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PROCESS PARAMETER OPTIMIZATION FOR 3D PRINTING USING THE TAGUCHI METHOD

Innocent Mapindu *, Takudzwa MacDonald Muhla, Kudakwashe Nigel Chinguwo and Antony Foya

Department of Industrial and Manufacturing Engineering, National University of Science and Technology (NUST), Bulawayo, Zimbabwe.
* Corresponding Author

ORCID Details
Innocent Mapindu: https://orcid.org/0009-0007-2024-1919
Takudzwa MacDonald Muhla: https://orcid.org/0000-0002-6212-8099
Kudakwashe Nigel Chinguwo: https://orcid.org/0009-0003-2659-6527
Antony G Foya: https://orcid.org/0009-0003-5215-8504

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ABSTRACT

Although fused deposition modeling (FDM) is the most widely used material-extrusion AM process, the mechanical performance and productivity of parts produced by FDM are sensitive to process parameter settings which are often selected by trial and error. In this paper, the Taguchi method was used to optimize four FDM process parameters (layer height, infill density, nozzle temperature, and print speed) with three process levels for two competing responses (tensile strength and print time). A Taguchi L9(3^4) orthogonal array is used to decrease the number of required experiments from 81 (full factorial) to 9 trials (replicated by 3, 27 specimens) for generic polylactic acid (PLA). The infill density factor was identified as the most dominant factor in the signal-to-noise (S/N) ratio analysis and analysis of variance (ANOVA) for the replicated data with regard to tensile strength (68.99% contribution, significant at 1%) and layer height was identified as the most dominant factor in the signal-to-noise (S/N) ratio analysis and analysis of variance (ANOVA) for the replicated data with regard to print time (51.77% contribution, significant at 1%). The individual optima are 0.10 mm layer height, 75% infill, 220°C nozzle temperature, and 40 mm/s print speed, both for the maximum strength (predicted 49.02 MPa) and minimum print time (predicted 8.69 min), which means that it conflicts on three of the four parameters. This tradeoff was successfully overcome by the equal weighting grey relational analysis (GRA) which determined a compromise setting of 0.30 mm layer height, 75% infill, 220°C nozzle temperature, and 80 mm/s print speed; the print speed (47.89%) and the nozzle temperature (30.34%) had the greatest contribution to the compromise grade. The single-response optimum and the GRA compromise are not exactly the same as one of the nine physically tested trials and thus confirmation experiments at the recommended setting are proposed before the results are adopted for production application. A resource-saving methodology and example for optimizing

Keywords: Fused Deposition Modeling; Taguchi Method; Design of Experiments; Orthogonal Array; Analysis of Variance; Grey Relational Analysis; Process Parameter Optimization; Tensile Strength; Additive Manufacturing

1 INTRODUCTION

After a few years, additive manufacturing (AM) has gone from a niche rapid-prototyping method to a manufacturing method that can be used in production. Fused deposition modeling (FDM), also known as fused filament fabrication (FFF), is the material-extrusion technique with the widest application in AM, due to its low equipment costs, availability of a large range of materials, and simplicity of use [1]. The overall terminology and principles of the FDM are formalized in ISO/ASTM 52900 [5] and parts are built by extruding a melted thermoplastic filament, through a nozzle, layer by layer according to a sliced digital model.

The mechanical properties and the time and cost of creating an FDM part are controlled by a set of process parameters, which include principally layer height, infill density and pattern, nozzle (extrusion) temperature, print speed, raster (build) orientation, and the number of shell perimeters [7] [8]. These parameters often work against each other, particularly when it comes to part quality and production speed: Greater production speed (thicker layers, looser infill, faster deposition) tends to increase production time, and vice-versa. In practice, most users stick with the default slicer profile or with one factor at a time experiments, which are not only time-consuming but also damage test pieces, and may lead to a non-optimum setting or even a poor compromise between conflicting objectives.

It provides a systematic alternative, known as statistical design of experiments (DOE). The Taguchi method is a particularly interesting approach within the DOE for process optimization because it minimizes the number of experimental trials compared to a full factorial design, yet does not compromise the ability to separate the relative influence of each parameter and statistically rank them [2, 3, 4]. In discrete-part manufacturing quality engineering, taguchi designs have been widely employed and, in the last decade, they have been increasingly utilized for the parameter optimization of FDM processes, often in combination with analysis of variance (ANOVA) for checking the statistical significance of the experiments and grey relational analysis (GRA) to combine multiple, conflicting responses into a single compromise recommendation [9], [10], [11], [12], [13]. The four typical parameters of FDM, layer height, infill density, nozzle temperature, and print speed, are adjusted simultaneously to assess their contribution to the mechanical response (tensile strength) and productivity response (print time) in this paper using a saturated Taguchi L9(3^4) orthogonal array with real experimental replication.

