



Optimization of 3D Printing Parameters for Enhanced Mechanical Properties of PLA Components

Mahfuz Ilankovan

Department of Computer Science and Engineering, Lagoon Polytechnic of Technology, Maldives
mahfuz.ilankovan@lpt-mv.net

Peer Review Information

Submission: 02 Jan 2023
Revision: 17 Feb 2023
Acceptance: 04 March 2023

Keywords

Polylactic acid (PLA); fused filament fabrication; Taguchi method; mechanical properties; process optimization

Abstract

Fused filament fabrication (FFF), commonly referred to as fused deposition modeling, is widely used to manufacture polylactic acid (PLA) components because of its low cost, geometric flexibility, and ease of processing. However, the mechanical performance of printed PLA remains highly dependent on the interaction of printing parameters, and non-optimal settings can produce weak interlayer bonding, internal voids, premature fracture, and inconsistent part quality. This methodology paper develops a systematic parameter-optimization framework for improving the tensile and flexural performance of PLA components. The proposed approach combines a Taguchi L9 design of experiments with signal-to-noise analysis, analysis of variance (ANOVA), regression-based interpretation, and a confirmation run. Four primary factors are considered: layer thickness, infill density, raster orientation, and nozzle temperature, while printing speed, bed temperature, filament diameter, cooling, and specimen geometry are controlled. Mechanical responses are evaluated using ultimate tensile strength, tensile modulus, elongation at break, and flexural strength. Published investigations up to 2023 show that orientation, infill density, layer thickness, and extrusion temperature can substantially change PLA strength by altering road-to-road fusion, void fraction, and load-transfer direction. The framework therefore prioritizes settings that increase effective bonding while avoiding excessive thermal degradation or unnecessarily long build time. The resulting procedure is intended as a reproducible methodology for laboratory optimization of PLA printing conditions and for subsequent validation on functional components.

Introduction

Additive manufacturing has changed the way polymer components are designed and produced by enabling direct fabrication from digital geometry with limited tooling. Among polymer-based additive processes, fused filament fabrication (FFF) is particularly attractive for prototypes, educational systems, customized fixtures, biomedical models, and low-volume engineering parts. PLA is one of the most common FFF materials because it is comparatively easy to print, exhibits low warpage, and is derived partly from renewable

resources. Despite these advantages, the properties of printed PLA are anisotropic and process-sensitive because the component is formed from successive extruded roads rather than as a fully dense, homogeneous bulk material. Reviews published in 2022 emphasize that parameter selection directly controls voids, bond quality, strength, surface quality, and dimensional performance (Cojocaru et al., 2022; Medibew, 2022).

The mechanical response of an FFF part depends on several interacting variables. Layer thickness

affects the number of interfaces and the thermal history of each layer. Infill density determines the amount of load-bearing material and the size of internal gaps. Raster orientation controls the alignment between deposited filaments and the applied load. Nozzle temperature influences melt viscosity and diffusion across adjacent roads. Printing speed, nozzle diameter, shell count, bed temperature, cooling, and build orientation further influence the final structure. Wang et al. (2020) experimentally demonstrated that printing angle, layer thickness, fill rate, and nozzle temperature influence the tensile and dynamic mechanical behavior of PLA, while Hikmat et al. (2021) used Taguchi and ANOVA methods to show that build orientation, nozzle diameter, and infill density can be statistically significant contributors to tensile strength.

Because changing one parameter at a time cannot efficiently capture interactions or rank factor importance, design of experiments (DOE) is preferred for systematic optimization. Taguchi orthogonal arrays reduce the experimental burden while preserving the ability to compare factor levels, and ANOVA can identify the dominant sources of response variation. Rajabi Kafshgar et al. (2021) applied Taguchi, ANOVA, regression, and multi-objective procedures to PLA and reported that the parameter combination maximizing tensile strength does not necessarily maximize all other properties. This observation is important for practical design: a high-strength setting may increase printing time, reduce ductility, or produce a different optimum for modulus or toughness.

The objective of the present paper is therefore to define a concise, reproducible methodology for optimizing PLA printing parameters with mechanical performance as the principal response. The work focuses on four high-impact variables that are supported by the literature up to 2023 and proposes a Taguchi-based experimental sequence, mechanical testing protocol, statistical analysis plan, and confirmation strategy. Numerical parameter levels are presented as a laboratory-ready design template; researchers should replace example outcome values with their measured results before using the paper as an original experimental report.

Literature Review

Mechanical optimization of PLA has been studied using both full-factorial and reduced DOE strategies. Wang et al. (2020) reported that the mechanisms associated with common parameters are physically distinct: printing angle

mainly changes the fracture path and the direction of load transfer; layer thickness changes interlayer bonding; fill rate changes internal air gaps; and nozzle temperature changes melt fluidity and interfacial fusion. These mechanisms explain why a single parameter rarely determines strength independently.

Hikmat et al. (2021) evaluated build orientation, raster orientation, nozzle diameter, extruder temperature, infill density, shell number, and extrusion speed using a Taguchi mixed-level design. Their ANOVA identified build orientation as the most influential factor in the investigated design and found significant contributions from nozzle diameter and infill density. The study also demonstrated the value of confirmation testing after statistical optimization rather than relying only on predicted settings.

