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Effect of 3D Printing Parameters on Dimensional Accuracy Using the Taguchi and Response Surface Methodology (RSM)

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***Abstract*— Advances in technology in the manufacturing industry have driven the use of 3D printing as a fast and efficient prototyping solution. This study aims to optimize the process parameters of FDM 3D printing using PLA+ material with ASTM D-638-04 type specimens. The process parameters tested include printing speed, nozzle temperature, layer thickness, infill rate, and bed temperature, each at three levels. Optimization was performed using the Taguchi method and Response Surface Methodology (RSM), with a focus on dimensional accuracy (length, width, and thickness) as the primary response. The optimal parameters obtained from the Taguchi method are printing speed of 45 mm/s, nozzle temperature of 240°C, layer thickness of 0.30 mm, infill rate of 100%, and bed temperature of 55°C. Meanwhile, the RSM method yielded the following optimal parameters: printing speed of 50 mm/s, nozzle temperature of 240°C, layer thickness of 0.30 mm, infill rate of 100%, and bed temperature of 60.65°C.**

***Keyword*: 3D Printing, RSM Method, Taguchi Method, Dimensional Accuracy**

I. INTRODUCTION

Following the three previous ones, Industry 4.0 derives from the idea of the fourth industrial revolution. (Gilchrist, 2016; Xu et al., 2018). The first industrial revolution was distinguished by mechanization driven by steam power; the second was defined by mass manufacturing employing electricity; the advent of automation and information technology characterized the third (Karabegović et al., 2020; Xu et al., 2018). The current phase, Industry 4.0, is marked by the integration of digital technology into manufacturing processes, including cloud computing, smart sensors, and the Internet of Things(Karabegović et al., 2020). It aims to create smart, linked factories and supply networks to increase operating efficiency and production. (Xu et al., 2018). A great change in the manufacturing sector that merges modern digital developments with conventional industrial methods is known as Industry 4.0 (Edverton, 2024; KUMAR, 2024). The utilization of advanced data analytics, networked equipment, and the broad adoption of digital technologies across organizational structures are all part of this trend (KUMAR, 2024). Driving Industry 4.0 are the major technologies: the Internet of Things, advanced data analytics, artificial intelligence, cyber-physical systems, and additive manufacturing (Edverton, 2024). When Industry 4.0 is introduced in the industrial sector, a few administrative and technological problems show themselves. Two significant technical hurdles are a shortage of staff expertise and infrastructure. (Alsaadi, 2022). Managerial challenges encompass issues related to strategy, organization, and human resources (Bajic et al., 2021).

With the rapid development of technology in the modern era, particularly in the manufacturing sector, the concept of Industry 4.0 has become increasingly popular. The process of creating product design prototypes has become an important part of the development cycle in this field. On the other hand, the prototyping process often takes a lot of time. Therefore, a method is needed to speed up this stage, for example, by using a 3D printer. This technology has become a vital component in the industry due to its ability to produce prototypes quickly and efficiently. The term "3D printing" refers to the additive manufacturing process, which involves creating three-dimensional objects by layering material until the desired geometry is achieved. Usually referred to as 3D printing, additive manufacturing (AM) started in the 1980s with the invention of stereolithography (SLA), a method that produces items layer by layer using photopolymerization (Huang et al., 2020). Additive manufacturing (AM) has emerged as a game-changing technology across a wide range of industries, especially in aerospace. It provides notable benefits such as enhanced design flexibility, the ability to produce lightweight structures, and significantly faster prototyping (C et al., 2024;

Khorasani et al., 2022). Additive Manufacturing (AM) facilitates the fabrication of intricate geometries, patient-specific implants, and tailored scaffolds designed for applications in tissue engineering (Mobarak et al., 2023).

