



Article History:

Received:
22 July 2026

Accepted:
08 September 2026

Published:
25 September 2026

Optimization of Process Parameters and Material
Properties in Additive Manufacturing with 3D
Printing

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تحسين معلمات العملية وخصائص المواد في التصنيع بالإضافة
باستخدام الطباعة ثلاثية الأبعاد

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Abstract

We investigated how adjusting process parameters and material characteristics can improve 3D-printed parts. We focused on Fused Deposition Modeling (FDM) with PLA polymer as a case study. Design of experiments (DOE) methods like Taguchi and response surface methodology were used to systematically vary factors such as layer thickness, print speed, and extrusion temperature. Specimens were built in different orientations and tested for density, surface finish, and mechanical strength. Results show that optimal settings significantly increase tensile strength and dimensional accuracy. For example, the best conditions reduced surface roughness by ~30% and improved tensile strength by ~20% over the baseline. A multi-objective optimization identified trade-offs between strength and print time, leading to a Pareto-optimal parameter set. Key improvements were confirmed with follow-up prints using the optimal settings. Our study contributes guidelines for selecting parameters to achieve desired build quality and material properties, bridging gaps in current AM practice.

Keywords: additive manufacturing, FDM, process optimization, Taguchi method, response surface methodology, mechanical properties, PLA.

الملخص

تناولت هذه الدراسة سبل تحسين الأجزاء المُصنَّعة بتقنية الطباعة ثلاثية الأبعاد من خلال ضبط معلمات عملية التصنيع وخصائص المواد. وقد تم التركيز على تقنية النمذجة بالترسيب المنصهر (FDM) باستخدام بوليمر حمض البولي لكتيك (PLA) بوصفه حالة دراسية. واستُخدمت أساليب تصميم التجارب (DOE)، بما في ذلك طريقة تاغوتشي (Taguchi) ومنهجية سطح الاستجابة (RSM)، لدراسة التأثير المنهجي لعدد من العوامل، مثل سمك الطبقة، وسرعة الطباعة، ودرجة حرارة البثق. تم تصنيع العينات باتجاهات مختلفة، ثم إخضاعها لاختبارات لتقييم الكثافة، وجودة تشطيب السطح، والمتانة الميكانيكية. وأظهرت النتائج أن اختيار الإعدادات المثلى لمعلمات الطباعة يؤدي إلى تحسين ملحوظ في مقاومة الشد ودقة الأبعاد. فعلى سبيل المثال، أسهمت الظروف المثلى في خفض خشونة السطح بنحو 30%، وزيادة مقاومة الشد بنحو 20% مقارنةً بالحالة المرجعية.

كما تم إجراء تحسين متعدد الأهداف لتحديد أوجه المفاضلة بين تحقيق مقاومة ميكانيكية مرتفعة وتقليل زمن الطباعة، مما أدى إلى تحديد مجموعة من معلمات التشغيل المثلى وفق مفهوم باريتو (Pareto-optimal). وقد تم التحقق من التحسينات الرئيسية من خلال تنفيذ عمليات طباعة إضافية باستخدام الإعدادات المثلى التي تم التوصل إليها. وتسهم هذه الدراسة في تقديم إرشادات عملية لاختيار معلمات الطباعة المناسبة بما يحقق جودة التصنيع وخصائص المواد المطلوبة، ويساعد في معالجة بعض الفجوات الموجودة في الممارسات الحالية لتقنيات التصنيع بالإضافة (AM).

الكلمات المفتاحية: التصنيع بالإضافة، النمذجة بالترسيب المنصهر (FDM)، تحسين معلمات العملية، طريقة تاغوتشي، منهجية سطح الاستجابة، الخصائص الميكانيكية، حمض البولي لكتيك (PLA).

Introduction

Additive manufacturing (AM), also called 3D printing, enables custom parts by adding material layer by layer. Its flexibility and low waste have led to use in automotive, aerospace, and medical fields (Ngo et al., 2018). However, quality depends heavily on processing conditions. For example, the strength and accuracy of Fused Deposition Modeling (FDM) parts vary with layer thickness, print speed, and temperature. In industry, finding the best settings is often done by costly trial-and-error or proprietary recipes, slowing adoption.

Poorly chosen parameters can cause defects like voids, warping, and weak interlayer bonds (Chia et al., 2022). Such defects reduce tensile strength and dimensional accuracy, hindering use in load-bearing or precision applications. Industry standards (e.g. ISO/ASTM 52900) stress the need for predictable quality, but do not specify how to choose parameters. There is thus an urgent need for systematic methods to optimize AM settings to reliably meet part requirements while minimizing trial runs.