1.1 PROBLEM STATEMENT

The process parameters that have the biggest impact on strength (layer height, infill density, and print speed in particular) generally have opposing effects on strength and on build time. If this trade-off is not approached in a well structured, quantitative manner, engineers will either over-engineer parts, thereby consuming material and machine time and expense, or under-engineer them which may lead to early mechanical failure in service.

For a routine parameter study, a full factorial investigation of each of the four parameters at three different levels would require 34 = 81 experimental runs, which is impractical, especially for each run in this study, which necessitates a destructive tensile test. It is necessary to have an experimental design that (a) significantly reduces the number of physical trials needed, (b) still gives a statistically sound ranking of the parameters that are most important for each response, and (c) offers a systematic way of reconciling the different optima for different responses into one set of parameters recommended for the design. To meet this need, this paper proposes using a Taguchi L9(3^4) orthogonal array, with the analysis of variance (ANOVA) performed with replications and grey relational analysis.

Aim

The aim of this study is to determine the optimal fused deposition modeling process parameter combination.

Objectives

- To design a Taguchi L9(3^4) orthogonal array experiment for four FDM process parameters (layer height, infill density, nozzle temperature, print speed), each at three levels.
- To manufacture and test replicated PLA tensile specimens for each of the nine trials and record tensile strength and print time.
- To compute signal-to-noise ratios and perform analysis of variance (ANOVA) on both responses in order to rank the process parameters by their percentage contribution to variance.
- To identify the individual optimal parameter combination for tensile strength and for print time, and to quantify the predicted response with a 95% confidence interval.
- To apply grey relational analysis (GRA) to obtain a single compromise parameter setting that balances tensile strength and print time.
- To recommend confirmation experiments and further work needed to validate and extend the optimization.

2 SUMMARY OF LITERATURE REVIEW

In a systematic survey of the FDM process-parameter optimization studies, Dey and Yodo [7] concluded that the parameters that are most commonly studied are layer thickness, raster angle/orientation, infill density and pattern, build orientation and nozzle/bed temperature, while mechanical strength, dimensional accuracy and build time are most commonly optimized. They found that most of the published studies optimize only one response variable by using full factorial design, Taguchi design, or response surface design. Gao et al [8] also analyzed how process parameters affect the mechanical properties of FDM components and endorsed layer thickness, infill density and raster orientation and build orientation as being always key process parameters across a large spectrum of thermoplastic materials. By using Taguchi design, Heidari-Rarani et al. [9] optimized the parameters of FDM (infill density, printing rate, and layer thickness) for PLA tensile specimens, which showed that the parameters optimized by Taguchi design for the maximum value of elastic modulus and ultimate tensile strength were 80% infill density, printing speed of 40 mm/s and layer thickness of 0.1 mm.

These results also support the results of the present study, which showed that the higher the infill density and the thinner the layers the more tensile strength the part will have. Sultana et al. [10] used a Taguchi L9 array to examine wood-PLA composite parts with infill density, nozzle temperature, print speed and layer thickness as factors; all of these factors were the same as used in this paper, and it was also found that infill density and layer thickness were the most significant factors influencing the mechanical properties. In multi-response optimization, the Taguchi design was used together with grey relational analysis (GRA) to optimize multiple responses of PETG FDM, as shown by Thejasree et al. [13] which showed that GRA was well suited for reconciling conflicting quality and productivity responses, the same approach adopted in this paper in Sections V-C and VII-F. Under uniaxial tension loading, Buss et al. [12] studied how infill density, print pattern, and build orientation affected flexural strength of FFF PLA parts, thereby reinforcing the fact that infill density is still an important factor in loading the part other than uniaxial tension.

Aldawood et al. [11] performed additional systematic parameter testing on polycarbonate and PLA samples, and concluded that an optimal parameter set is material- and machine-dependent and cannot just be copied from one study to another without re-optimization. Although the reviewed studies have shown that the two main parameters that affect the mechanical strength of the 3D printed structure are the layer height and infill density, there are relatively fewer which consider four process parameters and have a truly replicated error term, and a productivity response (print time) with a strength response (print strength) in a single Taguchi–GRA study. To fill this gap, this paper employs the saturated $L9(3^4)$ design experiment and both the analysis of variance (ANOVA) and the grey relational compromise solution approach can be used.

