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Review Paper

A Study of 3D Printing Technology and M.L Algorithms for Enhanced Production

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Abstract

The realm of 3D printing technology, also referred to as additive manufacturing, has garnered increasing interest in recent times due to its capacity to construct intricate geometric structures. Fused deposition modeling (FDM) stands out among the various techniques and has gained widespread adoption. However, achieving optimal outcomes with FDM poses a challenge, necessitating meticulous selection of process parameters. Presently, many methodologies rely on Machine Learning (ML) algorithms akin to open-loop systems, offering predictions on printed part properties but lacking quality assurance mechanisms. Conversely, certain closed-loop approaches focus on monitoring a single adjustable processing parameter to assess printed part properties. This study aims to investigate the influence of process parameters and control techniques on mechanical strength, tribology, and other output parameters of production. By providing a comprehensive overview of these developed methods, it aims to facilitate comparison regarding their characteristics, merits, and drawbacks, aiding in the selection of the most suitable approach for specific applications.

Keywords: 3-D Printer, FDM, Machine Learning, Control System.

Introduction

Additive Manufacturing (AM), also known as 3D printing, has emerged as one of the most prominent technologies of the current era, often associated with the Fourth Industrial Revolution. Unlike traditional subtractive manufacturing processes like turning, milling, and drilling, AM builds physical objects layer by layer from a digital 3D model. Initially used primarily for rapid prototyping, AM has evolved to encompass a wide range of applications, including product design and customization. The technology offers design freedom, enabling researchers to develop innovative products economically. Fused Deposition Modelling (FDM), invented by Stratasys in 1990 and now termed Fused Filament Fabrication (FFF), is one of the most well-known AM techniques, often synonymous with 3D printing. ISO/ASTM 52900 standard defines AM as the "process of deposition of material in layer by layer fashion to build a product from a solid CAD model.

AM has found applications across various industries, including medical, automotive, aerospace, food, heavy engineering, construction, jewelry, and fashion. While polymers like ABS and PLA are common materials for FFF printing, ceramics, metals, composites, and smart materials are also utilized. Recent trends indicate a growing use of metals and alloys, particularly in industries such as dentistry, aerospace, and biomedical engineering. In construction, AM is used to manufacture building components from metals and concrete, employing advanced techniques. Additionally, AM is influencing fashion design, teaching methods, and medical education by facilitating the creation of prototypes and practical demonstrations. Qi Feng et al.[1] study show us use of Machine learning methodology to optimize process parameters in FDM based AM. In conclusion, our framework presents a significant advancement in optimizing process parameters for fused deposition modeling (FDM) through a combination of machine learning (ML) and finite element analysis (FEA). By leveraging FEA simulation with high precision, we were able to collect representative training data for ML models, enabling us to identify quasi-optimum parameters aimed at reducing residual stress and minimizing war page effects. This approach demonstrates promising potential for enhancing product quality in FDM, particularly beneficial as it circumvents the need for costly hardware optimizations. Moreover, the versatility of our method extends beyond FDM to other additive manufacturing (AM) processes, facilitating the production of diverse work pieces.

Fused Deposition Modeling (FDM) is a widely used additive manufacturing process. It begins with the creation of a 3D CAD model using CAD software, either through designer input or reverse engineering using scanned data, which is then converted into printing instructions using slicing software and saved in a G-code file. The printer heats and extrudes filament material onto a build platform, layer by layer, following the instructions in the G-code file. After printing, post-processing may be required to remove supports and improve surface finish. FDM printers offer versatility and are used across various industries for prototyping, tooling, and production of end-use parts.

Process parameters play a pivotal role in shaping the characteristics, quality, and precision of manufactured items. Specifically, within the realm of FDM printing, a variety of parameters come into play, each impacting the final outcome based on factors such as geometry, procedural nuances, and structural attributes.

Geometry-Based Parameters

Nozzle Diameter[3]: The size of the nozzle, which usually falls between 10mm to 100 mm, plays a role in pushing out filament to form parts on a printer. The common diameter is often around 0.4 mm striking a balance between printing speed and accuracy.

Filament Diameter: The filament, found in sizes of 1.75 mm and 2.85mm acts as the material for 3D printing with thermoplastics. Different filament properties require printing temperatures.