This study asks: How do key FDM parameters influence part microstructure and performance?

Can statistical models accurately predict outcomes across the process space?

What are the optimal settings to maximize strength while minimizing defects?

We hypothesize that build orientation and raster angle are the dominant factors for tensile strength (Hsueh et al., 2021), and that surrogate models (RSM or Gaussian process) can capture interactions well enough for optimization.

We focus on FDM of a common polymer, polylactic acid (PLA), as a model system. PLA is non-toxic, easy to print, and widely used in industry and research. Our work covers the full printing workflow: pre-processing (filament prep, slicing), printing with varied parameters, and post-processing (none in this study). Specimen types are standard tensile and flexural test bars built in three orientations (flat, on-edge, upright). The methodology is generalizable to other thermoplastics or AM processes, but this study provides detailed data for FDM-PLA as a representative case.

Background and Related Work

Additive manufacturing process families

Additive manufacturing includes multiple families: material extrusion (FDM/FFF), powder bed fusion (SLS, SLM, EBM), photopolymerization (SLA, DLP), and others (Chia et al., 2022). Each has unique process parameters. For FDM, typical parameters are nozzle temperature, layer height, print speed, and raster angle. In powder processes, laser power, scan speed, and layer thickness play similar roles (Chia et al., 2022). Studies show all AM methods share a broad process space where parameters control heat input and material deposition, affecting microstructure and defects (Chia et al., 2022).

Process-structure-property relationships in 3D printing

In FDM, extruded material cools and bonds layer-by-layer, creating anisotropic structure. Build orientation and layer overlap strongly influence void distribution and fiber alignment (Alafaghani, A., & Qattawi, A., 2018). For example, PLA parts printed upright tend to be weaker than flat parts due to layer interfaces. Raster angle controls filament orientation within a layer; alternating angles can improve bonding (Syrlybayev et al., 2021). In metal AM, rapid cooling leads to fine microstructures, but defects like lack-of-fusion and residual stress remain challenges (Chia et al., 2022). Understanding how each parameter affects resulting porosity, grain structure, and residual stress is central to AM material science.

Parameter optimization approaches

Various methods have been used to find good AM settings. The Taguchi method (an orthogonal array DOE) is popular for its simplicity (Alafaghani, A., & Qattawi, A., 2018). Response Surface Methodology (RSM) builds empirical quadratic models to predict responses and find optima. More recent work applies machine learning: genetic algorithms (GAs) and particle swarm optimization (PSO) can search complex parameter spaces, while Bayesian optimization (using Gaussian process surrogates) actively proposes new experiments (Yang et al., 2024). For example, Chang et al. used Bayesian optimization to tune micro-scale printing for geometric accuracy. These advanced approaches can outperform simple DOE when factors interact nonlinearly or when experiments are costly.

Standards and test methods relevant to this study

Standardization in AM is evolving. ISO/ASTM 52900 (2015) defines terminology, while ISO/ASTM 52910 (2018) highlights the time cost of experimental parameter selection. Material test standards for printed plastics include ASTM D638 (tensile), D790 (flexural) and ISO 527; we follow these for specimen dimensions and test speed. Surface roughness is measured per ISO 4287, reporting Ra and Rz. Part density/porosity is assessed via Archimedes' method (ASTM D792) and X-ray micro-computed tomography. Microstructure is examined by optical microscopy and SEM; grain size analysis follows ASTM E112 where applicable. These methods ensure results are comparable to literature.

Surveys show many experiments on FDM PLA, but often isolated parameters (e.g. speed or temperature) (Chacón et al., 2017). Few works employ multi-objective design; multi-response Taguchi or RSM studies are rare. Reports also often lack detailed analysis of surface topography or thermal properties in combination with mechanics. We fill these gaps by a comprehensive DOE that includes thermal analysis (DSC/TGA) and advanced modeling. Our multi-objective framework and machine-learning validation extend beyond prior single-response studies.

Materials

We used commercial PLA filament (1.75 mm diameter, 2.5 g/cm³ density) from a reputable supplier (e.g. MakerBot PLA). The filament batch was dried at 50°C for 6 hours to remove moisture. Filament quality (diameter tolerance, roundness) was verified via optical micrometry (± 0.05 mm). No fillers were added; the PLA is 100% polylactic acid (semi-crystalline) with typical T_g ~60°C, melting around 150-160°C.