Currently, technological advances in manufacturing are developing rapidly. One notable innovation is the emergence of 3D printing technology as an alternative in the production process of an object. This technology enables the direct creation of solid objects from digital files through a layered printing process, revolutionizing conventional methods of producing components and prototypes. Additive manufacturing, or 3D printing, is the process of building three-dimensional objects by gradually adding material layer after layer until the entended form is reached. (Helena et al., 2020). This technology has attracted considerable interest across multiple industries for its capability to manufacture intricate structures rapidly and at a reduce cost. (Helena et al., 2020).

The goal of a research study is to reduce surface roughness in PLA-printed goods by improving the FDM 3D printing process parameters. (Rosyadi et al., 2024). The work employed an L27 orthogonal array and the Taguchi method to systematically vary six important parameters: orientation, infill pattern, layer thickness, printing speed, infill density, and nozzle temperature. The findings show that nozzle temperature and printing speed are the most significant variables influencing surface quality; the ideal settings are 200°C for the nozzle, 100% infill density, 90 mm/s printing speed, 0.25 mm layer thickness, hexagonal infill pattern, and 30° orientation. Surface roughness measurements and ANOVA analysis supported these findings, and additional tests demonstrated how well the modified parameters produced smoother 3D printed surfaces.

Nugraha et al. (2022) describe how to optimize variables in the Fused Deposition Modeling (FDM) 3D printing process.(Nugraha & Wahyujati, 2022). The focus is on the use of recycled filament made from polypropylene (PP) plastic. The aim is to determine the optimal print temperature (print temperature), layer thickness (layer thickness), and print speed (print speed) to produce printed products with optimal dimensional quality and tensile strength. By using recycled plastic as the material for 3D printing filament, this study also aims to reduce the amount of plastic waste. For ASTM D638-10 Type 1 tensile test specimens, a print temperature of approximately 260°C, a layer thickness of 0.12 mm, and a print speed of 50 mm/s are the optimal choices. Printing temperature and layer thickness have a significant influence on the tensile strength of printed products, while printing speed does not have a significant influence, according to statistical ANOVA analysis. The mathematical model generated from the Box-Behnken Response Surface Methodology (RSM) can predict the most suitable parameter combinations to achieve the best printing results.

The research I conducted on dimensional accuracy in FDM 3D printing machines using PLA+ (Polylactic Acid) filament material with ASTM D-638-04 type specimens, using parameters to obtain length, width, and thickness dimensions with the process parameters used being printing speed (40 mm/s), (45 mm/s), (50 mm/s), nozzle temperature (240°C), (245°C), (250°C), layer thickness (0.20 mm), (0.25 mm), (0.30 mm), infill rate (98%), (99%), (100%), and bed temperature (55°C), (60°C), (65°C). The optimization of these process parameters was performed using the Taguchi method and RSM to print products using 5 parameters and 3 levels in the dimensional accuracy response.

This study aims to identify the most suitable parameters for the 3D printing process using PLA+ (polylactic acid) filament to achieve the desired length, width, and thickness of the printed object. The analysis method applied in this study is based on a review and evaluation of various relevant previous studies to support the achievement of accurate and high-quality results.

Optimization of the 3D printing process can be done by utilizing the Taguchi method and Response Surface Methodology (RSM) with the help of Minitab software. These two methods are proposed in this study to analyze the relationship between process variables and optimize the output response. In this context, the Taguchi method and RSM are used to examine and determine the best parameters to improve the dimensional accuracy of the printed results using PLA+ filament. Based on reviews of previous studies, this approach has proven effective in addressing process optimization issues and contributing to product quality improvement by identifying the most optimal parameter values.

II. RESEARCH METHOD

II. 1. 3D Printing

3D printing is one of the additive manufacturing technologies that can print a 3-dimensional (3D) object at a relatively low cost and in a short period of time. This is very useful for faster manufacturing processes. Fused Deposition Modeling (FDM) is a widely adopted 3D printing technique due to its ease of use, accuracy, and low cost (Cano-Vicent et al., 2021). It creates 3D structures by layer-wise extrusion of melted plastic filaments, allowing for the production of complex geometries. The tests were conducted by ASTM D-638-04 specimen standards using a Creality K1 FDM-based 3D printer with dimensions of 220 mm x 220 mm x 250 mm.

