodically, doubling every 3.4 months, on average [134]. Research from 2021 showed that training a deep neural network (DNN) NLP model can produce carbon emissions roughly equal to 60% of what an average vehicle emits over its lifetime [135]. While inference uses considerably less power, its consumption has still increased from 0.1 to 20 joules from 2012 to 2022 [133]. Consequently, manufacturers must balance the accuracy benefits of complex AI models with the need to limit energy use and reduce environmental impact. The challenges of integrating AI into AM systems exist as computational needs, data access, and model sophistication, but AI has the potential to revolutionize the processes [133]. However, these challenges are barriers to the effectiveness of these technologies in manufacturing systems.
4. Incorporating AI/ML into industrial settings usually provides the opportunity to work with operational data available on internal servers or control room systems [133]. However, there is a high risk of cyberattacks because breaches on such systems could result in catastrophic equipment damage, safety hazards, and significant financial loss. The global average cost of a data breach increased from $3.86 million in 2020 to $4.35 million in 2021, with U.S. figures reaching nearly $8.5 million [133]. Cybersecurity measures and AI-powered security systems can significantly reduce the costs by 70% incurred due to a breach [133].
5. The economic potential of AI/ML in AM remains a barrier in adopting AI/ML industrially. High capital costs for computational infrastructure, energy-intensive model training, and cybersecurity concerns all contribute to high operational costs. As suggested by Strubell et al. [136], the carbon footprint and energy demands of large-scale AI models are non-trivial due to its high operational costs.
6. FDM and extrusion-based methods both have slower printing speeds than conventional manufacturing, which makes their analogs more difficult to scale for large-scale production [137]. The unit cost for large batches

manufactured with these processes is still lower than for the other alternatives, but optimal print parameter setting using AI/ML improves output efficiency of the AM machine [137].

7. High-quality processing devices and operational power are essential for AI models, which increases operational cost [133]. This involves new hardware, software, and even power costing older systems. Companies will have to purchase cloud services and/or create on-premises data centers to have the necessary infrastructure for AI inclusion. The shortage of competent workers to run AI systems alongside failing infrastructure to integrate the desired technologies is another problem. Integration of artificial intelligence into industrial control systems has its cybersecurity weaknesses. Some operators from various industries are reluctant to integrate AI due to misconceptions and poor knowledge regarding the technology.

Although the prospects of strict cost control, increased productivity, and improved quality reinforced by elements of AI integration in AM are appealing, the challenges and cost implications cannot be underestimated. Many proponents could argue that the advantages of AI, including greater resource efficiency and reduced waste, could justify these challenges, however, the intricate nature of the investment is a barrier for multiple other businesses. The potential of AI to optimize the effectiveness and quality of FDM processes signifies its importance for the progression of AM technologies.

Several future recommendations have also been proposed to improve the quality of research and highlight creative and novel solutions to existing problems:

1. To take full advantage of integrating AI/ML in FDM, the implementation should focus on developing a comprehensive system that promotes multi-objective optimization, which improves the mechanical and thermal performance along with the cost, environmental impact, and scalability for mass production. The gap between experimental research and real-world application will require the partnership of material scientists, data engineers, and industry practitioners to solve the challenges posed by practical deployment.
2. Improving AI/ML models will be valuable in achieving better generalization across materials, machines, and environmental conditions. Future AI models need to be robust, adaptive, and capable of accurate predictions even if sparse or unreliable data is available.
3. Real-time production data should allow for closed-loop feedback, which provides the capability to learn from data and continuously enhance accuracy and FDM self-correction during operations.
4. It is essential to develop a centralized, open-access repository to solve the primary issues of limited, fragmented, and non-standardized datasets in the AM domain. This database should integrate various dataset types, material properties, process parameters, geometry, and performance metrics, gathered using consistent protocols. This resource would speed up AI/ML model training, reproducibility, and collaborative innovation between academia and industry.
5. Future implementation should focus on quality assurance and non-destructive testing (NDT) of composite prints. Algorithms capable of thermography, acoustic emission, and digital image correlation can be combined with ML models to detect delamination or voids during or post-printing.

6. Future work may be undertaken using AI-RSM hybrids for cost analysis predictive modeling. For instance, embedding an ANN or Random Forest in RSM-generated parameter space would allow the prediction of overall output quality and economically significant factors, like the material cost, time spent, and waste generated, thus enabling real-time decision-making in production settings.