3 METHODOLOGY

3.1 Taguchi Orthogonal Array Design

By considering process optimization as a robust design problem, the Taguchi method is able to test a subset of the factor combinations to estimate the main effect of each factor (this is referred to as a fractional factorial design) in this subset, the factors are orthogonal meaning that their factor levels are balanced so that the main effect of each factor is estimated with the least possible number of tests [2], [3], [4]. The standard $L9(3^4)$ orthogonal array would need only 9 trials, as opposed to $3^4 = 81$ trials a full factorial would require, for four factors at three levels each. There are 8 degrees of freedom (DOF) for the L9 array, the same as required for the four 3-level factors (2 DOF per factor × 4 = 8); there is no spare column to estimate 2-factor interactions, so this design is fully saturated. This is intentional for efficiency, and is a reasonable compromise where, as is commonly reported in the literature reviewed in Section IV, the main effects are larger than the interaction effects.

In the Taguchi framework, response quality is measured by the signal-to-noise (S/N) ratio, which is a single figure of merit combining both the mean response and the response variability that is always considered "higher is better," although the engineering goal may be to maximise, minimise or target the raw response. If the characteristic is LTB, then for a given trial i, n replications, the S/N ratio is

$$S/N\_LTB = -10 \cdot \log_{10} [(1/n) \cdot \Sigma (1/y^2)] \quad (1)$$

and for print time, a smaller-the-better (STB) characteristic,

$$S/N\_STB = -10 \cdot \log_{10} [(1/n) \cdot \Sigma (y^2)] \quad (2)$$

where y denotes an individual replicate observation and n = 3 is the number of replicates per trial. For each factor, the average S/N ratio and average raw-response mean are computed across the trials at each of its three levels, and the level with the highest average S/N ratio is taken as that factor's individual optimum.

3.2 Analysis of Variance (ANOVA)

Each of the 9 trials had 3 replications (27 specimens in total) so the ANOVA error term for this study is a true replication-based error term with 18 degrees of freedom (3 replicates × 9 trials − 9 trial means = 18), and not an error term obtained by pooling a low contribution factor as would be forced by the saturated L9 design (which itself has no spare degrees of freedom). The total of the raw response is calculated for each factor level, the sum of squares is calculated for each factor, the mean square is the sum of squares/degrees of freedom (2 per factor), and the F-ratio is the factor mean square/degrees of freedom (error mean square). Percentage contribution is the ratio of each one of its sum of squares to the overall sum of squares. Statistical significance is assessed against the F-distribution critical values for (2, 18) degrees of freedom: F(0.10) = 2.624, F(0.05) = 3.555, and F(0.01) = 6.013 [4].

The predicted response at any parameter combination is estimated using the additive Taguchi prediction model,

$$\hat{\eta} = \bar{\eta} + \Sigma\,(\bar{\eta}_j - \bar{\eta}) \quad (3)$$

where $\bar{\eta}$ is the grand mean of the response, and $\bar{\eta}_j$ is the mean response at the selected level of each significant factor; the summation runs over the factors set to their optimal levels. The 95% confidence interval half-width for this prediction is

$$CI½ = \sqrt{[\,F(1, DOF_e, 0.05) \cdot MS_e / n_eff\,]} \quad (4)$$

where MS_e is the error mean square from the ANOVA, F(1, 18, 0.05) = 4.414, and n_eff = N / (1 + total DOF used in the prediction), with N = 27 the total number of observations.

3.3 Grey Relational Analysis for Multi-Response Optimization

Because tensile strength and print time are optimized by different, partly conflicting parameter settings (Section VII-E), a single compromise setting was obtained using grey relational analysis (GRA) [6], [13]. Each response was first normalized onto a common [0, 1] scale, with 1 representing the ideal (ζ) reference sequence. For the larger-the-better tensile strength response,

$$x^*_i = (y_i - \min y) / (\max y - \min y) \quad (5)$$

and for the smaller-the-better print time response,

$$x^*_i = (\max y - y_i) / (\max y - \min y) \quad (6)$$

The grey relational coefficient (GRC) of trial i for a given response is then

$$\xi_i = (\Delta min + \zeta\cdot\Delta max) / (\Delta_{0i} + \zeta\cdot\Delta max) \quad (7)$$

where $\Delta_{0i} = |1 - x^*_i|$, Δmin and Δmax are the smallest and largest Δ_{0i} across all trials and both responses, and ζ = 0.5 is the conventional distinguishing coefficient [6]. The grey relational grade (GRG) of each trial is the simple (equal-weighted) average of its two GRCs, GRG = 0.5·ξ_TS + 0.5·ξ_PT, and the trial with the highest GRG is the best-performing tested compromise; the response-table procedure of Section V-A is then repeated on the GRG values to identify the compromise-optimal level of each factor.

