Advances in Science and Technology
Research Journal

Advances in Science and Technology Research Journal, 2026, 20(6), 356–367
https://doi.org/10.12913/22998624/218336
ISSN 2299-8624, License CC-BY 4.0

Received: 2026.01.14
Accepted: 2026.04.15
Published: 2026.05.01

Effect of technical parameters on polylactic acid shrinkage during 3D printing

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ABSTRACT

3D printing has become a key manufacturing method in modern production, yet the process remains complex due to material melting, extrusion behavior, and numerous interacting technical parameters. The final geometry and dimensional accuracy of printed parts are highly sensitive to factors such as material properties, printing settings, and machine precision, often leading to defects when parameters are not optimized. This study investigates the influence of four major FDM printing parameters – nozzle temperature, printing speed, printing angle, and infill percentage - on the shrinkage behavior of polylactic acid (PLA), one of the most widely used polymers for technical components. Each parameter was examined at three levels using a Taguchi L27 orthogonal array, resulting in 27 experimental conditions. For every condition, five specimens were fabricated, and each specimen's length was measured at three positions to determine the average shrinkage value. The Taguchi method was applied to evaluate shrinkage through the signal-to-noise (S/N) ratio, yielding an optimal S/N value of 26.0206 with the corresponding optimal parameter set: nozzle temperature 210 °C, printing speed 80 mm/s, printing angle 90°, and infill density 100%. ANOVA results further confirmed that nozzle temperature, printing angle, and infill percentage significantly affect shrinkage, while printing speed has a comparatively minor impact. The ranking of factor influence from highest to lowest is: printing angle, nozzle temperature, infill density, and printing speed. This study provides a systematic and practical optimization framework for minimizing shrinkage in PLA 3D-printed products, offering valuable guidance for enhancing dimensional accuracy and manufacturing quality in the additive manufacturing industry.

Keywords: 3D printing, polylactic acid (PLA), process parameters, shrinkage, Taguchi method.

INTRODUCTION

In recent years, 3D printing technology using plastic materials has made great strides, thanks to advances in material science and sustainable development orientation. One prominent trend is the use of biodegradable materials, of which polylactic acid (PLA) is a typical representative. Bardot et al. (2020) demonstrated that adding nanoparticles, such as cellulose or metals, to PLA not only significantly improves mechanical properties but also maintains the material's printability and biodegradability [1]. Besides PLA, the reuse and recycling of engineering plastics are also key research topics. Vidakis et al. (2021) showed that polyamide 12 can be recycled multiple times without significant loss of mechanical properties, thus opening up great potential for realizing a circular material model for 3D printing [2]. This conclusion is consistent with the review by Zhu et al. (2021), which emphasizes that a circular economy is possible in plastic 3D printing through material innovation and improved recycling processes [3]. Another promising approach is to utilize agricultural by-products as feedstock for 3D printing. Morales et al. (2021) developed printing filaments from rice husks combined with recycled polypropylene and found that lignocellulose in rice husks improves the thermal and mechanical properties of printed products

[4]. This result not only reduces waste but also improves the performance of printed materials. At the same time, studies on cellulose nanocrystals also show potential for liquid 3D printing. Yoon et al. (2021) used cellulose nanocrystals in a free-form double droplet printing model, thereby developing a plastic-like material with complex shaping capabilities, which is especially useful in the biomedical field [5].