II. 2. Material PLA

PLA (Polylactic Acid) material was chosen as the filament in 3D printers because PLA is a filament material that is very often used for 3D printing processes with FDM systems. Polylactic acid (PLA) is a biodegradable polymer gaining attention as an alternative to conventional plastics in various industries (Hussain et al., 2024). While PLA exhibits promising strength and stiffness, it faces challenges such as brittleness and slow composting rates (Multari & Pearson, 2024).

II. 3. DOE (Design of Experiment)

a) Taguchi Method

Taguchi's method uses a structured matrix called an Orthogonal Array to determine the minimum number of trials required to obtain comprehensive information about the variables. This matrix enables efficient experimentation with systematic variation in input parameters, while ensuring a balanced combination of variable levels and statistically meaningful results. (Alenezi et al., 2022). The Taguchi approach is an important development of the Design of Experiments (DOE) method, which provides a structured and efficient way to design and conduct experiments. Its main focus is to improve quality by minimizing variation and finding optimal conditions through robust design. Taguchi loss functions are divided into three types: Nominal-is-Best (values closest to the target are best), Smaller-is-Better (smaller values are better, e.g., for error rates), and Larger-is-Better (larger values are better, such as for strength or efficiency) (George & Tembhurkar, 2022).

b) RSM Method

Response Surface Methodology (RSM) is a statistical technique employed to enhance processes and investigate the connections between input factors and resulting responses. (A, 2023). RSM includes experimental design methods to explore parameter space, data-based statistical modeling to establish estimated relationships between process variables and results, and optimization techniques to determine the optimal values of process variables (Sarabia & Ortiz, 2009).

c) Orthogonal Array Matrix

In this study, five controllable factors were selected, each at three levels. These factors included print speed (mm/s), nozzle temperature (°C), layer thickness (mm), infill level (%), and bed temperature (°C). The experimental design used an orthogonal $L2^7$ (3^5) arrangement, consisting of 5 factors with a total of 27 experimental combinations in the Taguchi method and 92 combinations in the RSM method, each repeated twice.

Table 1
Level Setting

Independent Variable	Level 1	Level 2	Level 3
Printing Speed	40	45	50
Nozzle Temperature	240	245	250
Layer Thickness	0,20	0,25	0,30
Infill Rate	98	99	100
Bed Temperature	55	60	65

Table 2
Orthogonal Array Matrix

No.	printing speed (mm/s)	nozzle temperature (°C)	layer thickness (mm)	Infill rate (%)	bed temperature (°C)
1	40	240	0,20	98	55
2	40	240	0,20	98	60
3	40	240	0,20	98	65
4	40	245	0,25	99	55
5	40	245	0,25	99	60
6	40	245	0,25	99	65
7	40	250	0,30	100	55
8	40	250	0,30	100	60
9	40	250	0,30	100	65
10	45	240	0,25	100	55
11	45	240	0,25	100	60
12	45	240	0,25	100	65
13	45	245	0,30	98	55
14	45	245	0,30	98	60
15	45	245	0,30	98	65
16	45	250	0,20	99	55
17	45	250	0,20	99	60
18	45	250	0,20	99	65
19	50	240	0,30	99	55
20	50	240	0,30	99	60
21	50	240	0,30	99	65
22	50	245	0,20	100	55
23	50	245	0,20	100	60
24	50	245	0,20	100	65
25	50	250	0,25	98	55
26	50	250	0,25	98	60
27	50	250	0,25	98	65

$$d\quad(f) = \Sigma\, l - 1 \qquad (1)$$

d = degree of freedom
f = factor
L = level of each factor

By applying the formula mentioned above, the degrees of freedom (DOF) for each factor can be calculated as follows:

$$d\quad(A) = 3 - 1 = 2$$
$$d\quad(B) = 3 - 1 = 2$$
$$d\quad(C) = 3 - 1 = 2$$
$$d\quad(D) = 3 - 1 = 2$$
$$d\quad(E) = 3 - 1 = 2$$

d) S/N Ratio (Signal to Noise Ratio)