4 EXPERIMENTAL SETUP

A generic 1.75 mm polylactic acid (PLA) filament was used to 3D print specimens with a desktop FDM 3D printer using a 0.4 mm brass nozzle. A solid outer shell (2 perimeters, 3 top/bottom layers) was printed around each specimen, with the interior filled using the test filling, such that each specimen had a ±45° rectilinear infill and the long axis of the specimen was printed in the X–Y plane with a single build orientation used throughout all trials, leaving only the four factors in Table I as variables. Table II shows the nine combinations of the parameters of the $L9(3^4)$ orthogonal array, which were each printed three times, for a total of 27 specimens.

Specimens were conditioned at room temperature (23 ± 2 °C) and subjected to tensile testing at a crosshead speed of 5 mm/min in accordance with ASTM D638 [14] with ultimate tensile strength being measured as the maximum engineering stress at failure. Print time for each specimen was recorded from the slicer's estimated build time and compared to wall-clock time using the stop watch, from the start of the first layer to the end of the final layer.

Table 1: Factors and Levels

Code	Factor	Units	Level 1	Level 2	Level 3
A	Layer Height	mm	0.10	0.20	0.30
B	Infill Density	%	25	50	75
C	Nozzle Temperature	°C	200	210	220
D	Print Speed	mm/s	40	60	80

Table 2: L9(3^4) Orthogonal Array — Actual Parameter Values

Trial	Layer Ht (mm)	Infill (%)	Nozzle T (°C)	Speed (mm/s)
1	0.1	25	200	40
2	0.1	50	210	60
3	0.1	75	220	80
4	0.2	25	210	80
5	0.2	50	220	40
6	0.2	75	200	60
7	0.3	25	220	60
8	0.3	50	200	80
9	0.3	75	210	40

5 Results and analysis

This section presents the trial-level experimental results, the signal-to-noise (S/N) and ANOVA analysis of each response individually, and the grey relational analysis used to obtain a compromise parameter setting.

5.1 Trial Means and Signal-to-Noise Ratios

Table III shows the mean tensile strength (TS) and mean print time (PT) for three replicates in each of the nine L9 trials and their corresponding S/N ratios calculated using (1) and (2). Trial 3 (0.1 mm, 75%, 220 °C, 80 mm/s) produced the highest mean tensile strength (45.38 MPa), while Trial 7 (0.3 mm, 25%, 220 °C, 60 mm/s) produced the shortest mean print time (13.73 min).

Table 3: Trial means and s/n ratios

Trial	LH (mm)	Infill (%)	NozT (°C)	Speed (mm/s)	Mean TS (MPa)	S/N TS (dB)	Mean PT (min)	S/N PT (dB)
1	0.1	25	200	40	26.78	28.54	38.18	-31.64
2	0.1	50	210	60	36.33	31.2	37.91	-31.58
3	0.1	75	220	80	45.38	33.14	39.54	-31.94
4	0.2	25	210	80	22.39	27	16.91	-24.56
5	0.2	50	220	40	37.18	31.4	33.79	-30.58
6	0.2	75	200	60	37.78	31.53	35.48	-31

7	0.3	25	220	60	22.96	27.22	13.73	-22.75
8	0.3	50	200	80	23.07	27.26	15.56	-23.84
9	0.3	75	210	40	37.83	31.55	33.07	-30.39

5.2 Effect of Process Parameters on Tensile Strength

The average of the S/N ratio for tensile strength at each level of the four factors is plotted in Fig. 1. The trend is the steepest for infill density, showing a steady increase from 27.58 dB at 25% to 32.07 dB at 75%, while that of layer height is second steepest, decreasing from 30.96 dB at 0.10 mm to 28.67 dB at 0.30 mm, with a modest increase in nozzle temperature with increasing temperature, and a modest decrease in print speed with increasing speed. The trends are physically consistent with the bonding mechanics of FDM: higher infill density means more load-bearing material, smaller layers means more fused interlayer bonds per height, higher temperatures means better polymer chain diffusion across the bond line, and faster deposition means less time for polymer chain diffusion across the bond line.