Environmentally, 3D printing is also being explored as an effective solution in plastic waste management, especially in urban areas and in construction. Babaremu et al. (2022) emphasize the role of 3D printing in recycling waste plastic into valuable products, such as building materials and gardening equipment, thereby reducing plastic pollution [6]. In particular, Daniele et al. (2023) used recycled HDPE from old boats to produce 3D printing filaments, demonstrating that this material has good water resistance and high durability, making it suitable for outdoor applications and coastal environments [7]. In general, plastic 3D printing technology is developing towards integrating the following factors: multifunctionality, sustainability, and circularity. The combination of biomaterials, recycled plastics, and agricultural by-products not only improves the product's mechanical performance and applications but also plays an important role in protecting the environment and promoting the circular economy. One of the prominent materials in 3D printing is PLA – a bioplastic that is popular in fused deposition modeling (FDM) technology due to its biodegradability, high biosafety, and ease of processing. However, PLA still has a significant disadvantage: post-printing shrinkage, which negatively affects the product's dimensional accuracy and mechanical properties. Therefore, many studies have focused on optimizing 3D printing parameters to control and minimize shrinkage using modern statistical and modeling methods, such as Taguchi, analysis of variance (ANOVA), response surface methodology, grey relational analysis (GRA), and artificial intelligence. In the study of Hsueh et al. (2021), parameters such as raster angle, printhead temperature, and layer height were shown to significantly affect the tensile strength and geometrical deformation of PLA products. [8]. Changing the raster angle from 0° to 90° reduces the margin shrinkage by about 12%, thereby improving geometric stability. Zubrzycki et al. (2022) also showed that increasing the filling density from 20% to 80% can reduce dimensional error by up to 0.6 mm, particularly for samples with symmetrical geometries [9]. Al-Tamimi et al. (2023) studied the effect of multi-polymer material (PLA/ABS) and geometric structure, finding that changing the mesh structure in the sample design could reduce shrinkage from 3.2% to 1.7% [10]. The Taguchi method has been widely used as an experimental design tool for optimization. Hikmat et al. (2021) applied the Taguchi L9 matrix to optimize PLA printing parameters, combined with ANOVA to determine the influence of each factor. Layer height had the most decisive influence (41.9%), followed by printing speed (28.5%) and filling density (23.6%). [11]. Megersa et al. (2024) also used the L9 matrix to determine the optimal conditions that reduced shrinkage by up to 15% [12]. Tunçel (2024) showed that at 215 °C and a print speed of 40 mm/s, toughened PLA material achieved optimal Charpy impact strength [13]. The combination of Taguchi and GRA helps solve the multi-objective optimization problem. Patel et al. (2024) showed that 100% filling density and a printing speed of 50 mm/s simultaneously optimize tensile strength, stiffness, and geometric accuracy while reducing overall shrinkage by about 16% [14]. Tunçel et al. (2024) also demonstrated that with optimal printing parameters, the shrinkage of PLA composites can be reduced from 2.4% to less than 1.5% [15]. In addition to statistical methods, recent studies have applied artificial intelligence to simulate and optimize the 3D printing process. Yang et al. (2023) used the support vector regression model combined with the Cuckoo Search algorithm to predict geometric deformation, achieving an error of less than 3% compared to the experiment [16]. Rojek et al. (2020) proposed an optimization model using artificial neural networks (ANNs) and genetic algorithms to improve tensile strength and reduce dimensional errors in biomedical applications [17]. In a recent study, Dogan et al. (2025) applied a multi-objective optimization model to reduce shrinkage and increase impact resistance of cubic-structured PLA samples. Adjusting the printing speed and filling density improved impact energy absorption by 28% and reduced shrinkage by 20% [18]. Besides studies focusing on durability and geometric accuracy, several recent works have extended the analysis to the rheological and time-dependent properties of 3D-printed PLA materials. Szczygieł et al. (2025) studied stress relaxation during compression of PLA samples printed using material extrusion (MEX) technology, employing the Taguchi method to evaluate the influence of technological parameters such as layer height, shell count (number of contours), nozzle temperature, print orientation, and overlap. The results showed that layer height and number of shells were the two factors with the greatest influence on the stress reduction rate and the parameters of the Maxwell–Wiechert model, clearly reflecting the rheological-elastic nature of post-printing PLA. This study shows that 3D printing parameters not only affect instantaneous strength but also strongly influence time-dependent phenomena such as stress relaxation and strain, which are closely related to shrinkage and dimensional deviations of PLA printed products [19].

From the above studies, it is clear that shrinkage is a key factor affecting the accuracy and quality of PLA-printed products. The application of statistical tools and AI technology not only helps determine optimal conditions but also shortens testing time and improves the quality and efficiency of production. Through the synthesis and analysis of documents, the author found that minimizing shrinkage in 3D-printed PLA products is a critical task. If this problem is overcome, it will be possible to improve geometric accuracy and mechanical strength, and to expand the applicability of PLA in the production of technical spare parts, medical equipment, and consumer products. Therefore, the author proposes an optimization process to minimize shrinkage during 3D printing of PLA. The main parameters selected include: nozzle temperature, printing speed, printing angle, and filling density. The Taguchi method will be used to design the optimal experiment, while ANOVA will be used to evaluate the influence of each parameter on the product's shrinkage.

MATERIALS AND METHODS

Materials

Polylactic acid (PLA) is a popular bioplastic in 3D printing, produced from natural sources such as corn or sugarcane. PLA is easy to print, has good stiffness, a smooth surface, and minor warping, but is quite brittle and cannot withstand high temperatures. It is suitable for models and products that do not bear force. The plastic is provided by Meme 3D Company Limited, Vietnam. The printing parameters and initial properties of PLA plastic are listed in Table 1.