10. Conclusions

The primary aim of this review was to study the recent developments in FDM to pave the road for future research, while focusing on optimizing the FDM process by utilizing bio-degradable composites as a base material and performance comparison of RSM with AI and other ML algorithms. The following conclusions were made after a descriptive analysis:

1. Each filament, PLA, TPU, PBAT, and PETG, offers unique advantages for 3D printing. PLA excels in biodegradability and strength with fillers but lacks flexibility. TPU, especially with graphene, provides better

elasticity and printability, ideal for biomedical use. PBAT is flexible and eco-friendly but weaker mechanically, while PETG offers durability but is less biodegradable. While each material has strengths, limitations exist, and the choice should depend on the specific application and performance needs, if we have to choose one from the reviewed materials, PETG composites yielded the best overall performance, offering an optimal balance of cost, mechanical properties, thermal resistance, and biodegradability.

2. Based on comparative analysis, it is clear that RSM has a greater depth of process insight and control, which is critical for precise optimization in aerospace or biomedical manufacturing industries. RSM's strong capability of dealing with complex, multi-factor interactions and producing accurate predictive models, supported by regression and ANOVA, makes it invaluable in achieving production repeatability and reliability. When coupled with ANN and Genetic Algorithms, RSM provides deeper insights into parameter interactions and non-linear effects.

3. Compared to RSM, the Taguchi method offers greater simplicity and cost-effectiveness for initial screening and robust design in prototyping, it lacks the predictive capability and multi-response optimization, which makes it unsuitable for high-precision industrial environments where intricate process control is mandatory. So it is concluded that for comprehensive FDM process improvement, a hybrid strategy, starting with Taguchi for efficient factor screening and followed by RSM or ANN-GA for detailed optimization, can offer the best of both worlds, balancing efficiency with accuracy.

4. For topology optimization, switch to AI/ML models such as Res-U-Net and dual-model ANNs for high-accuracy tasks in speed-critical applications and ANN+DSD for parameter-sensitive FDM workflows. In case of defect detection, the 1D-CNN model outperformed all models in terms of accuracy (>95%) in the detection of the following defects in FDM: rough, normal fill, regular pattern, underfill, warping, cracks, spaghetti, stringing, and under extrusion. Moreover, it was found that by integrating the Swin Transformer algorithm with 1D-CNN, the accuracy further increased by 9.8% as compared to incorporating 1D CNN alone. For highly accurate predictions of mechanical properties in FDM-printed composites, ANNs outperform other AI techniques with the highest R^2 and lowest MSE. While CNNs excel in microstructure analysis and decision trees offer explainability, ANNs remain the best choice for non-linear modeling of process parameters and multi-property optimization.
5. Incorporating AI/ML into AM processes has proved helpful with accelerated parameter optimization, better quality assurance, and lowered costs for prototyping. Corporations such as Siemens Energy, Baker Hughes, Intellegens, and Xinix AI integrated AI into their systems for workflow automation, defect prediction, and design optimization on a high scale. Still, issues like data quality, integration with existing frameworks, uniformity in material properties, and interrelated attributes pose challenges. Generally, advancements in AI/ML technologies and their application in AM processes increase productivity and create innovations, though they still require some modifications for widespread industrial use.

Statements and Declarations

Author Contributions

Hammad Ahmad: Data curation, Formal analysis, Writing – original draft. **Arslan Ahmad:** Supervision, Writing – review & editing. **Saad Waheed:** Conceptualization, Formal analysis, Methodology, Visualization, Supervision, Writing – review & editing. **Shavaiz Ahmed:** Writing – original draft. **Ammar Tariq:** Writing – review & editing. **Muhammad.A.Khan:** Writing – review & editing. **Moinuddin Mohammed Quazi:** Writing – review & editing. **Muhammad Qasim Zafar:** Writing – review & editing. **Hassaan Khan:** Visualization. **Danish Shabbir:** Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This research received no external funding.

Data availability

This is a review article. The data is obtained from various articles.

Acknowledgments

The authors would like to express their gratitude to COMSATS University Islamabad (Wah Campus) for the provision of resources that were necessary for the completion of this work.

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2026-12-31
Taylor & Francis
https://doi.org/10.1080/2374068x.2026.2630731
Ahmad H, Ahmed A, Waheed S, et al., (2026) Advancements in fused deposition modelling (FDM): a comparison of advanced composite materials, optimisation strategies, and AI/ML integration. Advances in Materials and Processing Technologies, Available online 16 April 2026

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