The Signal-to-Noise ratio is used to evaluate each factor's role in reducing response variability and enhancing product consistency, identifying key parameters affecting output quality (Rashid, 2023). Based on the type of quality characteristic (smaller is better, larger is better, or target is best), the S/N ratio is calculated and used to find optimal settings for controllable factors (Mitra, 2011). This study applies to the Nominal-the-better criterion, suitable when a fixed target is desired, with the S/N ratio indicating process accuracy and stability by measuring how closely results align with the nominal value. The following formula can be used to calculate the SN ratio:

- Smaller the better

$$S\quad K_{s} = -10\, l\quad \left[\frac{1}{n}\sum_{i}^{n} y_i^2\right] \qquad (2)$$

$S\quad K_{s}$ = S/N Smaller the better
n = Amount of Data
y_i = i-th data

- Nominal the better

$$S\quad K_{n} = 10 \log\left[\frac{\mu^2}{\sigma^2}\right] \qquad (3)$$

$S\quad K_{n}$ = S/N Nominal, the better
μ = Average of Data

σ = Variation of Data

- The larger the better

$$S\ N_{L_i} = 10\log\left[\frac{1}{n}\sum_{i}^{n}\frac{1}{y_i^2}\right] \qquad (4)$$

$S\ N_{L_i}$ = S/N The Larger the better
n = Amount of Data
y_i = i-th data

e) Multiple Regression Analysis and Analysis of Variance (ANOVA)

To determine the influence of each process parameter and the significance of experimental variables, regression analysis and ANOVA (Analysis of Variance) were employed (Perzyk et al., 2008). The steps involved in the multiple regression process are expressed through the following equation:

$$y_1 = \beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4+\beta_5x_5+\varepsilon \qquad (5)$$

$$y_2 = \beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4+\beta_5x_5+\varepsilon \qquad (6)$$

$$y_3 = \beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4+\beta_5x_5+\varepsilon \qquad (7)$$

Were,
y_1 = response variable (length)
y_2 = response variable (width)
y_3 = response variable (thickness)
x_1, x_2, x_3, x_4, x_5 = Independent Variable
$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ = Coefficient Regression

Stages in working on multiple regression:

- Find the values of $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$
- The simultaneous correlation coefficient (R) and the coefficient of determination (R2) must be computed to ascertain the strength of the link. R² shows the percentage of the response variable's variance that the model can account for, whereas R represents the overall correlation between all independent variables and the dependent variable. The simultaneous correlation (R) is calculated using the following formula.

$$R = \sqrt{\frac{\beta_1.\sum x_1y + \beta_2.\sum x_2y + \ldots\beta_n.\sum x_ny}{\sum y^2}} \qquad (8)$$

- Perform an-F test

$$F = \frac{(R^2)/(k-1)}{(1-R^2)\,/\,(n-k)} \qquad (9)$$

K = number of independent variables, including intercept or constant (β0)
n = number of data points

II. 4. GRA Method (Grey Relational Analysis)

Grey Relational Analysis serves as a powerful approach for optimizing problems involving multiple responses by transforming them into an equivalent single-response optimization task (Fung & Tien, 2005). Through Grey Relational Analysis, Grey Relational Grade values are obtained to evaluate multiple responses (multiresponse), so that optimization of complex multiresponse can be converted into optimization of a single response with Grey Relational Grade as its objective function.