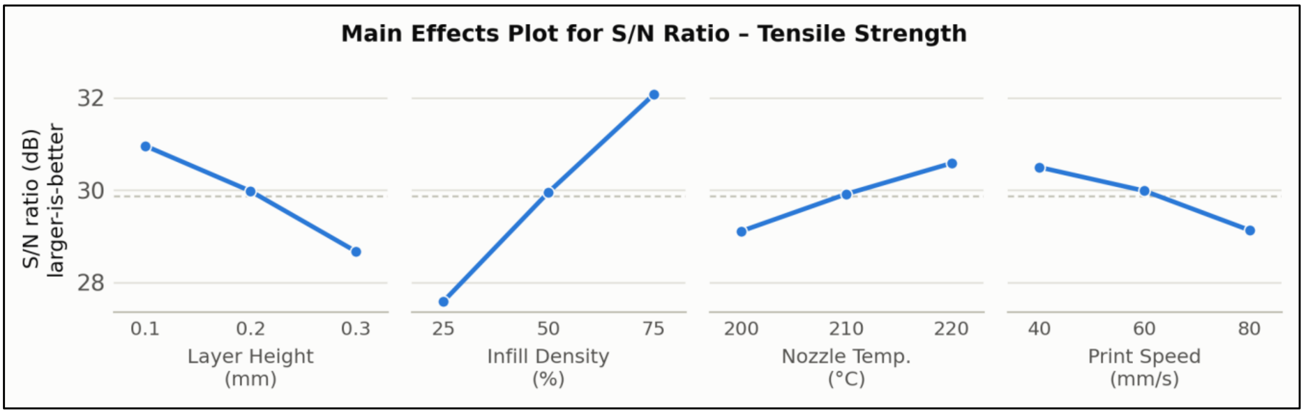

Figure 1: Main effects plot for S/N ratio — Tensile Strength (larger-is-better).

Table IV reports the underlying average S/N ratio and average raw mean at each factor level. Ranking factors by delta (max – min average S/N) confirms the visual trend of Fig. 1: infill density has the largest delta (4.49 dB), followed by layer height (2.29 dB), nozzle temperature (1.48 dB), and print speed (1.37 dB).

Table 4: Response table — s/n ratio, tensile strength

Factor	Level	Value	Avg S/N (dB)	Avg Mean (MPa)
A	1	0.1	30.96	36.16
A	2	0.2	29.98	32.45
A	3	0.3	28.67	27.95
B	1	25	27.58	24.04
B	2	50	29.96	32.19
B	3	75	32.07	40.33
C	1	200	29.11	29.21
C	2	210	29.92	32.18
C	3	220	30.59	35.17
D	1	40	30.5	33.93
D	2	60	29.98	32.36
D	3	80	29.13	30.28

Table 5: Anova — tensile strength (larger-the-better)

Source	DOF	SS	MS	F	%Contrib.	Sig.
A – Layer Height	2	304.24	152.12	233.45	17.59	1%
B – Infill Density	2	1193.16	596.58	915.53	68.99	1%
C – Nozzle Temp.	2	160.09	80.04	122.84	9.26	1%
D – Print Speed	2	60.26	30.13	46.24	3.48	1%
Error	18	11.73	0.65	—	0.68	—
Total	26	1729.48	—	—	100	—

ANOVA (Table V) confirms this ranking statistically: infill density accounts for 68.99% of the total variance (F = 915.53), layer height for 17.59% (F = 233.45), nozzle temperature for 9.26% (F = 122.84), and print speed for 3.48% (F = 46.24), with all four factors significant at the 1% level against F(2, 18, 0.01) = 6.013. The pooled error accounts for only 0.68% of the total variance and the coefficient of variation at the replicate level is low, 2-3%, in the raw tensile data. Upon application of (3) at the level combinations which maximize the S/N for each of the factors A1B3C3D1 (0.10 mm, 75%, 220 °C, 40 mm/s), the individual tensile-strength optimum can be obtained, and the results are summarized in Table VI, the 95% confidence interval for which is calculated from (4).

Table 6: Optimal parameters — tensile strength

Parameter	Value
A – Layer Height (optimal)	0.10 mm
B – Infill Density (optimal)	75 %
C – Nozzle Temperature (optimal)	220 °C
D – Print Speed (optimal)	40 mm/s
Grand mean tensile strength	32.19 MPa
Predicted tensile strength	49.02 MPa
95% confidence interval	48.05 – 50.00 MPa

5.3 Effect of Process Parameters on Print Time

Fig. 2 shows the average S/N ratio for the print time (where higher numbers are good, as with tensile strength). The layer height dominates, increasing from -31.72 dB at 0.10 mm to -25.66 dB at 0.30 mm, as doubling or tripling the layer height will reduce the number of layers that the printer has to deposit. The next largest trends are in infill density and print speed - both of which scale proportionately to the overall length of material deposited and nozzle temperature, which has little discernable slope as it relates to the physics of the extruding material, not the length of the path or number of layers deposited.