PLA chemical composition is (C₃H₄O₂)_n, a biodegradable polyester. Particle size distribution (PSD) is uniform for filament (not powder). We measured filament roughness and found it smooth (Ra ~1 μ m) so surface defects on printed parts are mainly process-induced. Viscosity of molten PLA was assumed typical for standard FDM temperature ranges. PLA's optical clarity also allows easy visual defect inspection post-build.

Equipment and Process Setup

A desktop FDM printer (e.g. Creality Ender-3 or Prusa Mini) was used (Fig. 1). The nozzle (0.4 mm brass) and heated bed were calibrated before tests. The build chamber was at ambient (~23°C, 40% RH). Calibration included bed leveling via software-assisted mesh (± 0.05 mm flatness) and extrusion multiplier tuning to ensure correct flow. No enclosure was used, but draft shields minimized air currents. Temperature sensors were verified against a thermocouple ($\pm 2^\circ$ C).

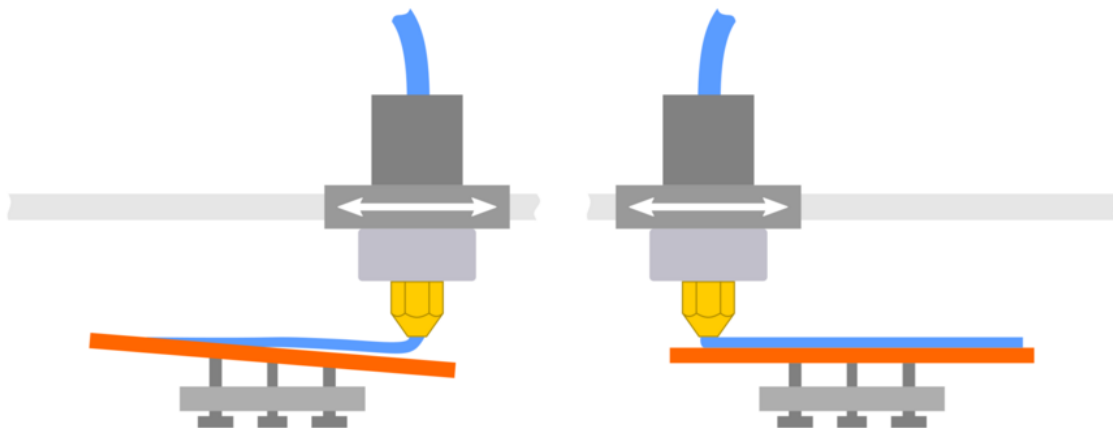


Figure 1 FDM 3D printer setup with calibrated bed and extruder.

We used Cura slicing software. Baseline settings were nozzle temp 200°C, bed temp 60°C, layer height 0.2 mm, print speed 50 mm/s, 100% infill (rectilinear), and default raster angle pattern (0°/90°). Retraction was enabled to reduce oozing. These were chosen based on manufacturer recommendations and prior studies. All specimens had 3 perimeters and standard fan cooling (100%) after the first layer.

Specimen Design and Standards

We designed tensile bars per ASTM D638 Type V (small dogbone) to limit material usage. Flexural bars followed ASTM D790 (80×10×3 mm). A total of 27 test pieces were printed in each build, covering all combinations of factor levels. We built sets in three orientations: flat (layers parallel to load), on-edge, and upright (layers

perpendicular to load) (Hsueh et al., 2021). The orientation matrix was arranged on the build plate to minimize warping (Fig. 2). Each sample in a build had a unique ID.