- Normalization

$$x'_i(k) = 1-\left|\frac{x_i(k)-x_U(k)}{m\quad |x_j(k)-x_U(k)|}\right| \qquad (10)$$

$x'_i(k)$ = Actual value of data-i
$x_U(k)$ = Target value (average of all data in that column)
$m\quad |x_j(k) - x_U(k)|$ = Maximum deviationfrom the target value

- Grey Relational Coefficient (GRC)

$$\gamma_i = \frac{\Delta_m + \zeta\,.\,\Delta_m}{\Delta_i + \zeta\,.\,\Delta_m} \qquad (11)$$

$$\Delta_i = |1 - x'_i| \qquad (12)$$

γ_i = GRC value for data-i, which shows how close the i data point is to the reference data
Δ_i = The absolute difference between the reference data and data-i
Δ_m = Minimum value of all Δ_i
Δ_m = Maximum value of all Δ_i
ζ = Differential coefficient (distinguishing coefficient), usually ranges between 0 Dan 1. Generally, ζ = 0,5 is used to balance sensitivity.

- Grey Relational Grade (GRG)

$$G\quad_i = \frac{1}{n}\sum_{k=1}^{n}\gamma_i(k) \qquad (13)$$

$G\quad_i$ = GRG for the i data point
$\gamma_i(k)$ = GRG for criterion k on data i
n = number of criteria (length, width, thickness)

II. 5. Research Process Diagram

To systematically investigate the influence of various process parameters on the mechanical properties of 3D-printed specimens and optimize the printing conditions, this study employed a structured experimental approach. The research methodology involved designing experiments using orthogonal arrays, followed by specimen preparation, dimensional measurements, and comprehensive statistical analysis. The workflow, depicted in Figure 1, outlines the step-by-step procedure, starting from determination and level setting, progressing through specimen design and printing, and concluding with advanced analyses such as Taguchi methods, Response Surface Methodology (RSM), Grey Relational Analysis (GRA), regression modeling, and final optimization**.**

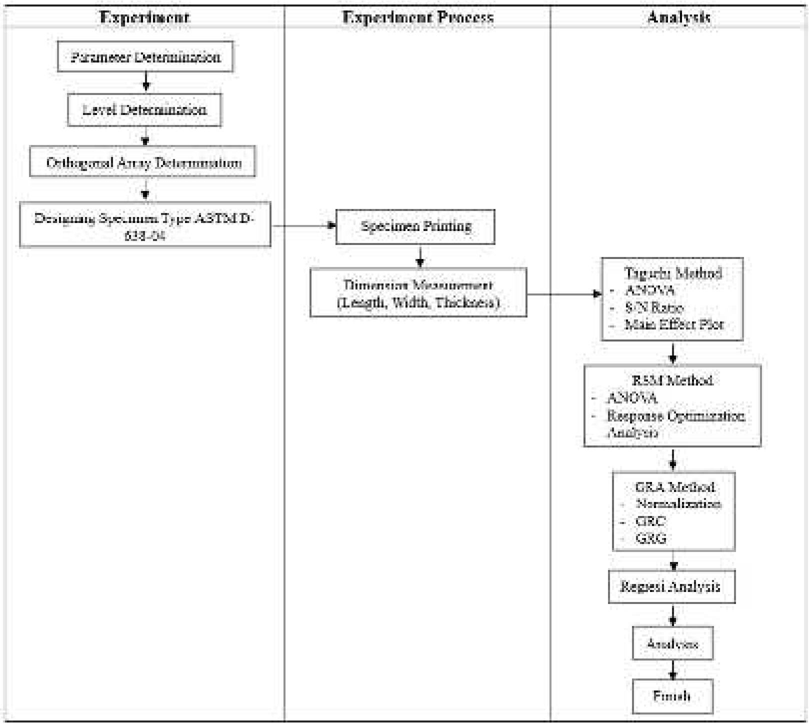


Figure 1: Research Process Diagram

III. RESULT AND DISCUSSION

III.1. Result

This section presents the findings of the statistical analyses conducted to evaluate the influence of process parameters on the geometrical accuracy of 3D-printed specimens. The primary objective was to identify significant variables and establish predictive models that can be used for process optimization. Two major statistical approaches were employed: the Taguchi method and Response Surface Methodology (RSM). Both methods were used to model the relationships between input parameters and output responses, enabling both single- and multi-objective optimization.