The experimental specimens were fabricated with dimensions of 100 × 40 × 4 mm as shown in Figure 1. After printing, dimensional measurements were performed using a digital caliper with an accuracy of 0.01 mm. For each experimental case, five specimens were manufactured. The length of each specimen was measured at three different positions along the longitudinal direction to minimize local geometric deviations. The average length was then calculated and used to determine the shrinkage percentage. The standard deviation was computed to evaluate the repeatability of the measurements.

It should be noted that dimensional measurements in FDM 3D printing can be affected by the stepwise movement of the print head and nozzle along the Y and Z axes, which may cause small positioning deviations between the CAD model and the printed part. However, in this study, all specimens were fabricated using the same machine, control system, and printing conditions, so such systematic positioning errors are expected to affect all experimental cases in a similar manner. As a result, this consistent behavior ensures the reliability of the comparative shrinkage evaluation and supports the validity of the optimization outcomes.

3D printing machiner

The Elegoo Neptune 4 Pro FDM 3D printer is a desktop printer with a printing area of 225 × 225 × 265 mm. The machine uses FDM technology with a high-speed extruder, supporting

Table 1. Properties of PLA

Parameter	Typical value	Unit
Nozzle temperature	190–220	°C
Bed temperature	35–60	°C
Print speed	< 100	mm/s
Layer height	0.1–0.3	mm
Infill density	10–100	%
Filament diameter	1.75	mm
Tensile strength	32 ± 5	MPa
Elongation at break	11.2 ± 3.1	%
Flexural strength	51 ± 3	MPa
Flexural modulus	2240 ± 120	MPa
Impact strength (Izod)	19 ± 3.7	kJ/m^2

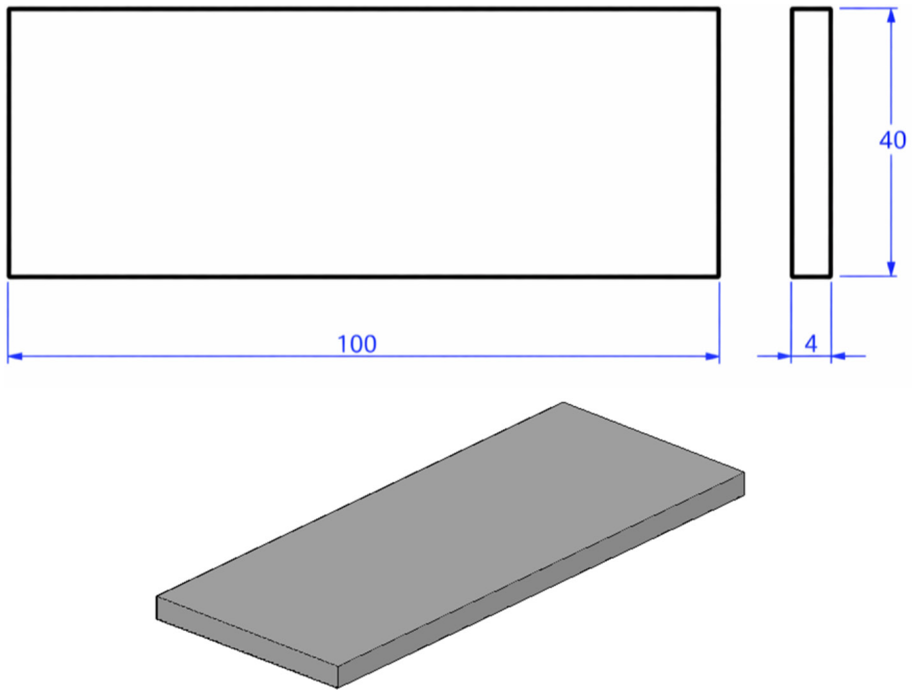

Figure 1. Dimensions and 3D image of the test specimen

temperatures up to 300 °C, enabling the printing of many materials, including PLA, ABS, PETG, and TPU. The Neptune 4 Pro integrates a dual-cooling system that automatically balances the 121-point printing table, helping improve accuracy and stability when printing complex details or when high smoothness is required. In each set of experimental parameters, five products are manufactured. The finished products will be marked and stored at room temperature. After each 3D printing experiment, the technical parameters will be reset for the following case. All products are printed with the Elegoo Neptune 4 Pro FDM 3D printer, and the test sample is being printed (Figure 2).