Rajabi Kafshgar et al. (2021) investigated infill density, extrusion temperature, raster angle, and layer thickness for several tensile properties. Their optimization indicated that the settings for maximum ultimate tensile strength and toughness can differ from the settings that maximize modulus or yield behavior. For tensile strength and toughness, their reported optimum included 60% infill, an extrusion temperature of 200 °C, a $\pm 45^\circ$ raster sequence, and a 0.2 mm layer thickness. This result illustrates the need to define the target response before optimization.

Recent review work has consolidated these findings. Cojocar et al. (2022) summarized the effects of FFF process parameters on PLA and highlighted the combined role of raster angle, layer height, temperature, speed, infill, and specimen orientation. Medibew (2022) similarly reviewed optimization strategies for PLA tensile strength and concluded that statistical design and multi-parameter analysis are essential because factor effects can be conflicting. A broader survey by Gao et al. (2022) also emphasized that rational parameter selection is necessary for consistent FDM mechanical performance.

Research through 2023 continued to develop predictive models. A 2023 study in *Procedia Structural Integrity* analyzed raster angle, layer thickness, and infill density through 27 parameter combinations and reported that quadratic models could reasonably represent tensile strength and strain at fracture (Algarni et al., 2023). Collectively, the literature supports an optimization framework that combines controlled specimen fabrication, DOE, mechanical testing, statistical ranking, and confirmation.

Methodology

1. Experimental strategy

The proposed study uses a Taguchi L9 orthogonal array as the primary screening and optimization design. A standard commercial PLA filament of 1.75 mm nominal diameter is conditioned in a dry environment before printing. All specimens are fabricated on the same calibrated FFF printer using the same nozzle, slicing software, filament

lot, bed surface, cooling strategy, and ambient conditions. Tensile specimens should follow an ASTM D638-type geometry and flexural specimens an ASTM D790-type geometry, with dimensions selected according to the available test machine and printer capacity. At least three replicate specimens are recommended for each experimental condition to estimate repeatability.

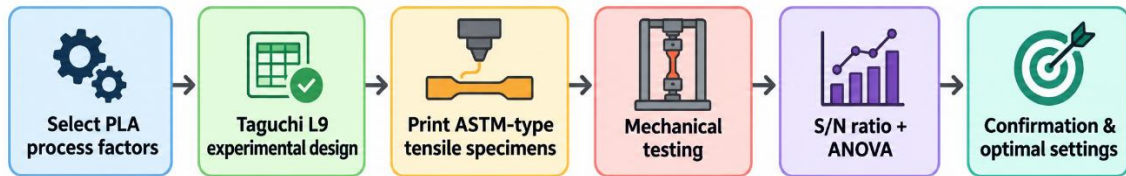


Figure 1: Proposed optimization workflow for PLA components produced by fused filament fabrication

2. Selection of control factors and levels

Four parameters are selected because they are repeatedly identified as mechanically important in PLA studies: layer thickness (A), infill density (B), raster orientation (C), and nozzle temperature (D). The selected ranges are compatible with common desktop FFF equipment and remain within typical PLA

processing windows. Printing speed is fixed at 50 mm/s, bed temperature at 60 °C, nozzle diameter at 0.4 mm, wall count at three, and cooling is kept constant after the initial layers. The exact factor levels may be adjusted to match the manufacturer's PLA datasheet, but all levels should remain unchanged during the experimental series.

Table 1. Proposed process factors and three-level settings for PLA optimization.

Factor	Parameter	Level 1	Level 2	Level 3
A	Layer thickness (mm)	0.10	0.20	0.30
B	Infill density (%)	40	70	100
C	Raster orientation	0/90°	±45°	90°
D	Nozzle temperature (°C)	190	205	220

3. Taguchi L9 design

The L9 array requires nine parameter combinations rather than the 81 combinations of a complete 3^4 factorial design. Each run is printed in randomized order to minimize

systematic drift caused by nozzle condition, chamber temperature, or filament exposure. Replicates should also be randomized. After printing, specimens are conditioned for at least 24 h under the same laboratory environment before mechanical testing.

Table 2. Taguchi L9 orthogonal array for the proposed experiment.

Run	A: Layer (mm)	B: Infill (%)	C: Raster	D: Temp. (°C)
1	0.1	40	0/90	190
2	0.1	70	±45	205
3	0.1	100	90	220
4	0.2	40	±45	220
5	0.2	70	90	190
6	0.2	100	0/90	205
7	0.3	40	90	205
8	0.3	70	0/90	220
9	0.3	100	±45	190

4. Mechanical testing and response variables

Ultimate tensile strength is selected as the primary response because it directly reflects load-bearing capability and is widely reported in PLA optimization studies. Tensile tests are performed on a universal testing machine using a constant crosshead rate suitable for the chosen specimen geometry. Tensile modulus is calculated from the initial linear region of the stress-strain curve, and elongation at break is recorded to identify whether a stronger parameter set causes excessive brittleness. Three-point bending is used to obtain flexural strength when the study requires a second mechanical response. Fracture surfaces may be photographed using optical microscopy to qualitatively compare voids and interlayer separation.