1. Taguchi Analysis

a) Dimensional Measurement of Specimen

Measurements on the specimens were conducted according to the specimen design outlined in ASTM Type 4 standards, with the standard dimensions as shown in Figure 2:

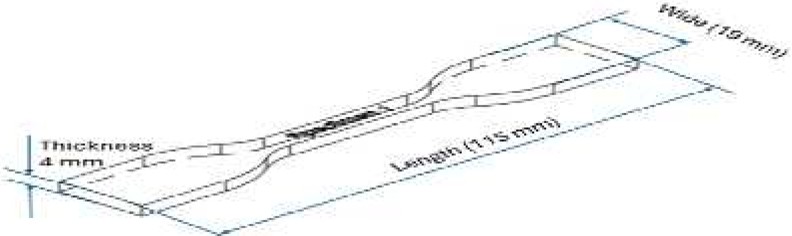


Figure 2: Specimen Dimensional

The dimensional measurement results of the specimens produced using the 3D printing machine are summarized in Table 3.

Table 3
Results of Measurement Dimension Specimen

No Experiment	printing speed (mm/s)	nozzle temperature (°C)	layer thickness (mm)	Infill rate	bed temperature (°C)	Result of measurement		
						Length	Wide	Thickness
1	40	240	0,20	98	55	114,800	18,590	3,380
2	40	240	0,20	98	60	114,800	18,440	3,570
3	40	240	0,20	98	65	114,800	18,400	3,360
4	40	245	0,25	99	55	114,780	18,590	3,440
5	40	245	0,25	99	60	114,800	18,305	3,375
6	40	245	0,25	99	65	114,630	18,670	3,270
7	40	250	0,30	100	55	114,650	18,480	3,480
8	40	250	0,30	100	60	114,650	18,580	3,415
9	40	250	0,30	100	65	114,730	18,730	3,510
10	45	240	0,25	100	55	114,650	18,590	3,490
11	45	240	0,25	100	60	114,650	18,400	3,425
12	45	240	0,25	100	65	114,700	18,670	3,300
13	45	245	0,30	98	55	114,750	18,450	3,520
14	45	245	0,30	98	60	114,680	18,510	3,475
15	45	245	0,30	98	65	114,720	18,570	3,445
16	45	250	0,20	99	55	114,800	18,530	3,405
17	45	250	0,20	99	60	114,840	18,410	3,380
18	45	250	0,20	99	65	114,750	18,585	3,455
19	50	240	0,30	99	55	114,780	18,480	3,555
20	50	240	0,30	99	60	114,790	18,510	3,500
21	50	240	0,30	99	65	114,690	18,490	3,420
22	50	245	0,20	100	55	114,750	18,450	3,430
23	50	245	0,20	100	60	114,730	18,330	3,420
24	50	245	0,20	100	65	114,790	18,415	3,290
25	50	250	0,25	98	55	114,770	18,510	3,420
26	50	250	0,25	98	60	114,780	18,490	3,370
27	50	250	0,25	98	65	114,870	18,495	3,345

b) ANOVA Analysis

The Analysis of Variance (ANOVA) for the Signal-to-Noise (S/N) ratios was conducted to evaluate the significance of each process parameter in influencing the robustness of the system. The results, presented in Figure 4, indicate that layer thickness had a statistically significant effect on the S/N ratio, as evidenced by an F-value of 52.01 and a p-value of 0.022, which is well below the conventional threshold of 0.05. This suggests that variations in layer thickness significantly impact the system's robustness compared to other parameters.