Printing setting and analysis method

Before 3D printing, many parameters need to be set. This study considers four main parameters, including nozzle temperature, printing speed, printing angle, and filling percentage. The experimental levels of four technological parameters, including nozzle temperature (190 °C, 200 °C, 210 °C), printing speed (40 mm/s, 60 mm/s, 80 mm/s), printing angle (0°, 45°, 90°), and filling percentage (50%, 75%, 100%), are shown in Table 2. These parameters were selected based on the material properties of PLA and reference from previous studies. Other parameters were kept at default values. The selection of these parameter levels was based on experimental and theoretical evidence to ensure optimal performance during the printing of PLA plastic products. All printing experiments were conducted under controlled laboratory conditions. The ambient temperature during fabrication was maintained at 23 ± 2°C, and the relative humidity was approximately 50 ± 5%, all specimens were manufactured under identical environmental conditions. The 3D image of the product is shown in Figure 1.

Taguchi method

To explore the relationship between input factors and output targets in the research and production process, the design of experiments method is a popular and effective tool. Within the design of experiments framework, many techniques are used, including the Taguchi method, Box-Behnken design, response surface methodology, and central composite design. Each method has its own advantages, though Taguchi is particularly valued for its ability to improve the quality of output products while minimizing the variability and costs associated with unnecessary input factors. Therefore, this study uses the Taguchi method to analyze the relationship between the technical parameters (inputs) and shrinkage (output). The data obtained from the orthogonal matrix in this method can be analyzed using ANOVA or other

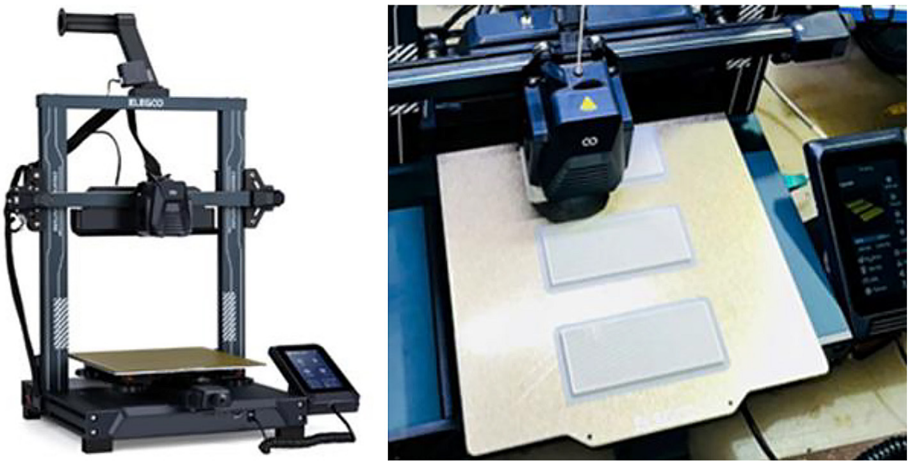

Figure 2. Elegoo Neptune 4 Pro FDM 3D Printer and the test sample is being printed

Table 2. Printing parameters

Parameters	Levels		
	1	2	3
A - Nozzle temperature (°C)	190	200	210
B - Print speed (mm/s)	40	60	80
C – Printing corner (°)	0	45	90
D - Infill density (%)	50	75	100

statistical techniques to determine the influence of each factor on the output [20]. The implementation process of the Taguchi method comprises seven steps, as shown in Figure 3 [21].

In this study, four technical parameters were selected for investigation: nozzle temperature, printing speed, printing angle, and filling ratio. Each parameter was considered at three different value levels. If all possible combinations were fully implemented, the total number of experiments to be conducted would be up to 81. However, to optimize the testing process and minimize the number of samples required while ensuring the representativeness and effectiveness of the results, the orthogonal array method was explicitly applied in Minitab. An orthogonal matrix L27 was designed, suitable for four factors at three levels, as shown in Table 3. Each experimental case was repeated five times, resulting in a total of 135 printed specimens. The use of multiple samples for each parameter combination allowed the calculation of mean values and standard deviations, thereby reducing random errors and improving the statistical reliability of the shrinkage evaluation. This sample size is consistent with previous Taguchi-based studies on FDM processes and is sufficient for subsequent S/N ratio and ANOVA analyses.

The Taguchi method uses the signal-to-noise ratio (S/N) to represent the mean and variability of quality characteristics simultaneously. It is an effective evaluation tool that helps determine the influence of input factors on the desired output. Within the framework of this method, three different types of objective functions are used to determine the signal-to-noise characteristics [22]:
A larger value is optimal:

$$SN = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \tag{1}$$

A smaller value is optimal:

$$SN = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}y_i^2\right] \tag{2}$$

Nominal value is optimal:

$$SN = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_n\right)^2\right] \tag{3}$$

where: i is the experimental number, y_i is the mean value of the characteristic given by the experiment, n is the number of experiments, y_n is the target value.