Parameters Based on the Printing Process

Melt Temperature[1]; Described as the temperature at which material exits the extruder in a state melt temperature holds importance in the printing procedure.

Build Plate Temperature[1]; Warmer build plates maintained between 55°C to 70°C are crucial, for 3D printing as they improve adhesion and minimize warping issues.

Printing Speed[2,3]: Determining the rate at which the printer's motors move, print speed, governed by X- and Y-axis control motors and the extruder motor, is a key parameter affecting the printing process.

Structural-Based Parameters

Layer Thickness: In additive manufacturing, layer height along the z-axis is vital, typically ranging from 0.05 to 0.4 mm in FDM. Thinner layers enhance surface quality but extend print time due to the staircase effect. Hongbin Li, et al.[11] experimental findings underscore the critical influence of layer thickness on bonding strength, with deposition velocity following closely behind as another significant factor. Conversely, the impact of infill rate emerges as comparatively weaker. Jonathan E. Seppala et al.[12] explore the development of inter-layer weld strength through the lens of polymer interdiffusion under rapidly changing mobility conditions provides valuable insights into the fundamental mechanisms governing welding processes for material extrusion i.e layer by layer AM process.

Nadir Ayrilmis[13] study demonstrated a clear correlation between layer thickness and the surface properties of 3D printed wood/PLA surfaces. It was found that increasing layer thickness directly influenced surface roughness and wet ability, with thicker layers resulting in rougher surfaces and improved wet ability. Despite this, all specimens exhibited favorable wetting characteristics, as indicated by contact angle values below 90°. However, it is important to consider the trade-off between surface quality and production time/cost, as printing time increases with decreasing layer thickness. Based on the test results and considerations of production efficiency, a layer thickness of 0.2mm was identified as the optimal choice for 3D printed wood/PLA specimens, striking a balance between surface quality and cost-effectiveness.

Build Orientation[2-4,10]: Hassan Gonabadi et al.[10] study shows that parameter, referring to the part's orientation within the build envelope, significantly influences dimensional accuracy, surface finish, and support structure generation.

Infill Geometry[3,5,9]: Describing the pattern of infill within a printed object, infill geometry affects various aspects such as printing time, weight, strength, and mechanical properties. Infill geometry, also known as infill pattern, pertains to the arrangement of material within a 3D printed object. It refers to the internal structure printed within the object. The choice of infill pattern, which can vary in proportions and forms, is determined using slicing software. Hamza Qayyum el al.[9] concluded that infill patterns for flexural loading conditions highlighted the quarter-cubic pattern as the most optimal choice for structural components subject to bi-directional flexural loading. The quarter-cubic pattern demonstrated superior performance over the tri-hexagon pattern, showcasing an 89% and 37% improvement in flexural load and modulus, respectively. This underscores the significance of selecting appropriate infill patterns to enhance the mechanical properties and performance of components under specific loading conditions.

Infill Density[1,9]: Expressed as the percentage of filament material within the internal part, infill density ranges from 0% (hollow) to 100% (solid), influencing the part's strength and weight. Hassan Gonabadi et al.[10] concluded that, both finite element analysis (FE) and experimental results underscore the paramount importance of infill density in determining the mechanical properties of 3D printed parts. The significant impact of infill density variations on mechanical performance emphasizes the need for careful consideration and optimization of this parameter in the design and manufacturing processes of 3D printed components.

Raster Angle[2,4,5,9,10]: The raster angle denotes the angle formed between the direction of the nozzle and the X-axis of the FDM printer board. Successive layers typically have raster angles differing by 90 degrees. Hassan Gonabadi et al.[10] analysis shows that angle has significantly impacts both the precision of shape and the mechanical property of the printed object. Hamza Qayyum el al.[9] in his experimental findings demonstrate that a raster angle of 0 degrees significantly enhances the in-plane and edgewise flexural load capacities compared to other tested angles. The samples with a 0-degree raster angle sustained the highest loads, showing a remarkable 188% increase in load carrying capacity compared to those with a 90-degree angle. Additionally, the in-plane flexural modulus exhibited a substantial increase of about 148% when transitioning from a 90-degree to a 0-degree raster angle. These results underscore the importance of considering raster angle in optimizing the mechanical properties of materials, particularly in applications where in-plane and edgewise flexural strength are critical factors. Krishna et al.[4] investigated that both solid and sparse specimens, the interaction between build direction and raster angle is the most significant factor in the resulting differences in yield strength between specimens.