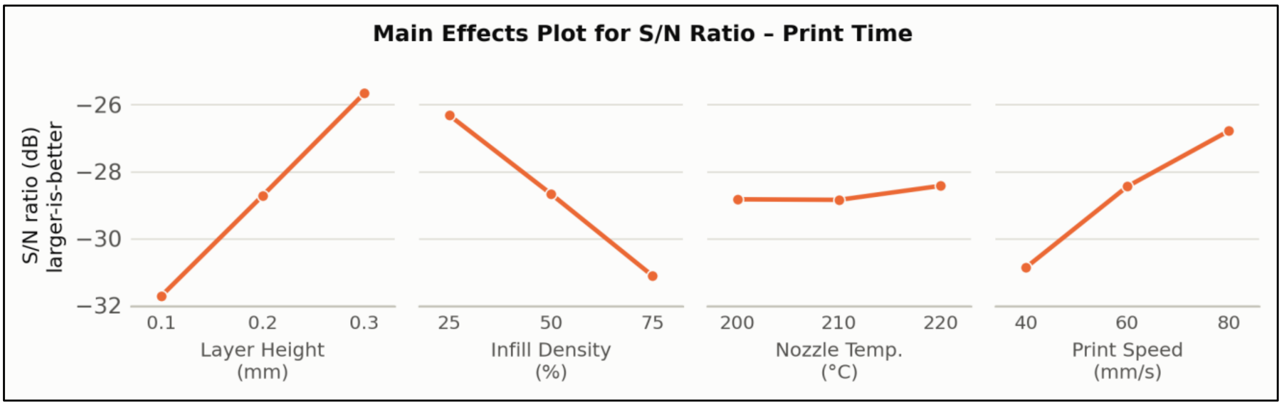

Figure 2: Main effects plot for S/N ratio — Print Time (smaller-is-better, S/N already inverted).

The ANOVA (Table VIII) shows that layer height accounts for the majority of variance: 51.77% (F = 2693.29); the infill density accounts for 28.08% (F = 1461.12); print speed accounts for 19.89% (F = 1034.79); and nozzle temperature accounts for just 0.09% (F = 4.50), significant only at the 5% level (F(2, 18, 0.05) = 3.555), but not the 1% level.

Table 7: Response table — s/n ratio, print time

Factor	Level	Value	Avg S/N (dB)	Avg Mean (min)
A	1	0.1	-31.72	38.54
A	2	0.2	-28.71	28.73
A	3	0.3	-25.66	20.79
B	1	25	-26.32	22.94
B	2	50	-28.66	29.09
B	3	75	-31.11	36.03
C	1	200	-28.83	29.74
C	2	210	-28.84	29.3
C	3	220	-28.42	29.02
D	1	40	-30.87	35.01
D	2	60	-28.44	29.04
D	3	80	-26.78	24

Table 8: Anova — print time (smaller-the-better)

Source	DOF	SS	MS	F	%Contrib.	Sig.
A – Layer Height	2	1423.77	711.89	2693.29	51.77	1%
B – Infill Density	2	772.4	386.2	1461.12	28.08	1%
C – Nozzle Temp.	2	2.38	1.19	4.5	0.09	5%
D – Print Speed	2	547.03	273.51	1034.79	19.89	1%
Error	18	4.76	0.26	—	0.17	—
Total	26	2750.34	—	—	100	—

The individual print-time optimum, A3B1C3D3 (0.30 mm, 25%, 220 °C, 80 mm/s), and its 95% confidence interval are given in Table IX.

Table 9: Optimal parameters — print time

Parameter	Value
A – Layer Height (optimal)	0.30 mm
B – Infill Density (optimal)	25 %
C – Nozzle Temperature (optimal)	220 °C
D – Print Speed (optimal)	80 mm/s
Grand mean print time	29.35 min
Predicted print time	8.69 min
95% confidence interval	8.07 – 9.31 min

5.4 Comparative Contribution of Process Parameters

The percentages of the variance explained by each of the factors are shown side by side in Fig. 3. The two most influential parameters switch rank between responses: infill density is the most important for tensile strength (68.99%) and the second most important for print time (28.08%) while layer height is most important for print time (51.77%) and second most important for tensile strength (17.59%). Nozzle temperature is a moderate and statistically significant factor in tensile strength (9.26 at 1%) but is essentially unimportant for print time (0.09%).

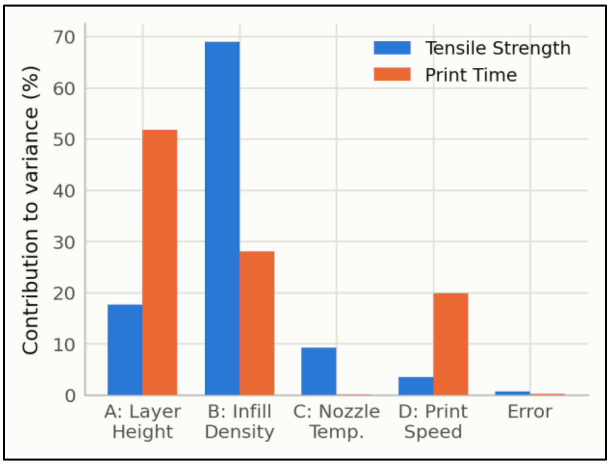

Figure 3: Percentage contribution of each factor to variance in tensile strength and print time.