The shrinkage of the product after going through the 3D printing process is calculated as follows [20]:

$$S = \frac{D_m - D_p}{D_m} \times 100 \tag{4}$$

where: S is shrinkage, D_m is the standard sample size, D_p is the product size.

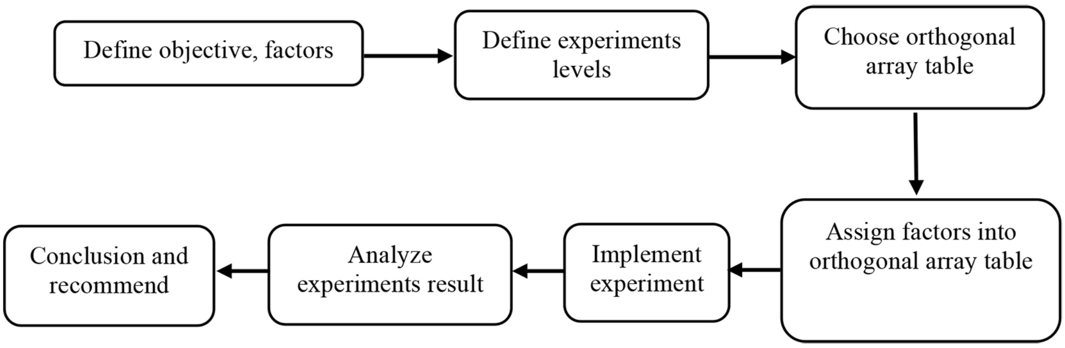

Figure 3. Taguchi process diagram

Table 3. Orthogonal array

Orthogonal array					Factors			
No.	A	B	C	D	Nozzle temperature	Print speed	Printing angle	Infill density
1	1	1	1	1	190	40	0	50
2	1	2	2	2	190	60	45	75
3	1	3	3	3	190	80	90	100
4	1	1	1	2	190	40	0	75
5	1	2	2	3	190	60	45	100
6	1	3	3	1	190	80	90	50
7	1	1	1	3	190	40	0	100
8	1	2	2	1	190	60	45	50
9	1	3	3	2	190	80	90	75
10	2	2	3	1	200	60	90	50
11	2	3	1	2	200	80	0	75
12	2	1	2	3	200	40	45	100
13	2	2	3	2	200	60	90	75
14	2	3	1	3	200	80	0	100
15	2	1	2	1	200	40	45	50
16	2	2	3	3	200	60	90	100
17	2	3	1	1	200	80	0	50
18	2	1	2	2	200	40	45	75
19	3	3	2	1	210	80	45	50
20	3	1	3	2	210	40	90	75
21	3	2	1	3	210	60	0	100
22	3	3	2	2	210	80	45	75
23	3	1	3	3	210	40	90	100
24	3	2	1	1	210	60	0	50
25	3	3	2	3	210	80	45	100
26	3	1	3	1	210	40	90	50
27	3	2	1	2	210	60	0	75

ANOVA analysis

ANOVA is a statistical method used to evaluate the relative influence of engineering parameters on the shrinkage of PLA materials. In ANOVA, two important indicators to consider are the P_{-value}, which indicates the level of statistical significance, and the F_{-value}, which represents the ratio of between-group to within-group variation.

$P_{-values}$ determine the importance of input factors: if the P_{-value} is less than 0.05 (corresponding to a 95% confidence level), the factor is considered to have a significant influence on shrinkage. Conversely, if the F_{-value} is less than the critical F-limit value [F] [23], then the corresponding factor is considered to have no significant influence and can be removed from the optimization process.

RESULTS AND DISCUSSION

Taguchi analysis

After conducting the orthogonal array design sample creation experiment, the average length of each sample was determined by measuring at three different locations and the nominal length of the specimen was fixed at 100 mm. From the measurement results, the shrinkage value for each sample was calculated using formula (4). In addition, in order to achieve the optimization goal of minimizing shrinkage, the signal-to-noise (S/N) value was calculated based on formula (2) in the Taguchi method. All the obtained results are presented in Table 4.

Figure 4 presents the shrinkage percentage of PLA specimens for 27 experimental cases, along with the corresponding standard deviation. The shrinkage values range from approximately 0.05% to 0.20%, indicating that all printing conditions are within a stable processing window for PLA. Higher shrinkage is observed under less favorable parameter combinations, while lower values correspond to optimized printing conditions.