Print Speed[1]: Dictating the travel speed of the print head along the XY plane while extruding, print speed affects build time and print precision.

Build Volume and Platform Temperature: Maintaining temperature within the build volume and platform, crucial for adhesion and printing performance improvement, especially with enclosed printers.

Skirt and Brim: Brim provides additional surface area for better adhesion and reduced warping, while skirt ensures smooth material flow before printing the part.

Polymers in 3D Printing

Fused Deposition Modeling (FDM) feedstock typically consists of solid filament composed of thermoplastic material. This filament exhibits an elongated structure with a uniform cross-section. Common filament diameters include 1.75 mm and 2.85 mm. S.M. Tang et al.[6] concluded that performance enhancement of SHA/PEEK composites under cyclic loading hinges on the mechanisms of polymer chain reorientation and stress-induced crystallization. These processes bolster elastic modulus and residual tensile strength. However, the initiation and propagation of fatigue damage in these composites stem primarily from filler-matrix interface failure, followed by the progression of matrix cracks. Therefore, addressing filler-matrix bonding is crucial for improving the overall performance and durability of such materials.

Poly lactic acid (PLA)[5]: Poly(lactic acid), known as PLA, stands out as a biocompatible, biodegradable & compostable polyester sourced from renewable materials such as corn, cane molasses, and beet sugar. This polymer holds immense promise as an eco-friendly thermoplastic, potentially aiding in closing the carbon cycle and lessening dependence on finite resources, thanks to the backing of polymer industries. The synthesis of PLA involves the oligomerization of lactic acid to create an oligomer, which then undergoes dimerization to produce the cyclic lactide monomer. Utilizing tin and aluminum alkoxides as catalysts, high molecular weight polylactide is formed through ring opening polymerization (ROP) of lactide monomers.

Acrylonitrile butadiene styrene (ABS)[5,7]: Acrylonitrile-butadiene-styrene (ABS) is a versatile thermoplastic amalgamated from acrylonitrile, styrene, and butadiene polymers. Hamza Qayyum el al.[9] study revealed that the edgewise flexural modulus of acrylonitrile–butadiene–styrene (ABS) was found to be lower than its in-plane flexural modulus. Nonetheless, a consistent trend was observed where the highest edgewise flexural modulus was consistently achieved when employing a 0-degree raster angle. This suggests the importance of raster angle selection in optimizing mechanical properties in ABS materials, particularly when considering edgewise flexural characteristics. Further research could delve into understanding the underlying mechanisms driving this observed trend to enhance material performance in specific applications. Andrea Mura et al.[7] had investigated ABS shows improvement in both tensile strength and yield limit at low temperatures.

Hamed Bakhtiari et al.[5] In conclusion, the study reveals significant insights into the performance of different infill patterns and raster angles in additive manufacturing, particularly with ABS and PC materials. The findings demonstrate that 45/45° grid infill patterns exhibit superior tensile fatigue characteristics compared to rectilinear patterns. Furthermore, within rectilinear patterns, those with a 0 raster angle outperform others. This angle also demonstrates exceptional flexural fatigue performance for both ABS and PC prints. Notably, Y prints demonstrate the highest tensile fatigue performance for ABS and Ultem 9085 FFF parts. Additionally, the study underscores that, akin to PLA prints, honeycomb infill patterns and a horizontal build orientation yield ABS samples with the most robust rotating bending fatigue performance. These findings provide valuable guidance for optimizing additive manufacturing processes and material selection to enhance part durability and performance.

Thermoplastic Polyurethane (TPU): Thermoplastic polyurethane (TPU) distinguishes itself as an elastomer endowed with complete thermoplastic characteristics, providing a combination of flexibility and processability. TPU demonstrates versatility in manufacturing processes, including compression, blow, and injection molding, as well as extrusion, solution coating, or vacuum forming, catering to a wide array of manufacturing needs. Its color options are diverse, and the property spectrum of TPU can be precisely tailored due to its segmented block copolymer structure, which incorporates both soft and hard segments. The selection between aromatic or aliphatic segments depends on the specific application, with aliphatic TPUs being favored for their environmental durability. The ratios and types of TPU's soft and hard segments can be adjusted to fulfill particular requirements, effectively balancing factors such as hydrocarbon resistance and flexibility.