5.5 Trade-off Between Tensile Strength and Print Time

The two optima for single-response disagree on three of the 4 parameters: tensile strength prefers thin layers (0.10 mm), high infill (75%) and slow printing (40 mm/s) while print time prefers thick layers (0.30 mm), low infill (25%) and fast printing (80 mm/s). The two optima only match in the nozzle temperature, with both showing a preference for the highest of the tested temperatures (220 °C). This is the anticipated physical compromise between part strength and build speed as reported in the FDM literature in Section IV and this is the reason for the multi-response reconciliation performed next by using grey relational analysis.

5.6 Grey Relational Analysis for Compromise Optimization

The grey relational grade (GRG) for each trial was calculated using (5)–(7) and the results are presented in Table X. Trial 7 (0.30 mm, 25%, 220 °C, 60 mm/s) had the highest GRG (0.669) followed closely by Trial 3 (0.667), while Trial 1 (0.10 mm, 25%, 200 °C, 40 mm/s) — which was closest to the conservative slicer settings — had the lowest value (0.364).

Table 10: Grey relational analysis — per-trial results

Trial	A	B	C	D	Mean TS	Mean PT	GRC TS	GRC PT	GRG	Rank
1	0.1	25	200	40	26.78	38.18	0.382	0.345	0.364	9
2	0.1	50	210	60	36.33	37.91	0.56	0.348	0.454	8
3	0.1	75	220	80	45.38	39.54	1	0.333	0.667	2
4	0.2	25	210	80	22.39	16.91	0.333	0.802	0.568	4
5	0.2	50	220	40	37.18	33.79	0.584	0.391	0.488	6
6	0.2	75	200	60	37.78	35.48	0.602	0.372	0.487	7
7	0.3	25	220	60	22.96	13.73	0.339	1	0.669	1
8	0.3	50	200	80	23.07	15.56	0.34	0.876	0.608	3
9	0.3	75	210	40	37.83	33.07	0.604	0.4	0.502	5

Repeating the level-average (response-table) procedure of Section V-A on the GRG values (Table XI) and Fig. 4 shows that print speed has the largest influence on the compromise grade (delta 0.163, 47.89% descriptive contribution), followed by nozzle temperature (0.122, 30.34%), layer height (0.098, 19.51%), and infill density, whose influence on the compromise grade is comparatively small (0.036, 2.27%) because its opposing effects on the two responses partly cancel.

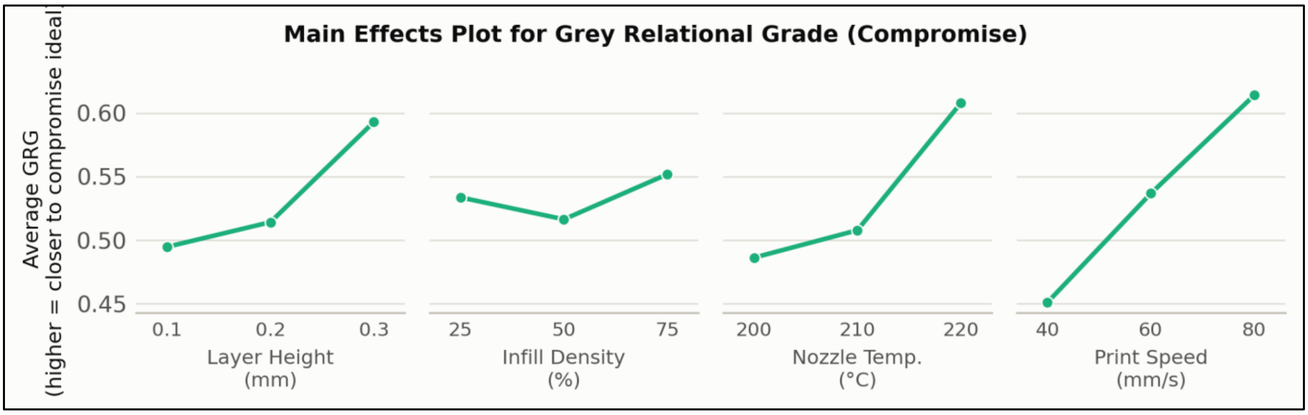

Figure 4: Main effects plot for the grey relational grade (compromise objective).