The error bars represent the standard deviation calculated from five samples per experiment,

Table 4. Shrinkage value and S/N for PLA

Orthogonal array					Factors				
No.	A	B	C	D	Average length	SD length	Shrinkage	SD shrinkage	S/N
1	190	40	0	50	99.80	0.016	0.20	0.016	13.9794
2	190	60	45	75	99.89	0.031	0.11	0.031	19.1721
3	190	80	90	100	99.92	0.031	0.08	0.031	21.9382
4	190	40	0	75	99.82	0.024	0.18	0.024	14.8945
5	190	60	45	100	99.87	0.021	0.13	0.021	17.7211
6	190	80	90	50	99.88	0.027	0.12	0.027	18.4164
7	190	40	0	100	99.85	0.020	0.15	0.020	16.4782
8	190	60	45	50	99.87	0.022	0.13	0.022	17.7211
9	190	80	90	75	99.91	0.031	0.09	0.031	20.9151
10	200	60	90	50	99.87	0.020	0.13	0.020	17.7211
11	200	80	0	75	99.87	0.019	0.13	0.019	17.7211
12	200	40	45	100	99.89	0.031	0.11	0.031	19.1721
13	200	60	90	75	99.91	0.019	0.09	0.019	20.9151
14	200	80	0	100	99.90	0.023	0.10	0.023	20.0000
15	200	40	45	50	99.86	0.016	0.14	0.016	17.0774
16	200	60	90	100	99.94	0.015	0.06	0.015	24.4370
17	200	80	0	50	99.88	0.023	0.12	0.023	18.4164
18	200	40	45	75	99.90	0.031	0.10	0.031	20.0000
19	210	80	45	50	99.88	0.018	0.12	0.018	18.4164
20	210	40	90	75	99.91	0.034	0.09	0.034	20.9151
21	210	60	0	100	99.89	0.013	0.11	0.013	19.1721
22	210	80	45	75	99.92	0.009	0.08	0.009	21.9382
23	210	40	90	100	99.95	0.018	0.05	0.018	26.0206
24	210	60	0	50	99.89	0.009	0.11	0.009	19.1721
25	210	80	45	100	99.93	0.036	0.07	0.036	23.0980
26	210	40	90	50	99.90	0.024	0.10	0.024	20.0000
27	210	60	0	75	99.91	0.019	0.09	0.019	20.9151
Average					99.89	0.022	0.11	0.022	19.4942

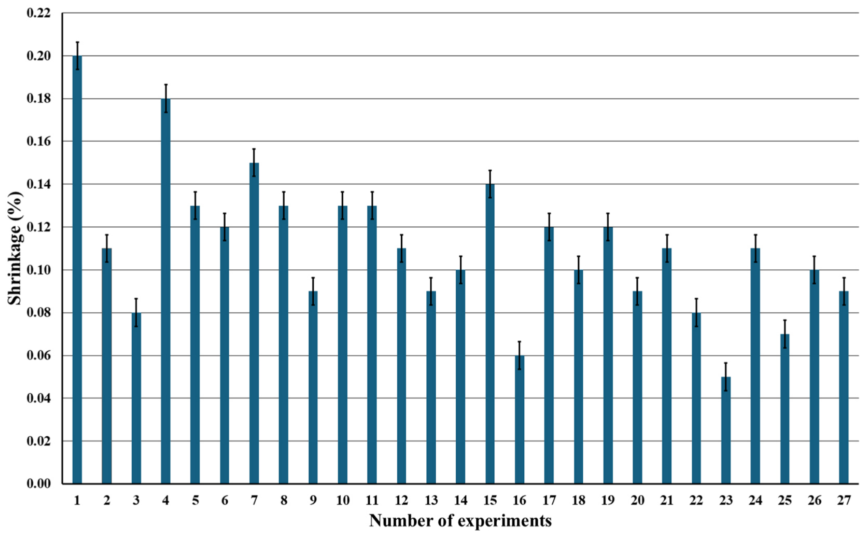

Figure 4. Shrinkage percentage of PLA specimens with corresponding standard deviation for 27 experimental cases

reflecting the repeatability of the process. In general, the standard deviation values are small compared to the mean shrinkage, demonstrating good measurement consistency and limited dimensional variation among samples produced under identical conditions. Although some cases show slightly higher dispersion, no significant variability is observed, confirming the reliability of the experimental procedure and supporting the validity of the Taguchi optimization and ANOVA analyses.

After obtaining S/N signal-to-noise results for 27 cases, we will determine the influence of the parameters on the shrinkage of the PLA material. The signal-to-noise values of the four parameters through each level are shown in Table 5. The optimal parameter combination can be determined by selecting the highest S/N value for each factor. Based on Figure 5, we can determine that the set of parameters A3, B3, C3, and D3 - corresponding to a nozzle temperature of 210 °C, a printing speed of 80 mm/s, a printing angle of 90°, and a filling percentage of 100% - is the optimal set.