Polybutylene terephthalate (PBT): Polyethylene terephthalate (PET or PETE) serves as a widely used thermoplastic polymer within the polyester family, boasting a range of properties such as stability, mechanical strength, and thermal resistance.

Recycled PET finds applications in various industries, including packaging, textiles, fibers, and automotive components. PET formulations span from unreinforced to glass-reinforced, flame-retardant, and flow-enhanced variants for improved heat resistance or engineering applications. Incorporating additives like glass fibers or CNTs enhances PET's impact strength, surface finish, and reduces warpage. PET exhibits semi-crystalline, colorless, and flexible properties, customizable from semi-rigid to stiff depending on processing methods.

Nylon: Originally renowned for its pioneering role in women's stockings, Nylon has undergone a transformation, branching out into a plethora of applications including fishing lines, trimmer lines, and fasteners, thanks to its remarkable properties. As a member of the polyamide family, Nylon is produced through the chemical reactions between molecules harboring carboxyl groups and those bearing amine groups. One notable variant, Nylon 6,6, is synthesized from hexamethylene diamine and adipic acid. This adaptable material has found its way into diverse industries such as automotive and household products, prized for its durability and malleability as a thermoplastic.

Polycarbonate[5]: Polycarbonate (PC) alloys are transparent thermoplastics with an amorphous structure, highly regarded for their light transmission characteristics, which closely mimic those of glass. These polymers are prized for their exceptional impact resistance and thermal stability, rendering them versatile for diverse applications. Despite being available in different colors, PC alloys maintain superb light transmission akin to glass. They excel in scenarios where transparency and impact resistance are crucial and can be augmented with fire-retardant additives without compromising material integrity.

Use of Ml in 3D Printing Processes

Sood et al.[14] had investigated the impact of five processing parameters (layer thickness, part build orientation, raster angle, raster width, and air gap) on the compressive strength of FDM built parts. Results show the anisotropic and brittle nature of ABSP400 parts. A developed relationship between compressive stress and process parameters explains 96.13% of variability, aiding future engineering applications. Response surface plots elucidate factor interactions. Maintaining strong fiber-fiber bonds is crucial, achieved by controlling distortions during part build. Anisotropy arises from polymer molecule alignment with flow direction and weak interlayer bonding. Non-linear response plots indicate complex parameter-output relationships, supported by ANN predictions. Optimization via QPSO yields maximum compressive stress of 17.4751 MPa with optimal parameter values: layer thickness 0.254 mm, orientation 0.036°, raster angle 59.44°, raster width 0.422 mm, and air gap 0.00026 mm.

Sood et al.[15] employs central composite design to analyze process parameters (layer thickness, orientation, etc.) for FDM processed ABS parts. Validation is done through ANOVA and Anderson–Darling test. Microphotographs reveal wear complexities such as interfacial adhesive bonds, scratching, fatigue, and surface cracks. Response surface plots highlight the importance of minimizing distortion during part build for reducing wear. A nonlinear relationship between process parameters and wear is observed. The study proposes an empirical equation linking process parameters and wear, optimized using quantum behaved particle swarm optimization. Artificial neural network (ANN) is employed for efficient output-input mapping, aiding prediction with less data. Results are applicable to shop floor practitioners. ANN prediction aligns with quantum behaved particle swarm optimization findings. Future work could explore comparing RP technologies for quality and cost-efficiency**.**

Vijayaraghavan et al.[16] investigated that enhanced MGGP approach addresses poor generalization, proposing a superior method for evaluating wear strength in FDM components. Outperforming standard MGGP and SVR models, it matches ANN model performance. Parametric analysis confirms model robustness, revealing key input parameters and nonlinear relationships. Notably, wear strength decreases with layer thickness and raster width, while increasing with air gap. Im-MGGP's strong generalization benefits RP experts seeking accurate wear strength predictions in uncertain conditions. Offering explicit wear strength-input parameter relationships, it's applicable offline for predictive use on the shop floor. Further optimization can maximize wear strength, while future research aims to assess environmental impacts of 3D printed FDM components using this improved computational approach.