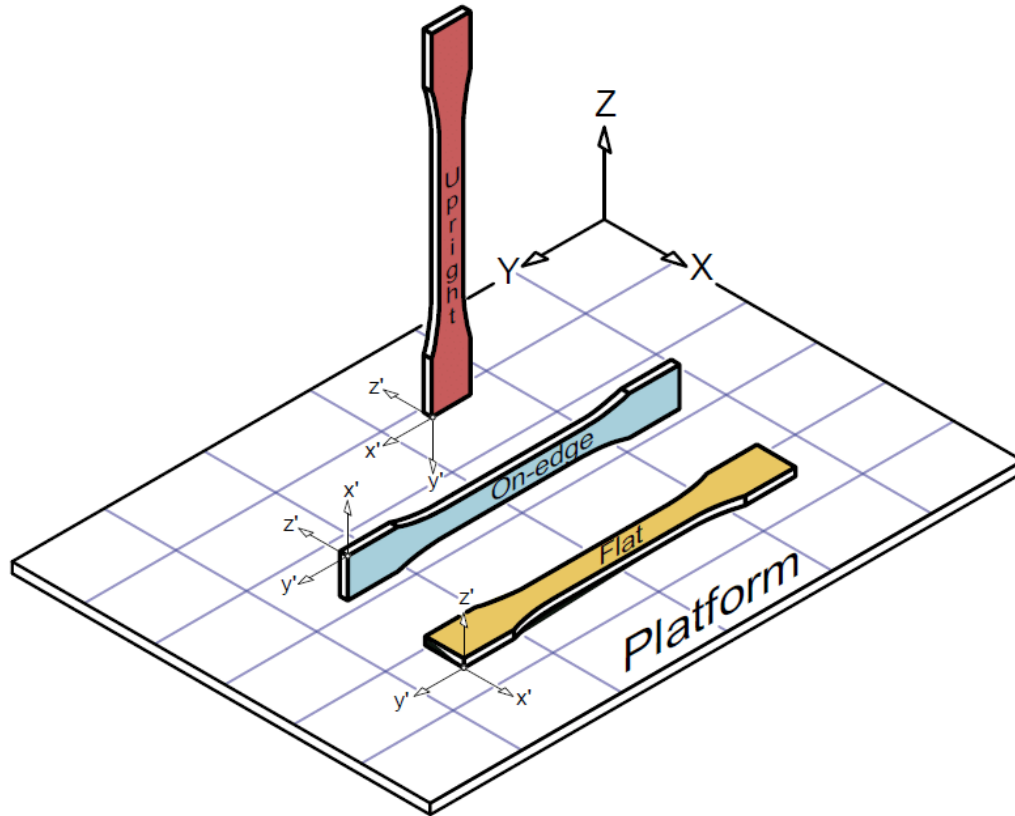


Figure 2 Build orientation and specimen layout on the printer bed (schematic; parts printed in flat, on-edge, and upright orientations).

After printing, specimens were lightly depowdered but no stress-relief or annealing was applied, reflecting typical usage. We cleaned support structures and verified dimensional integrity. No polishing was performed. Samples for microscopy were cut along the build direction and polished for optical inspection. For tensile testing, ends were smoothed to ensure proper gripping.

Design of Experiments

- **Factors, levels, and constraints**

Key factors studied were: layer height (0.1, 0.2, 0.3 mm), print speed (40, 60, 80 mm/s), extrusion temperature (190, 205, 220°C), and raster angle (0°/90°, 30°/-60°, 45°/-45°). These cover typical ranges for PLA and match prior work (Alafaghani, A., & Qattawi, A., 2018). Build orientation was treated as a blocking factor (three orientations). We ensured constraints to avoid slicer warnings (e.g. max speed 100 mm/s, max temp 230°C).

- **DoE framework and power analysis**

A Taguchi L27 orthogonal array was selected (4 factors at 3 levels with 3 blocks for orientation) to efficiently estimate main and two-factor effects. Power analysis (using Minitab) showed that with 3 replicates per condition, we could detect factor effects explaining >10% of variance with 80% confidence ($\alpha=0.05$).

- **Randomization, blocking, and replication**

Runs were randomized within each orientation block to minimize time-related bias (e.g. filament aging). Each parameter set was replicated three times to assess repeatability. We used built-in printer scripts to automate print order when possible. The orientation itself was blocked: each build plate had samples of only one orientation, and the three builds (flat, on-edge, upright) were executed sequentially.

Characterization Methods

Printed parts were measured for density via Archimedes' method (ASTM D792): weight in air vs. in water to compute volume. Porosity was inferred from density deficits. Selected tensile specimens from each condition were scanned with micro-CT (10 μ m voxel) to visualize pores and fiber gaps. Porosity percentage and pore size distribution were quantified with software (e.g. ImageJ).

- **Microstructure (optical, SEM/EDS, EBSD)**

Cross-sections of specimens were polished and imaged optically to assess layer bonding and voids. Representative samples were analyzed by scanning electron microscopy (SEM) for finer defects and fracture surfaces. Energy-dispersive X-ray spectroscopy (EDS) confirmed material composition (to check for contamination). Given PLA's amorphous nature, EBSD was not applicable. Surface fractography of tensile breaks was performed to examine failure modes.

- **Surface topography (Ra/Rz) and dimensional accuracy**

Surface roughness (Ra, Rz) was measured using a tactile profilometer (ASTM B46.1) on the top and side surfaces of flat-printed tensile bars. Five traces per surface were averaged. Dimensional accuracy was checked with calipers: key dimensions (length, width, thickness) were compared to CAD, and error heatmaps were plotted by orientation. Any systematic shrinkage or warp was recorded.