The Delta S/N ratio value chart in Figure 6 shows the influence of 3D printing parameters on PLA material shrinkage, in which the printing angle parameter (printing corner C) has the most significant influence, with a Delta value of 3.3922, demonstrating an important role in distributing thermal stress and maintaining the shape of the part after printing. Next is the print head temperature (nozzle temperature A), with a Delta of 3.1568, highlighting the importance of adjusting the plastic's viscosity and controlling thermal expansion, thereby directly affecting shrinkage. Infill Density D also has a significant influence (Delta 3.0130), as high density increases strength and reduces deformation during cooling. Meanwhile, printing speed (print speed B) has the least influence (Delta 1.3692), as it only indirectly affects the cooling process and geometric stability. From these results, thermal and shaping-related factors (print angle, print head temperature, filling density) play a more important role in optimizing PLA shrinkage. In contrast, kinetic factors such as print speed have less influence and should

Table 5. S/N ratio results of PLA materials

Serial number	Nozzle temperature A (°C)	Print speed B (mm/s)	Printing corner C (°)	Infill density D (%)
Level 1	17.9151	18.7264	17.8610	17.8800
Level 2	19.4956	19.6608	19.3685	19.7096
Level 3	21.0720	20.0955	21.2532	20.8930
Delta	3.1568	1.3692	3.3922	3.0130
Rank	2	4	1	3

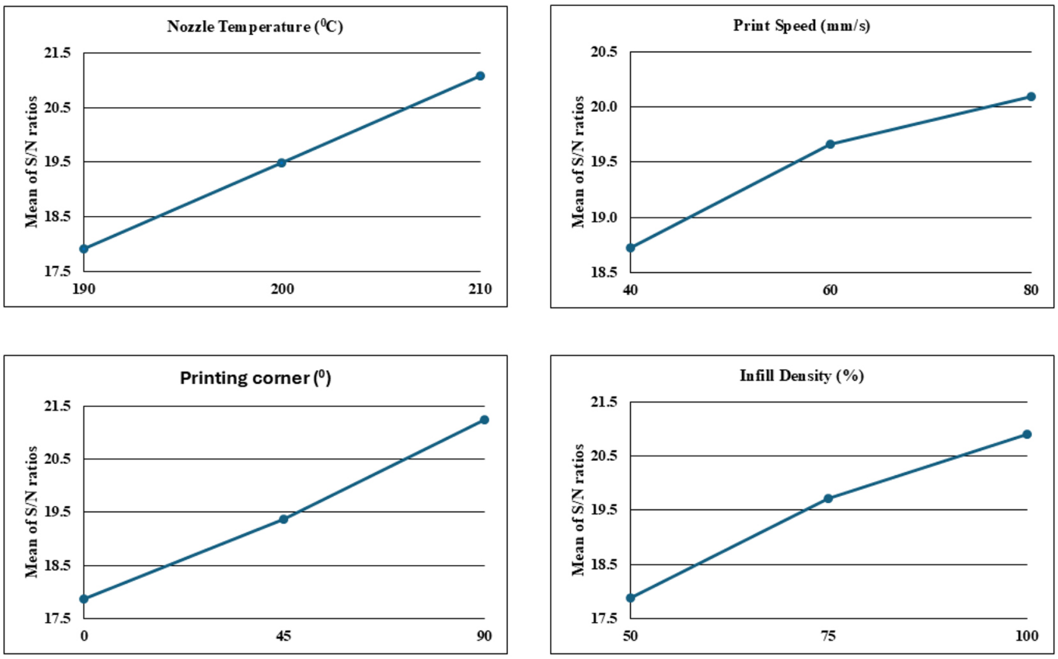

Figure 5. Effect of parameters on shrinkage of PLA material

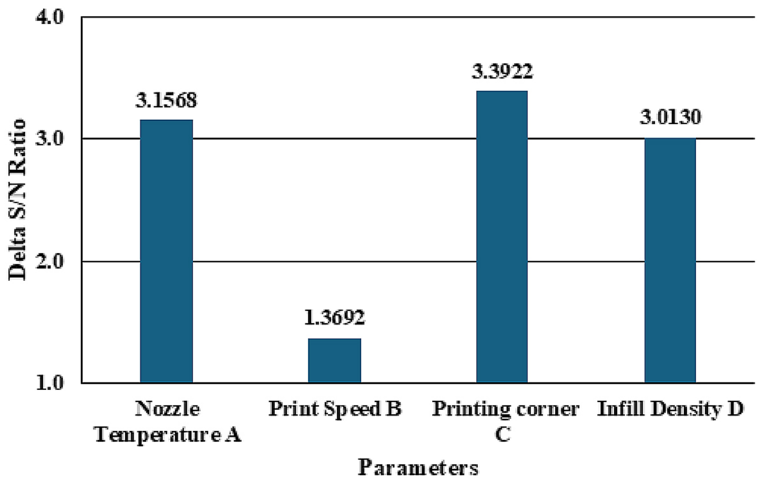

Figure 6. Delta values of factors affecting the shrinkage of PLA material

not be prioritized for adjustment when the goal is to reduce shrinkage.