Analysis of Variance for SN ratios

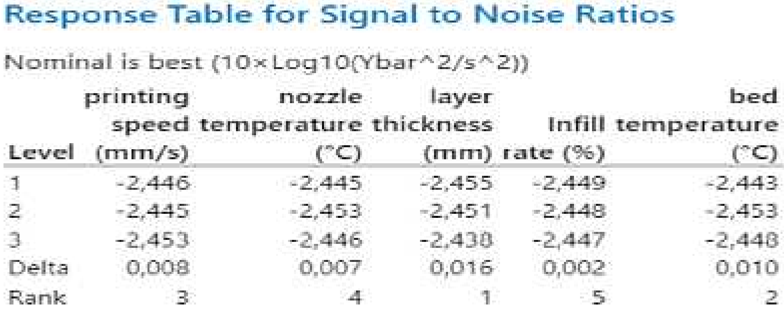
Source	DF	Seq SS	Adj SS	Adj MS	F	P
printing speed (mm/s)	2	0,000401	0,000401	0,000200	1,51	0,250
nozzle temperature (°C)	2	0,000283	0,000283	0,000142	1,07	0,367
layer thickness (mm)	2	0,001291	0,001291	0,000645	4,87	0,022
Infill rate (%)	2	0,000017	0,000017	0,000009	0,06	0,938
bed temperature (°C)	2	0,000431	0,000431	0,000216	1,63	0,228
Residual Error	16	0,002121	0,002121	0,000133		
Total	26	0,004544				

Figure 3: ANOVA Result

In contrast, the other process parameters—printing speed, nozzle temperature, infill rate, and bed temperature—did not show significant effects on the S/N ratio. Their respective p-values were all greater than 0.05 (ranging from 0.396 to 0.930), indicating that these factors do not contribute substantially to the variability in the response. The residual error accounted for the remaining unexplained variance in the model.

c) Signal-to-Noise Ratios Analysis

The Signal-to-Noise (S/N) ratio analysis was conducted to evaluate the robustness of the process against variations in experimental conditions. The S/N ratios were calculated using the "Nominal is best" criterion, which is appropriate for responses where the target value is optimal and deviations from this target are undesirable. The results, presented in Figure 3, indicate that the layer thickness parameter had the highest impact on the S/N ratio, as evidenced by its rank of 1 and a delta value of 0.016. This suggests that variations in layer thickness significantly affect the robustness of the process compared to other parameters. In contrast, the bed temperature parameter ranked second (rank = 2) with a delta value of 0.010, indicating its moderate influence on the S/N ratio. The printing speed, nozzle temperature, and infill rate showed minimal differences in S/N ratios across their respective levels, as reflected by their small delta values (0.008, 0.007, and 0.002, respectively). These findings highlight that layer thickness plays a critical role in ensuring process stability and minimizing variability, while other parameters contribute less to the robustness of the system.



Response Table for Signal to Noise Ratios

Nominal is best (10×Log10(Ybar^2/s^2))

Level	printing speed (mm/s)	nozzle temperature (°C)	layer thickness (mm)	Infill rate (%)	bed temperature (°C)
1	-2,446	-2,445	-2,455	-2,449	-2,443
2	-2,445	-2,453	-2,451	-2,448	-2,453
3	-2,453	-2,446	-2,438	-2,447	-2,448
Delta	0,008	0,007	0,016	0,002	0,010
Rank	3	4	1	5	2

Figure 4: Response Table for S/N Ratios of Length, Width, and Thickness

d) Main Effect Plot S/N Ratios Analysis

The Main Effects Plot for Signal-to-Noise (S/N) Ratios provides a visual representation of how each process parameter influences the robustness of the system. The plot illustrates the meaning S/N ratios across different levels of five key parameters: printing speed (mm/s), nozzle temperature (°C), layer thickness (mm), infill rate (%), and bed temperature (°C).

The results indicate that layer thickness has the most significant impact on the S/N ratio, as evidenced by its steep decline in the plot (Figure 4). This suggests that variations in layer thickness led to substantial changes in the system's robustness compared to other parameters. In contrast, the effects of printing speed, nozzle temperature, infill rate, and bed temperature appear relatively minor, with their respective lines showing minimal fluctuations across different levels.

