



Effects of Printing Speed, Infill Density, and Layer Thickness on the Tensile Strength of FDM-Printed PLA: Experimental Evaluation and ANN Modelling

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ABSTRACT

Background: The tensile performance of fused deposition modelling components depends on thermal bonding, internal geometry, and deposition conditions. This study evaluated whether printing speed, infill density, and layer thickness could be used to improve the tensile strength of polylactic acid specimens and model the resulting response. **Methods:** ASTM D638-type tensile coupons were designed in SolidWorks, sliced in SuperSlicer, and printed on a Creality Ender 3 with 1.75 mm PLA and a 0.4 mm nozzle. A three-factor, three-level full factorial design generated 27 parameter combinations: printing speed of 40, 60, or 80 mm/s; infill density of 5, 10, or 15%; and layer thickness of 0.12, 0.20, or 0.28 mm. Tests were conducted on a 100 kN universal testing machine at 5 mm/min. A 3-4-1 feed-forward artificial neural network trained by the Levenberg-Marquardt algorithm was used to estimate tensile strength. **Results:** Measured strength ranged from 8.76 to 17.46 MPa, with an overall mean of 13.58 MPa. Mean strength increased from 11.44 to 15.75 MPa across the investigated layer-thickness range and from 12.55 to 14.99 MPa across the infill-density range, whereas printing speed produced a smaller main-effect trend. For the 27 reported observations, model predictions achieved RMSE = 0.121 MPa, MAE = 0.081 MPa, $R^2 = 0.9974$, and $r = 0.9987$. The highest observed response occurred at 40 mm/s, 5% infill, and 0.28 mm layer thickness. **Conclusions:** Within the tested domain, layer thickness and infill density governed the principal response trends, and the neural network closely reproduced the available observations. Independent validation, raw replicate analysis, and a confirmation experiment are required before the reported setting can be generalized as an optimum.

Keywords: additive manufacturing; artificial neural network; fused deposition modelling; full factorial design; PLA; tensile strength

1 INTRODUCTION

Material extrusion, commonly termed fused deposition modelling (FDM) or fused filament fabrication, constructs polymer components by depositing successive roads of molten thermoplastic. Its accessibility, low material waste, and ability to produce complex geometry support rapid prototyping and low-volume production. The same layerwise mechanism, however, introduces voids, imperfect road-to-road fusion, and direction-dependent properties that can make printed parts substantially weaker than conventionally processed polymers [1-4].

Polylactic acid (PLA) is widely used because it prints at moderate temperature, has comparatively low warpage, and is derived partly from renewable feedstocks. Mechanical performance remains sensitive to build orientation, raster strategy, extrusion temperature, layer thickness, deposition speed, infill geometry, and specimen conditioning. Early studies established the anisotropic behaviour of material-extrusion parts [3], while subsequent investigations quantified effects of deposition parameters on dimensional accuracy and strength [4-10]. Reviews have consequently emphasized that process-property relationships are coupled and machine-material specific [11,12].

Layer thickness alters the number of interfaces and the thermal history of a part; infill density changes the effective load-bearing area and internal void fraction; and printing speed affects the residence time and thermal bonding of adjacent roads. Published results do not always agree on the direction or magnitude of these effects because the investigated parameter ranges, materials, machines, orientations, and infill patterns differ [7-10,13-15]. Statistical design of experiments and artificial neural networks (ANNs) have therefore been used to model nonlinear interactions and identify promising parameter combinations [5,11,16,17].



A remaining practical gap is transparent reporting of small experimental data sets used for machine-learning-assisted optimization. Excellent in-sample agreement may not demonstrate predictive performance when the number of adjustable network parameters is large relative to the available observations. The present work evaluates a complete 3^3 factorial data set for PLA tensile strength and reports both observed response trends and ANN agreement metrics. The objective was to identify the most influential trends within the tested domain and to assess whether the reported ANN provides an adequate basis for proposing a candidate high-strength setting.

2 MATERIALS AND METHODS

2.1 Material and equipment

Commercial 1.75 mm PLA filament was processed on a Creality Ender 3 material-extrusion printer fitted with a 0.4 mm nozzle. Test geometry was prepared in SolidWorks and exported as an STL file. SuperSlicer was used to generate G-code. Tensile testing was performed using a universal testing machine with a reported 100 kN capacity. Figure 1 shows the printer used in the study.