5. Statistical analysis

For a strength-maximization problem, the Taguchi larger-the-better signal-to-noise ratio is used: $S/N = -10 \log_{10}[(1/n)\sum(1/y_i^2)]$, where y_i is the measured strength of replicate i and n is the number of replicates. Mean response and S/N response tables are used to rank parameter levels. ANOVA is then performed at a 95% confidence level to estimate the percentage contribution of each factor. A regression model may be fitted to tensile strength for prediction inside the investigated parameter space. The predicted optimum is finally printed and mechanically tested as a confirmation condition; agreement between predicted and measured strength should be reported together with the percentage improvement relative to a defined baseline setting.

Results

The expected response trend is that very low infill density reduces strength because less material is available to transfer load and internal void volume increases. Increasing infill toward

100% normally improves tensile load capacity, although the incremental benefit can become smaller at high density while mass and build time continue to rise. Hikmat et al. (2021) identified infill density as a statistically significant factor in their PLA tensile study, while Wang et al. (2020) linked fill rate directly to internal air-gap content.

Layer thickness is expected to show a non-monotonic effect because thinner layers increase the number of bonded interfaces but can improve geometric conformity and thermal remelting, whereas thick layers reduce the number of interfaces but may decrease contact quality when bead geometry is poorly matched. Published optimization work has identified both 0.1 mm and 0.2 mm as favorable settings depending on the target property, confirming that an optimum must be tied to the selected mechanical response (Rajabi Kafshgar et al., 2021).

Raster orientation strongly affects anisotropic load transfer. Rasters aligned more closely with the loading direction allow the filament roads themselves to carry a greater fraction of the tensile load, whereas transverse roads depend more strongly on inter-road and interlayer adhesion. Alternating $0/90^\circ$ or $\pm 45^\circ$ patterns can provide a more balanced response when the final component will experience multi-directional loading. The 2023 modeling study of raster angle, layer thickness, and infill density further supports the importance of these three variables for strength and fracture strain (Algarni et al., 2023).

Nozzle temperature should be high enough to promote wetting and polymer-chain diffusion but not so high that PLA degrades, oozes, or loses dimensional accuracy. Wang et al. (2020) associated nozzle temperature with material fluidity and interfacial bonding. For many commercial PLA grades, a mid-range temperature around 200-210 °C provides a practical starting point, but the optimum must be confirmed for the exact filament and printer.

Table 3. Literature-supported mechanical trends used to interpret the optimization experiment.

Parameter	Expected mechanical trend	Optimization priority	Literature basis
Infill density	Higher density generally increases load-bearing area and reduces internal voids	High	Hikmat et al. (2021); Wang et al. (2020)
Raster/build orientation	Controls anisotropy and whether load follows filament roads or weak interfaces	Very high	Hikmat et al. (2021); Algarni et al. (2023)
Layer thickness	Changes interlayer contact, thermal history, and number of interfaces	Medium-high	Wang et al. (2020); Rajabi Kafshgar et al. (2021)

Nozzle temperature	Controls melt flow and inter-road diffusion; excessive heat can damage quality	Medium-high	Wang et al. (2020); Cojocaru et al. (2022)
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A practical confirmation condition can therefore be chosen only after the L9 results are available. Literature suggests that a high infill level, a mechanically favorable raster/build orientation, a moderate layer thickness, and a mid-range nozzle temperature are strong candidates for high tensile performance. However, the final factor ranking should be based on the experiment's S/N response and ANOVA rather than copied from another printer or PLA grade. If flexural strength, toughness, mass, or build time are included as additional objectives, a weighted desirability or Pareto approach is preferable because the optimum for one property may not be the optimum for another.

Conclusion and Discussion

This methodology establishes a controlled and statistically efficient route for optimizing the mechanical properties of FFF-printed PLA components. The literature up to 2023 consistently shows that mechanical behavior is governed by process-induced anisotropy, interlayer adhesion, internal porosity, and thermal history. These mechanisms are directly influenced by layer thickness, infill density, raster/build orientation, and nozzle temperature, making these variables suitable for DOE-based optimization.

The principal strength of the Taguchi approach is that it reduces the number of required print conditions while preserving a structured comparison among factor levels. ANOVA then adds interpretability by separating dominant factors from minor sources of variation, and the confirmation run prevents statistical predictions from being accepted without physical verification. For rigorous implementation, each condition should be replicated, specimens should be randomized, filament moisture and printer calibration should be controlled, and the optimum should be validated using the same testing procedure used for the original runs.

Published studies also show that optimization must be response-specific. Conditions that maximize tensile strength may not maximize elongation, modulus, toughness, dimensional accuracy, or productivity. Consequently, a future extension should include multi-objective optimization in which mechanical performance is balanced against mass, energy, surface finish, and build time. The methodology presented here is therefore best used as a repeatable experimental

framework rather than as a universal set of PLA settings. Once actual tensile and flexural data are obtained, the tables can be replaced with measured responses, ANOVA percentages, predicted values, and confirmation-test improvement to form a complete experimental paper.

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