Vosniakos et al.[17] recommends using meta-models derived from diverse data sources, like software from the RP machine for accurate building time estimates and CAD applications for precise volumetric error calculations. It emphasizes shape accuracy by analyzing volumetric error distribution per slice to improve dimensional fidelity assessment. Additionally, it employs Genetic Algorithms (GAs) for optimization to handle complex, multi-parameter problems efficiently. Various criteria are combined into a single weighted metric to tailor solutions. To minimize the need for extensive simulation scenarios for neural meta-model training, careful selection of discrete input values for process parameters is crucial. This approach requires expertise in prototype interpretation and may involve formal techniques such as Taguchi's Design of Experiments (DoE)**.**

Equbal et al.[18] study investigates the impact of five factors (layer thickness, part build orientation, raster angle, raster to raster gap, and raster width) on the dimensional accuracy of FDM build parts. Taguchi's design of experiment is used to identify optimal factor levels and significant interactions. Shrinkage predominantly affects length, width, and hole diameter, while thickness consistently exceeds desired values. To enhance dimensional accuracy, four performance characteristics are targeted for minimization. Optimal factor settings vary for each characteristic. Grey Taguchi method is employed to determine settings satisfying all characteristics simultaneously, revealing specific optimal factors. Two predictive models, one fuzzy and one ANN-based, are proposed, with the fuzzy model showing superior performance due to its independence from training datasets. The proposed models outperform Taguchi's model by considering non-linearities inherent in FDM processes. Additionally, the study demonstrates the application of Taguchi OA for rule formation and suggests improvements for weight determination in grey relational grade calculation.

Sood et al.[19] investigates the impact of five factors (layer thickness, part build orientation, raster angle, raster-to-raster gap, and raster width) on the dimensional accuracy of FDM build parts. Taguchi's design of experiment is utilized to identify optimum factor levels and significant interactions. Shrinkage predominantly affects length, width, and diameter, while thickness consistently exceeds the desired value. To enhance dimensional accuracy, four performance characteristics are considered. Optimal settings vary for each characteristic. The grey Taguchi method is employed to determine settings that simultaneously minimize all four characteristics. Results suggest specific factor levels for optimum performance. Grey relational analysis, validated by a back propagation neural network, confirms the model's suitability with a small error margin.

Li, Z. et al.[20] uses an ensemble learning method employed for predicting surface roughness in FFF processes, utilizing multiple sensors for real-time data collection. Features extracted from sensor signals in both time and frequency domains were used. To enhance efficiency and prevent over fitting, a subset of 40 features was selected via RF based on importance. The predictive models were trained using an ensemble of six machine learning algorithms: RF, AdaBoost, CART, SVR, RR, and RVFL network. Experimental results demonstrate the models' effectiveness in predicting surface roughness of 3D printed specimens, with the ensemble outperforming individual learners based on RMSE and RE metrics[20].

Noriega et al.[21] study proposes a method to enhance the precision of the distance between parallel faces in FDM manufactured prisms. By using optimized CAD model dimensions instead of theoretical ones, the disparity between actual and target values is reduced. The distance parameter's actual value serves as a quality indicator, while part size and orientation act as configuration parameters. The design of the test geometry enables easy scalability and nesting, thereby reducing testing efforts. This nesting capability is recommended for experimental meta-models. The accuracy of the distance between faces is crucial for both manufacturing and mechanical design. An ANN model is developed to predict actual dimensions of FDM parts based on experimental data. An innovative approach is employed to optimize the ANN, balancing accuracy, computational efficiency, and complexity. The prediction accuracy surpasses FDM manufacturing accuracy, validated by comparing prediction error (Ep) with manufacturing error (EM). The ANN is further utilized in a reverse design process within an optimization algorithm, significantly reducing EM in experimental validation. However, applying this methodology to different geometries may require new parameter selection and experimentation. Further research is needed to assess its robustness across various geometries and improve parameterization understanding**.**

Jiang et al.[22] Utilizing BP neural network and Genetic Algorithm, optimal process parameters are determined: platform movement speed at 16mm/s, material extrusion speed at 16mm/s, nozzle diameter at 0.6mm, and fiber spacing at 1.8mm. Experimental verification validates these parameters, aided by different fluorescent agent colors for clarity. Initially, bone scaffold preparation suffers from issues like overlap, accumulation, and uneven fiber spacing due to slow platform movement and fast extrusion speed. However, algorithm optimization improves scaffold preparation, ensuring uniform fiber spacing and better porosity**.**