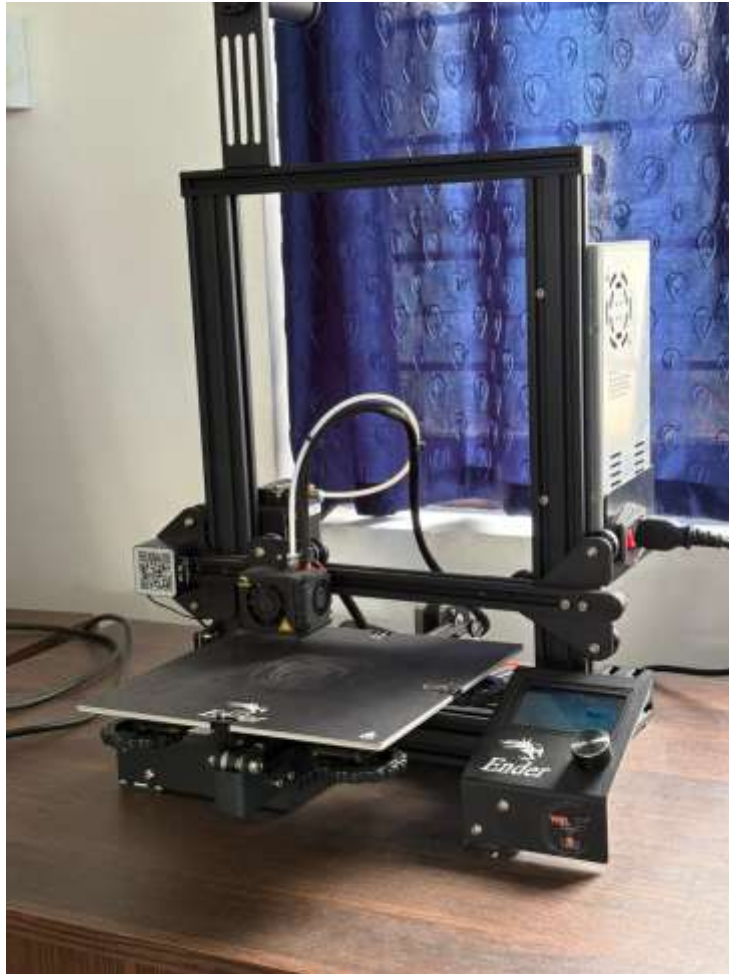


Figure 1 Creality Ender 3 material extrusion printer used for specimen fabrication

2.2 Specimen design and fabrication

The coupon geometry followed the ASTM D638 Type I configuration reported in the project record, with an overall length of 165 mm, narrow-section width of 13 mm, grip width of 19 mm, and nominal thickness of 4 mm. The drawing and solid model are shown in Figures 2 and 3. The STL model was oriented and sliced using a consistent workflow; only the three factors listed in Table 1 were varied in the recorded experimental matrix. Other slicer variables were intended to remain constant, although their numerical settings were not retained in the source record.

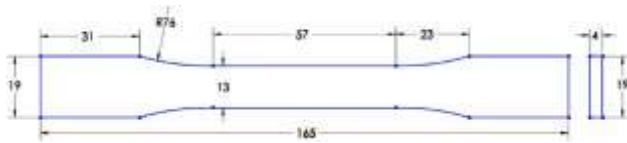


Figure 2 ASTM D638-type coupon dimensions



Figure 3 Three-dimensional coupon model

Table 1 Experimental factors and levels

Factor	Unit	Level 1	Level 2	Level 3
Printing speed	mm/s	40	60	80
Infill density	%	5	10	15
Layer thickness	mm	0.12	0.20	0.28

All 27 combinations were fabricated, corresponding to a full factorial design. Representative printing and the completed specimen set are shown in Figures 4 and 5. The source report states that testing was repeated; however, it provides one response per factor combination and does not provide replicate-level measurements. Consequently, the manuscript treats the 27 reported responses as the analyzable observations and does not estimate within-setting repeatability.