In addition, the findings of this study are consistent with recent international research on dimensional accuracy and shrinkage behavior of PLA in FDM-based 3D printing. Frunzaverde et al. (2023) reported that printing parameters such as layer height and nozzle temperature significantly influence the dimensional accuracy of PLA components, mainly due to their effect on heat transfer and solidification behavior during printing. Where nozzle temperature and printing orientation (printing angle) were identified as dominant factors affecting shrinkage [24]. Similarly, Li et al. (2025) demonstrated that nozzle temperature and printing speed have a pronounced impact on dimensional deviations along different axes of PLA printed parts. Their findings which indicate that proper control of thermal-related parameters is essential for minimizing shrinkage and improving dimensional stability in FDM-printed PLA products [25]. Overall, these results confirm that the trends observed in this study are consistent with established research, thereby reinforcing the reliability and practical relevance of the proposed parameter optimization strategy.

In summary, in the PLA plastic 3D printing process, to minimize shrinkage, priority should

Table 6. ANOVA results of PLA material

Source value	Sum of squares	Degree of freedom	Mean square	F-value	P-value	%C Contribution
A	44.845	2	22.423	11.01	0.0001	24.40
B	8.8100	2	4.405	2.16	0.144	4.79
C	51.995	2	25.997	12.77	0.000	28.29
D	41.478	2	20.739	10.18	0.001	22.57
Error	36.657	18	2.036			19.95
Total	183.785	26				100
	R = 80.05%					

be given to adjusting the printing angle, nozzle temperature, filling percentage, and finally, the printing speed.

ANOVA analysis

The ANOVA method was used to determine the significance of each parameter in the designed experimental study.

From the ANOVA results Table 6, we can see that the $P_{\text{-values}}$ for factors A, C, and D are less than 0.05, indicating that these factors have a statistically significant effect on shrinkage at the 95% confidence level. On the other hand, the $P_{\text{-value}}$ for parameter B is greater than 0.05, indicating that this parameter has little effect on shrinkage in PLA plastic 3D printing technology.

At the same time, all three factors A, C, and D have $F_{\text{-values}}$ greater than [F] = 3.37, so these parameters are effective parameters for shrinkage. Parameter B has an $F_{\text{-value}}$ less than [F] = 3.37, so B is an ineffective parameter and can be eliminated.

On the other hand, based on %C, we have the influence of the parameters on the shrinkage of the PLA material during 3D printing, from high to low: printing angle, nozzle temperature, filling percentage, and finally printing speed.

CONCLUSIONS

In this study, the orthogonal array design method was applied to design 27 experiments corresponding to different parameter sets. The Taguchi method was used to determine the optimal parameter set for PLA shrinkage. The results showed that a nozzle temperature of 210 °C, a printing speed of 80 mm/s, a printing angle of 90°, and a filling percentage of 100% resulted in the least shrinkage. In addition, the ANOVA method showed the significance level of each process parameter. The results showed that nozzle temperature, printing angle, and filling percentage were significant factors affecting PLA shrinkage, whereas printing speed was not. At the same time, we also know the level of influence of each factor on PLA shrinkage: the printing angle has the most significant impact, followed by nozzle temperature; the third is filling percentage; and finally, printing speed has the least impact.

Under the optimized parameter combination, the minimum shrinkage achieved in this study was approximately 0.05%, demonstrating the effectiveness of the proposed parameter optimization approach for improving dimensional accuracy in FDM-based PLA printing. The results of this research provide a practical and systematic process for minimizing shrinkage and related defects in 3D-printed plastic products, while also establishing a reliable experimental database that can be directly applied by engineers and practitioners in industrial settings. Future work will focus on investigating the influence of controlled thermal environments, such as enclosed printing chambers, extending the proposed methodology to other thermoplastic materials, and developing predictive models to further enhance dimensional stability and process optimization in additive manufacturing.

Acknowledgements

We acknowledge Thu Dau Mot University, Ho Chi Minh City University of Technology and Education, and Material Testing Laboratory (HCMUTE). They allowed me to join their team and access the laboratory and research machines. With their appreciated support, it is possible to conduct this research.

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