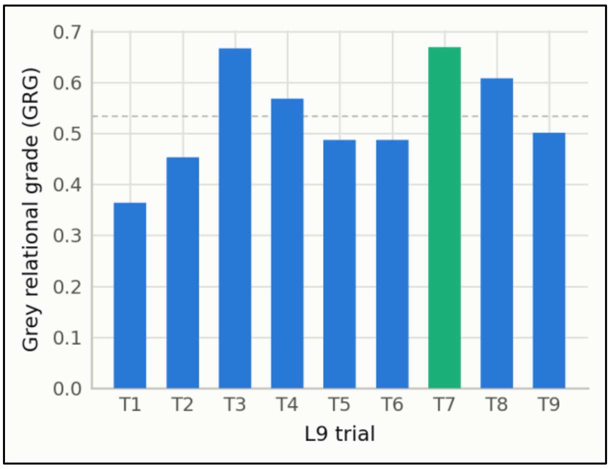

Figure 5: Grey relational grade by L9 trial (Trial 7 highlighted as the best-performing tested trial).

Table 11: GRG response table by factor level

Factor	Level	Value	Avg GRG
A	1	0.1	0.4947
A	2	0.2	0.5142
A	3	0.3	0.593
B	1	25	0.5336
B	2	50	0.5164
B	3	75	0.5519
C	1	200	0.4862
C	2	210	0.5078
C	3	220	0.6079
D	1	40	0.451
D	2	60	0.5368
D	3	80	0.6141

Table 12: GRG delta/rank and compromise-optimal levels

Factor	Delta GRG	Rank	Compromise Level	%Contrib.
A – Layer Height	0.0983	3	0.30 mm	19.51
B – Infill Density	0.0355	4	75 %	2.27
C – Nozzle Temp.	0.1217	2	220 °C	30.34
D – Print Speed	0.1631	1	80 mm/s	47.89

Since the L9 array is fully saturated with four factors, an error term is not computed and the %Contribution column in Table XII is more of a sum-of-squares breakdown than the result of an F-test for significance. The resulting compromise-optimal combination is A3B3C3D3 (0.30 mm layer height, 75% infill density, 220 °C nozzle temperature, 80 mm/s print speed), which is different than Trial 7 (best tested trial) only slightly in infill density (75% vs. 25%) which the compromise procedure favors due to the (small) strength increase that this offers, while being identical in every other respect.

5.7 Confirmation and Physical Interpretation

None of the 3 optima are the same as one of the 9 trials actually tested in the L9 array; all 3 optima are new and not tested before. As in the Taguchi tradition [3] [4] the results of a confirmation experiment would be used to validate predicted responses (49.02 MPa; 8.69 min; or the GRA compromise) before considering them as a validated production result. If a confirmation run is not possible now, Trial 7 is the best performing setting that is actually tested (GRG = 0.669) that provides a validated near-compromise option.

Physically, the results suggest practitioners should focus on nozzle temperature and the two parameters that influence the strength the most: infill density and layer height. Nozzle temperature is well within the upper half of the manufacturer-recommended range (220 °C in this case) for a slight, but statistically significant, increase in strength with no measurable difference in print time. Layer height is by far the most critical parameter to adjust when tuning FDM settings for strength, while infill density is the other.

6 CONCLUSION

In this paper, a Taguchi L9(3^4) orthogonal array, replicated ANOVA, and grey relational analysis were used to perform optimization of four factors of the FDM process – layer height, infill density, nozzle temperature and print speed – for two conflicting responses, tensile strength and print time, using just 9 experimental runs (total 27 replicated specimens), compared to 81 experimental runs required by the full factorial design. The parameter with the highest contribution to the tensile strength (68.99%) was infill density, followed by layer height (51.77%). The layer height and infill density were significant at 1% level and the other two were significant at 5% level for at least one response. The optimum settings for the two responses differed for three of the four parameters (layer height, infill density, and print speed), with only nozzle temperature being the same for both: the highest temperature tested (220 °C). This conflict was solved by using the gray relational analysis, which gave a single compromise setting of 0.30 mm layer height, 75% infill density, 220 °C nozzle temperature, and 80 mm/s print speed, with print speed (47.89%) and nozzle temperature (30.34%) being the most decisive factor in the compromise grade. Of the physically run trials, the best was Trial 7 (0.30 mm, 25%, 220 °C, 60 mm/s), which provides a near-compromise to be followed in case of confirmation runs at the predicted optima. Overall, it was concluded that the Taguchi-ANOVA-GRA methodology is a practical, statistically sound and resource efficient process optimization framework for FDM well suited for manufacturing laboratories with limited testing capacity.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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