Figure 4 Fabrication of a tensile coupon



Figure 5 Printed coupons covering the 27 settings

2.3 Tensile testing

Coupons were loaded in tension at a crosshead speed of 5 mm/min using a nominal gauge length of 50 mm. Tensile strength was recorded in N/mm², numerically equivalent to MPa. Figures 6 and 7 show the universal testing machine and a mounted coupon. The available report did not retain load-extension curves, strain measurements, failure-location records, or raw replicate results; analysis was therefore restricted to tensile strength.



Figure 6 Universal testing machine



Figure 7 Coupon mounted for tensile testing

2.4 Neural-network model and statistical analysis

A multilayer fully connected feed-forward ANN was configured with three input neurons, one hidden layer containing four neurons, and one output neuron for tensile strength (Figure 8). Training used the Levenberg-Marquardt algorithm. The architecture contains 21 adjustable weights and biases. The source report did not specify data normalization, initialization, training-validation-test partitioning, random seed, epochs, regularization, or early-stopping criteria. The model should therefore be interpreted as a fit to the available data rather than as independently validated prediction performance.

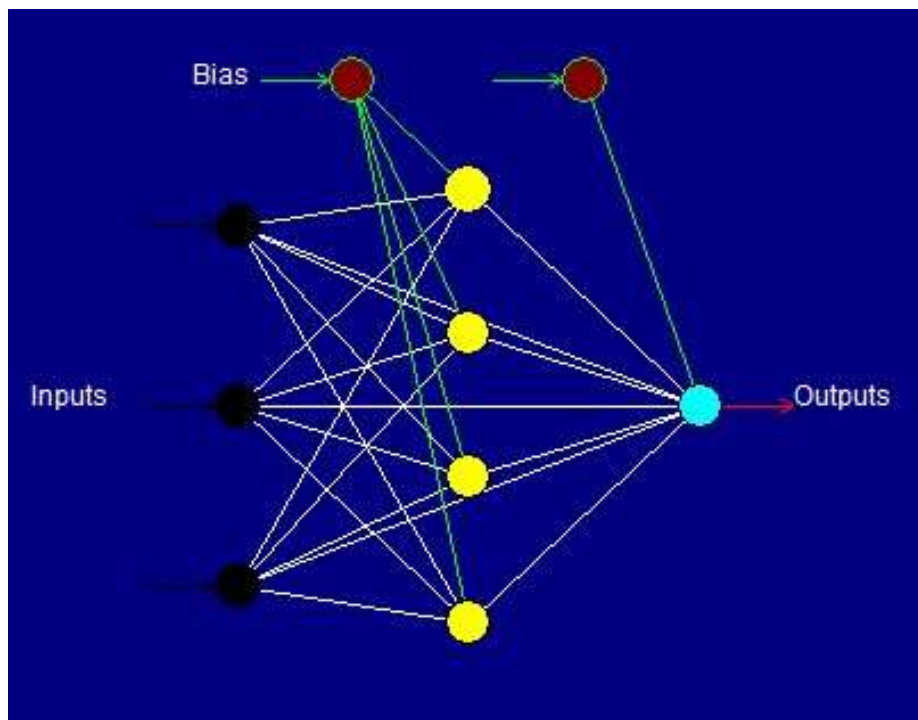


Figure 8 Reported 3-4-1 feed-forward artificial neural-network architecture

Model agreement was recalculated from the reported measured and predicted values using root-mean-square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), and Pearson correlation coefficient (r). Factor-level marginal means were calculated by averaging the nine observations at each level. The source also reports an ANN-genetic algorithm workflow, but population size, crossover and mutation rules, constraints, stopping criteria, and independent confirmation tests were not documented. Accordingly, the highest observed setting is reported as a candidate optimum within the tested grid.



3 RESULTS

3.1 Experimental responses

The measured tensile strengths spanned 8.76-17.46 MPa, with a mean of 13.58 MPa and a sample standard deviation of 2.42 MPa. Table 2 provides the full experimental data set and ANN estimates. The maximum observed value, 17.46 MPa, occurred at 40 mm/s, 5% infill, and 0.28 mm layer thickness; the minimum occurred at 40 mm/s, 5% infill, and 0.12 mm layer thickness.