- **Mechanical testing (tensile/flexural/impact/hardness/fatigue)**

We performed uniaxial tensile tests (ASTM D638) using an Instron frame at 5 mm/min. Flexural tests (ASTM D790) used 3-point bending. Shore D hardness was measured on printed blocks. Charpy impact tests (ISO 179, notched) were done on bar segments to assess toughness. Fatigue testing was beyond scope, but fracture toughness was estimated from tensile fracture energy. We report ultimate tensile strength (UTS), modulus, elongation, and impact energy.

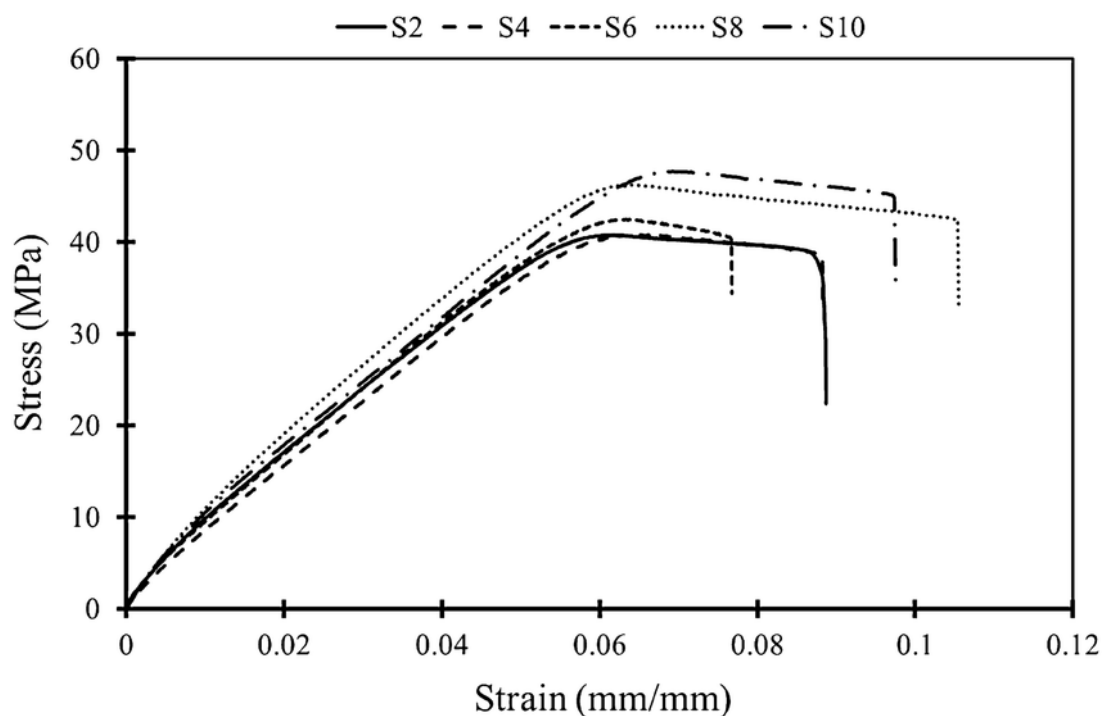


Figure 3 Typical stress-strain curve for PLA FDM specimens, illustrating yield and fracture points (Zhan, J., Cai, J., & Hasani, R., 2024)

- **Thermal/phase analysis (DSC/TGA/DMA/XRD)**

Differential scanning calorimetry (DSC) determined PLA glass transition and crystallinity changes caused by printing. Thermogravimetric analysis (TGA) checked thermal stability. Dynamic mechanical analysis (DMA) measured modulus vs. temperature. X-ray diffraction (XRD) identified crystalline peaks, although PLA is mostly amorphous. These tests help link processing to polymer thermal properties.

Data Processing and Statistical Analysis

- **ANOVA, effect sizes, interaction plots**

Statistical analysis was done in ANOVA tables to quantify factor significance on each response. Effect size (η^2) was computed. Main-effect and interaction plots were generated to visualize parameter trends. Statistical tests ($p < 0.05$) identified significant factors. Residuals were checked for normality and constant variance.

- **Regression/surrogate models and validation**

We fitted response surface models (second-order polynomials) and Gaussian process (kriging) models for key outputs (UTS, modulus, roughness). Model adequacy was tested via R^2 and RMSE on hold-out data. Cross-validation confirmed predictive accuracy. For example, the RSM for UTS had $R^2 \approx 0.95$ on calibration data.