Mohamed et al.[23] increased layer thickness which marginally improves the dynamic modulus of elasticity due to fewer layers, enhancing deformation resistance in FDM-manufactured parts. More contour lines result in continuous enhancement of dynamic modulus by reducing porosity. However, increasing air gap, raster angle, build orientation, and road width decreases dynamic modulus. Positive air gap values reduce density, while minimal raster angles and X-axis build orientations improve curve definition and minimize stair-stepping. Optimal parameter settings (A = 0.3302 mm, B = zero air gap, C = 0˚, D = 0˚, E = 0.4572 mm, F = 10) maximize dynamic mechanical performance. ANN modeling outperforms fractional factorial modeling in predicting dynamic modulus. The study's limitation lies in examining process parameters at only two levels, suggesting the need for future research with more levels for accurate assessment.

Bayraktar et al.[24] studied how FDM production parameters affect maximum tensile strength. It focuses on melt temperature, layer thickness, and raster pattern orientation. Results show that samples with crisscross raster pattern exhibit the highest tensile strength, followed by horizontal, and then vertical patterns. Higher melt temperatures generally improve tensile strength. Increased layer thickness decreases tensile strength for crisscross and vertical patterns but enhances it for horizontal patterns due to better molecular diffusion. ANN models accurately predict tensile strength, with the criss cross pattern yielding the lowest deviation. ANOVA analysis highlights raster pattern's significant influence on tensile strength.

Vahabli et al.[25] had investigated that FDM's main limitation lies in the surface quality of fabricated parts due to its layered manufacturing principle. To enhance surface roughness, pre-fabrication optimization of parameters is crucial. Traditional analytical methods fall short in predicting roughness accurately across all surface angles. Hence, this paper proposes an RBFNN, fine-tuned via empirical data and ICA optimization, yielding superior accuracy. The RBFNN-ICA model outperforms traditional methods, reducing MAPE to 3.64% and MSE to 2.27. Sensitivity analysis confirms optimal settings for neuron count (55) and spread (0.3913). This neural network model, integrating intelligent optimization, offers the most effective means of predicting surface roughness, considering various factors like material properties and support burrs.

Papazetis et al.[26] study advocates a methodology combining Taguchi design of experiments and trained Artificial Neural Networks (ANN) to optimize shape fidelity and material flow rate in material extrusion Additive Manufacturing (AM) systems. It identifies factor windows ensuring material deposition stability and defect-free parts across various machines. An ANN trained on 27 inputs, utilizing Taguchi OA design, effectively represents data range and recognizes complex relationships between factors and response. By optimizing ANN architecture using Taguchi technique, its performance is enhanced, enabling prediction of maximum and minimum flow rates. The study warns against relying solely on factor main effects for optimization, emphasizing the significance of interactions between factors. It suggests that flow rate prediction based on random level combinations within factor windows isn't sufficient for shape fidelity assurance, especially for intricate surfaces. However, limitations include the inability to predict specific defects and the influence of material properties on extrusion phenomena, potentially altering calculated rate limits but not overall process trends.

Conclusion

In summary, the extensive research presented in the paragraphs investigates various aspects of Fused Deposition Modeling (FDM) additive manufacturing processes. Several studies delve into the optimization of processing parameters to enhance different performance characteristics such as compressive strength, dimensional accuracy, wear strength, surface roughness, and dynamic modulus of elasticity. Notably, methodologies including central composite design, Taguchi's design of experiments, and ensemble learning techniques like Artificial Neural Networks (ANN) and Genetic Algorithms (GAs) are employed to analyze and optimize these parameters effectively. The findings underscore the importance of controlling factors like layer thickness, part build orientation, raster angle, and others to achieve desired outcomes in FDM manufacturing. Additionally, innovative approaches such as the integration of ANN models and meta-models derived from diverse data sources offer promising avenues for improving prediction accuracy and process optimization. However, while these studies provide valuable insights and methodologies for enhancing FDM processes, there remain areas for further exploration, such as assessing the robustness of these approaches across different geometries and investigating their environmental impacts. Overall, the research contributes significantly to advancing the understanding and optimization of FDM additive manufacturing processes, offering practical insights for industry practitioners and researchers alike.

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