Table 2 Full factorial observations and ANN estimates

Run	Speed mm/s	Infill %	Layer mm	Measured MPa	ANN MPa	Abs. error MPa
1	40	5	0.12	8.76	8.945	0.185
2	40	5	0.20	11.59	11.570	0.020
3	40	5	0.28	17.46	17.458	0.002
4	60	5	0.12	9.23	9.345	0.115
5	60	5	0.20	11.42	11.420	0.000
6	60	5	0.28	16.86	16.860	0.000
7	80	5	0.12	11.48	11.355	0.125
8	80	5	0.20	11.94	11.821	0.119
9	80	5	0.28	14.23	14.262	0.032
10	40	10	0.12	10.19	9.972	0.218
11	40	10	0.20	15.94	15.940	0.000
12	40	10	0.28	15.44	15.421	0.019
13	60	10	0.12	12.57	12.688	0.118
14	60	10	0.20	12.76	13.101	0.341
15	60	10	0.28	14.03	14.033	0.003
16	80	10	0.12	11.07	11.070	0.000
17	80	10	0.20	13.23	13.138	0.092
18	80	10	0.28	13.63	13.630	0.000
19	40	15	0.12	14.17	14.215	0.045
20	40	15	0.20	14.94	14.763	0.177
21	40	15	0.28	16.21	16.210	0.000
22	60	15	0.12	13.36	13.360	0.000
23	60	15	0.20	15.63	15.615	0.015
24	60	15	0.28	17.38	17.216	0.164
25	80	15	0.12	12.15	12.051	0.099
26	80	15	0.20	14.59	14.814	0.224
27	80	15	0.28	16.48	16.394	0.086

3.2 Main response trends

Marginal means showed the clearest monotonic increase with layer thickness: mean strength rose by 4.30 MPa from 0.12 to 0.28 mm. Increasing infill density from 5% to 15% increased the marginal mean by 2.44 MPa. Mean strength decreased by 0.66 MPa between printing speeds of 40 and 80 mm/s (Table 3). These averages describe the experimental domain but do not isolate interactions or establish causality without a complete inferential model and replicate error term.

Table 3 Marginal mean tensile strength by factor level

Factor	Level 1 mean MPa	Level 2 mean MPa	Level 3 mean MPa	Range MPa
Speed: 40, 60, 80 mm/s	13.856	13.693	13.200	0.656
Infill: 5, 10, 15%	12.552	13.207	14.990	2.438
Layer: 0.12, 0.20, 0.28 mm	11.442	13.560	15.747	4.304

The project report assigned model-derived relative importance values of 20.61% to printing speed, 30.86% to infill density, and 48.54% to layer thickness (Figure 9). Because the calculation method was not documented, these values are reproduced as reported rather than treated as formal analysis-of-variance contributions.

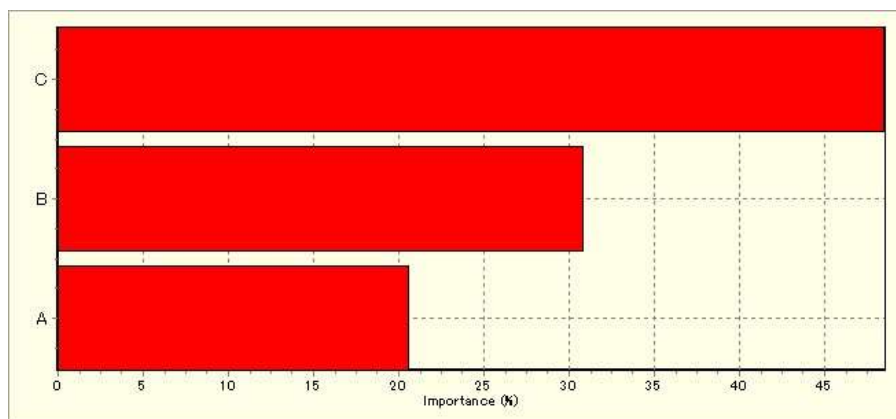


Figure 9 Reported model-derived parameter importance: A, printing speed; B, infill density; C, layer thickness

3.3 ANN agreement and candidate setting

Across the 27 reported pairs, recalculation yielded $RMSE = 0.121$ MPa, $MAE = 0.081$ MPa, $R^2 = 0.9974$, and $r = 0.9987$. The largest absolute discrepancy was 0.341 MPa for run 14. The report-generated comparison plot is reproduced in Figure 10. The proposed setting of 40 mm/s, 5% infill, and 0.28 mm layer thickness coincides with the best measured run and produced measured and model-estimated strengths of 17.46 and 17.458 MPa, respectively. No separate confirmation specimen was reported.