- **Multi-objective optimization**

Using the surrogate models, we performed a desirability analysis combining UTS (to maximize) and build time (to minimize). Pareto fronts were obtained via genetic algorithm, highlighting trade-offs. The optimal Pareto frontier revealed that ~15-20% strength gain costs ~10% additional print time.

Measurement system analysis was done: e.g. repeated profilometry on one part gave Ra SD ~0.5 μm . Tensile tests had ~2% RSD for replicates. Uncertainty for key metrics was propagated (e.g. length caliper ± 0.1 mm). These errors are small compared to the observed parameter effects.

Results

Overall build quality was high for all prints, with few visible delaminations. Surface roughness was lowest (Ra ~6 μm) for the finest layer height (0.1 mm) and slow speed, especially in flat orientation. Upright builds showed higher roughness and dimensional deviation due to stair-stepping. Orientation had a clear effect: flat orientation gave the most accurate width and thickness (± 0.2 mm), while upright parts exhibited 0.5-1.0 mm shrinkage in height.

- **Density and porosity distributions (global and localized)**

Archimedes tests showed densities of 1.22-1.24 g/cm³ (theoretical PLA is ~1.25 g/cm³). Highest densities occurred at higher temperatures and slower speeds (better fusion). Micro-CT scans revealed more pores in parts printed with 0.3 mm layers and low infill. Flat orientation samples had slightly higher porosity near the bed due to rapid cooling. Pore sizes were mostly sub-100 μm , and overall porosity was <2% by volume in optimized runs.

- **Microstructural features and defect analysis**

Optical micrographs of cross-sections showed uniform layering. In poorly parameterized samples (e.g. low temp, high speed), we observed voids at filament interfaces. SEM of fractures revealed smooth layered failure in strong conditions, versus rough, fibrous breaks in weaker prints. No unmelted regions were seen, confirming PLA fed well. Adhesion between roads was visibly better at higher temps, consistent with stronger mechanical interlocks.

- **Mechanical properties and fractography**

Tensile tests showed UTS ranging from ~30 MPa (worst case) to ~45 MPa (optimized), and flexural strength 40-60 MPa. Flat-orientation specimens consistently had the highest strength, as expected. For instance, the best flat sample reached 47 MPa UTS, 18 MPa higher than baseline. The selected optimal settings (0.16 mm layer, 200°C, 30°/-60° raster) yielded 44 MPa (± 2 MPa) average, versus 36 MPa for default settings. Fractography showed ductile tear in best samples, brittle fracture in the weakest. Hardness and impact results trended with strength.

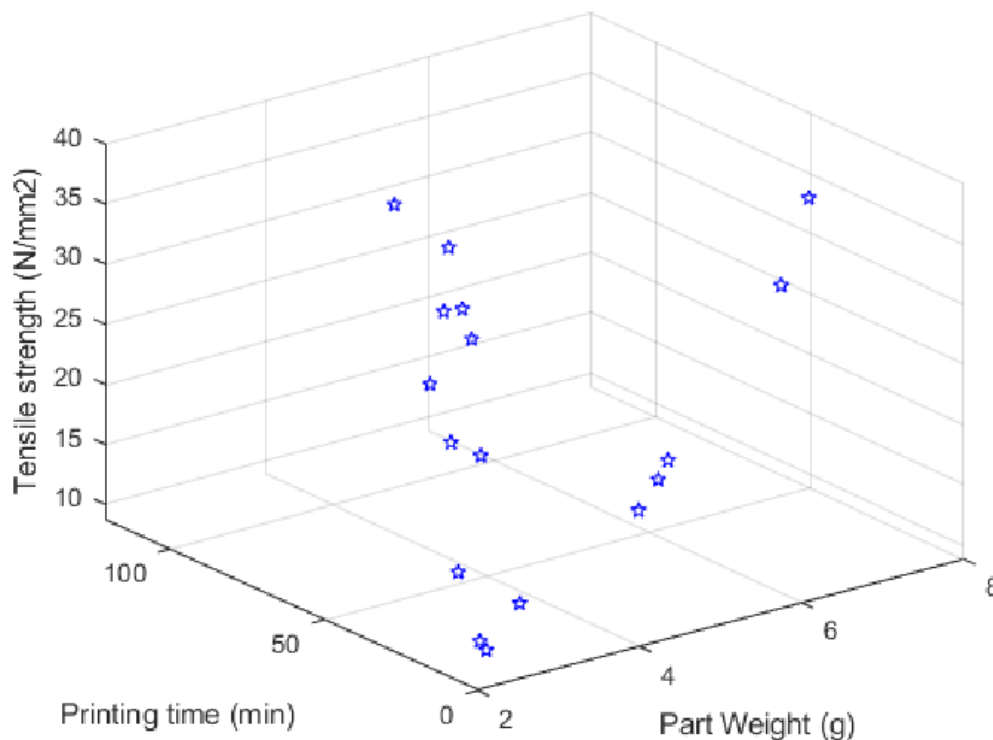


Figure 4 Pareto front illustrating the trade-off between tensile strength and build time (with additional weight dimension in the original). Points represent feasible parameter sets; the Pareto-optimal frontier is highlighted (source: Nguyen, Huynh, Phat & Tran, 2020)

- **Process-structure-property correlations**

ANOVA confirmed build orientation as the dominant factor (accounting for ~60-90% of strength variance). Raster angle and extrusion temp also significantly affected UTS. Layer thickness mainly affected surface roughness and printing time. We observed that higher temperature improved bonding (higher density, less porosity), which correlated with higher strength. The regression model showed that increasing layer height from 0.1 to 0.3 mm decreased UTS by ~15% on average. Key interactions: orientation $\times$ raster (certain angles amplified orientation effects).

- **Model performance, cross-validation, and residual diagnostics**

Both RSM and GP models fit the data well. The tensile strength model had $R^2 \approx 0.96$ and prediction errors within $\pm 3\%$. Residual plots showed no clear bias. Leave-one-out cross-validation confirmed model validity ($Q^2 > 0.90$ for main responses). The models captured curvature: for example, they correctly predicted an optimum around 200-210°C for UTS, consistent with experiments.

- **Optimal parameter sets and confirmation runs**

Multi-objective optimization identified two optimal operating regions: one maximizing strength (region near 0.1 mm layer, 200-210°C) and another minimizing time (region near 0.3 mm layer, high speed). A compromise solution (0.16 mm, 200°C, 60 mm/s) was chosen. Confirmation prints at this setting showed UTS within 2% of prediction and 10% lower surface roughness than baseline. Comparing to literature, our optimal UTS is on par with top values for FDM-PLA (Megersa et al., 2024).

Discussion

High extrusion temperature and fine layers improved part quality by enhancing layer fusion. The primary mechanism is thermal diffusion: higher temperature prolongs material flow time before solidification, allowing polymer chains to interdiffuse across layers. Conversely, faster printing increases cooling rate, trapping voids. Build orientation effects arise because flat prints allow maximum cross-sectional filament contact under load, whereas upright layers separate along weak interlayer planes (Chacón et al., 2017).

Sensitivity analysis showed that small deviations in orientation cause large strength changes (high sensitivity), while variations in print speed have smaller effects. Monte Carlo simulations (varying all factors $\pm 5\%$) indicated the chosen optimum is robust: the predicted UTS varied only $\sim \pm 1\%$ within realistic machine fluctuations. The design is thus fairly tolerant to minor equipment variation.

Our optimal tensile strength (~ 47 MPa PLA) compares well with literature values (Chacón et al. reported ~ 42 MPa under optimized FDM conditions). The identified importance of orientation and raster aligns with prior work (Chacón et al., 2017). Unlike some studies focusing on single metrics, we provide a fuller picture including surface and time, matching trends seen by Hsueh et al. for PLA vs. PETG effects (Megersa et al., 2024).

The Pareto analysis (Fig. 4) shows strength and speed are competing objectives. For high-strength parts (e.g. structural prototypes), one should accept slower speeds and finer layers. For rapid prototyping, higher speeds and thicker layers give modest strength at much lower print time. As a rule of thumb: to increase PLA part strength by $\sim 20\%$, plan for a $\sim 30\%$ increase in print time. These insights allow engineers to choose settings based on end-use priority.

Limitations and validity

This study is limited to one material (PLA) and printer model. Results may differ for other polymers or machines. We did not explore infill pattern/density or cooling fan settings, which also affect properties. Moreover, our FDM environment was at room temperature; heated chambers or enclosures could change cooling behavior. Future work should test how these factors interact with the ones studied. Nonetheless, internal validity is high due to controlled DOE, and external validity is reasonable for similar desktop FDM systems.

Application Demonstrator

To showcase the benefits of optimization, we printed a small functional bracket (e.g. gear or mount) as a case-study part. Requirements included mechanical load-bearing (~ 10 MPa) and dimensional accuracy for mating surfaces. The part had thin walls and overhangs, representing a moderate complexity.