Figure 10 Reported comparison of measured and ANN-estimated tensile strength across the 27 runs

4 DISCUSSION

The experimental domain produced a broad tensile-strength range, confirming that process selection materially affected the structural response. Layer thickness showed the largest marginal change and the highest reported importance. This result is plausible for the present printer-material-window because larger layers can alter bead geometry, thermal retention, and the effective number of interfaces. Nevertheless, several studies have observed reduced strength at greater layer height or strong interactions with orientation and temperature [7-10,13-15]. The present finding should therefore be treated as local to the recorded material, geometry, orientation, and parameter bounds rather than a universal FDM rule.

Infill density increased the marginal mean, consistent with the larger load-bearing cross-section and reduced void fraction expected at higher infill [9,13-15]. Yet the single highest result occurred at only 5% infill. This apparent contradiction indicates interaction among the factors or unreported specimen-to-specimen variation: a main-effect average summarizes all nine combinations and need not predict the best individual combination. The low infill range, 5-15%, also limits extrapolation to dense structural prints.

Printing speed had the smallest marginal range. Slower printing may allow more stable extrusion and thermal bonding, although speed effects depend strongly on melt temperature, cooling, flow calibration, and the machine's acceleration profile. Since these controls were not numerically documented, the observed decline at 80 mm/s cannot be separated from other process conditions.

The ANN reproduced the supplied observations with very small errors. However, the 3-4-1 network has 21 adjustable weights and biases for only 27 observations, and no held-out test set or cross-validation procedure was documented. The



reported agreement is therefore vulnerable to resubstitution bias and cannot by itself establish generalization. Related optimization studies demonstrate the usefulness of response-surface and neural-network approaches when validation and uncertainty are reported [11,16,17]. For this data set, the ANN is best viewed as a compact interpolator within the tested grid.

4.1 Limitations and implications

Four limitations constrain interpretation. First, raw replicate measurements were unavailable, preventing estimation of experimental error, confidence intervals, and repeatability. Second, temperature, raster angle, build orientation, bed temperature, and infill pattern were not numerically recorded in the final matrix. Third, ANN training and genetic-algorithm settings were incomplete, preventing exact computational reproduction. Fourth, the proposed condition was not tested in an independent confirmation experiment. These limitations do not invalidate the observed data, but they require cautious language and additional verification before engineering adoption.

For practice, the results support screening layer thickness and infill density before fine-tuning printing speed on the same printer-material system. Future experiments should preserve raw replicate data, measure density and failure location, randomize print and test order, and record environmental and slicer controls. A nested cross-validation protocol and an independent confirmation batch should be used when an ANN or genetic algorithm is employed for optimization.

5 CONCLUSION

A three-factor, three-level full factorial study evaluated tensile strength of 27 FDM-printed PLA settings. Strength ranged from 8.76 to 17.46 MPa. Within the investigated ranges, layer thickness produced the largest marginal change, followed by infill density, while printing speed showed a smaller trend. The reported 3-4-1 ANN closely reproduced the supplied observations (RMSE 0.121 MPa; R^2 0.9974), and the highest observed response occurred at 40 mm/s, 5% infill, and 0.28 mm layer thickness. Because the model was not independently validated and no separate confirmation run was provided, this combination should be regarded as a candidate setting within the tested grid. Future work should use replicated randomized experiments, fully documented process controls, cross-validated modelling, fracture-surface analysis, and confirmation testing over broader infill and layer-thickness ranges.

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DATA AVAILABILITY

The 27 setting-level observations analyzed in this study are reported in Table 2. Replicate-level measurements, load-extension curves, model code, and neural-network training partitions were not available in the project record.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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