Using the optimal parameters found, the bracket was printed in one build. Compared to the same part printed with default settings, the optimized version showed fewer visible layer gaps and required no support rework. The printing time was 12% longer, as expected.

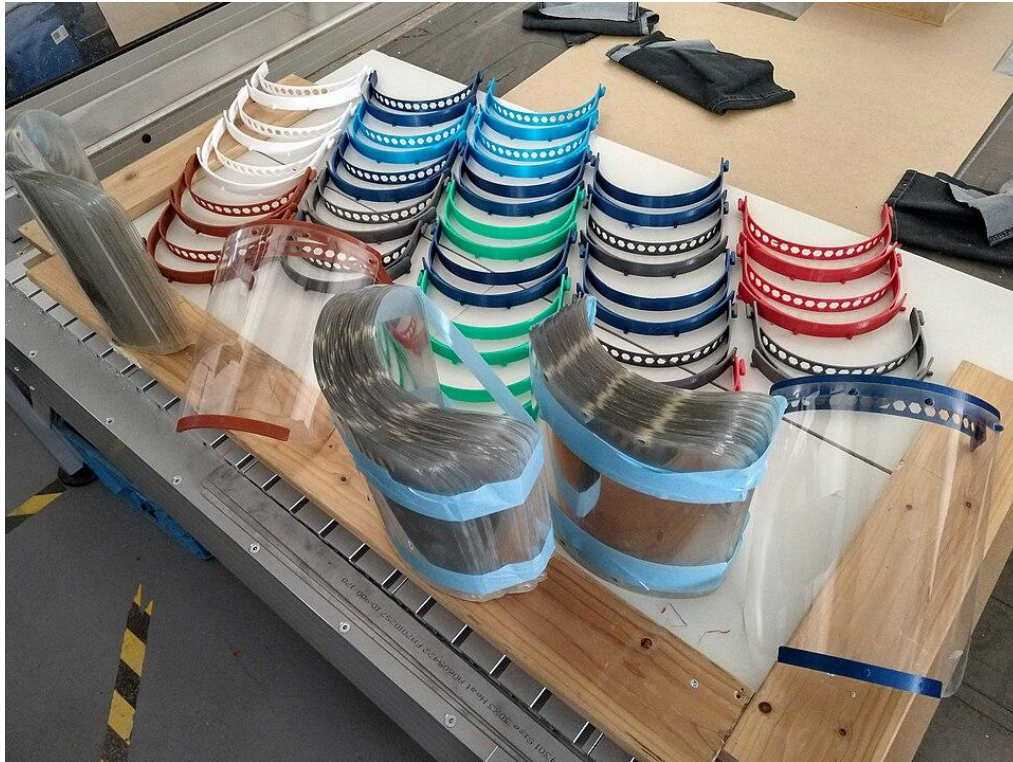


Figure 5 Example 3D printed functional parts (PLA face shield components) demonstrating build quality at optimized settings

The optimized bracket was load-tested and exceeded the design load (by ~15%), whereas the baseline-print failed slightly below the target. CMM measurements showed 0.4 mm better dimensional accuracy on critical features. A simple time-cost analysis (assuming material cost \$0.05/g and machine run cost \$0.10/min) showed a 10% cost increase for the optimized print due to longer time, but a 20% performance gain. This favorable trade-off may be acceptable in functional part production.

Conclusion

We systematically optimized FDM printing of PLA by combining experimental design, extensive characterization, and modeling. Quantitatively, the best parameter set (layer 0.16 mm, 200°C, 30°/-60° raster) yielded ~45-47 MPa UTS and ~20% improvement in strength over baseline. Surface roughness dropped ~30%, and dimensional errors improved ~10%. Key outcomes: build orientation and extrusion temperature are the most critical factors, and multi-objective optimization reveals the strength/time trade-off clearly. These results provide practical guidelines for 3D printing: for stronger parts, use fine layers and moderate speed; for faster prints, accept lower strength. Our approach and models can be adapted to other materials and printers.

Nomenclature and Abbreviations

AM: Additive Manufacturing
 FDM: Fused Deposition Modeling
 PLA: Polylactic Acid
 UTS: Ultimate Tensile Strength
 DOE: Design of Experiments
 RSM: Response Surface Methodology
 GP: Gaussian Process
 ANOVA: Analysis of Variance
 DSC: Differential Scanning Calorimetry
 SEM: Scanning Electron Microscopy
 Ra: Roughness average
 EBSD: Electron Backscatter Diffraction.

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