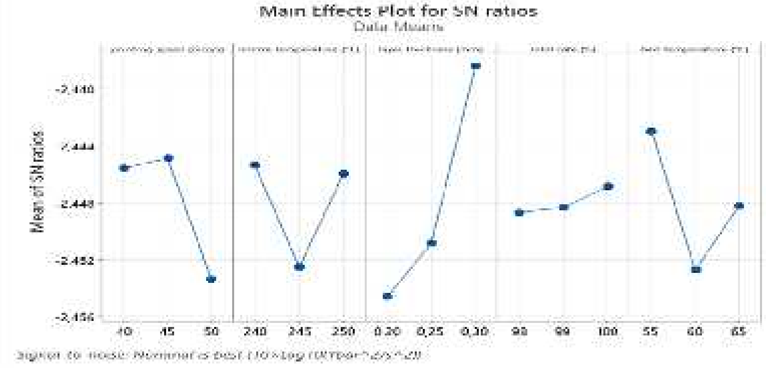


Figure 4: Main Effect Plot for S/N Ratios of Length, Width, and Thickness

2. RSM Analysis

a) Dimensional Measurement

The results of the specimen measurements conducted using Response Surface Methodology (RSM) are summarized in Table 4.

Table 4
Results of Measurement Specimen for RSM

No Experiment	printing speed (mm/s)	nozzle temperature (°C)	layer thickness (mm)	Infill rate	bed temperature (°C)	Result of measurement		
						Length	Wide	Thickness
1	40	240	0,25	99	60	114,520	18,605	3,470
2	50	240	0,25	99	60	114,590	18,485	3,535
3	40	250	0,25	99	60	114,560	18,500	3,635
4	50	250	0,25	99	60	114,590	18,490	3,600
5	45	245	0,2	98	60	114,530	18,555	3,450
6	45	245	0,3	98	60	114,500	18,410	3,470
7	45	245	0,2	100	60	114,550	18,500	3,510
8	45	245	0,3	100	60	114,530	18,600	3,390
9	45	240	0,25	99	55	114,560	18,340	3,540
10	45	250	0,25	99	55	114,420	18,490	3,500
11	45	240	0,25	99	65	114,500	18,580	3,390
12	45	250	0,25	99	65	114,480	18,650	3,500
13	40	245	0,2	99	60	114,470	18,570	3,460
14	50	245	0,2	99	60	114,470	18,470	3,510
15	40	245	0,3	99	60	114,540	18,370	3,380
16	50	245	0,3	99	60	114,590	18,450	3,580
17	45	245	0,25	98	55	114,580	18,460	3,550
18	45	245	0,25	100	55	114,570	18,630	3,500
19	45	245	0,25	98	65	114,460	18,340	3,575
20	45	245	0,25	100	65	114,480	18,460	3,550
21	45	240	0,2	99	60	114,580	18,515	3,390
22	45	250	0,2	99	60	114,580	18,480	3,380
23	45	240	0,3	99	60	114,480	18,465	3,500
24	45	250	0,3	99	60	114,480	18,565	3,480
25	40	245	0,25	98	60	114,480	18,605	3,490
26	50	245	0,25	98	60	114,530	18,478	3,490
27	40	245	0,25	100	60	114,530	18,660	3,510
28	50	245	0,25	100	60	114,530	18,450	3,500
29	45	245	0,2	99	55	114,430	18,390	3,380
30	45	245	0,3	99	55	114,460	18,400	3,495
31	45	245	0,2	99	65	114,530	18,500	3,460
32	45	245	0,3	99	65	114,540	18,640	3,430
33	40	245	0,25	99	55	114,590	18,472	3,396
34	50	245	0,25	99	55	114,535	18,518	3,574
35	40	245	0,25	99	65	114,538	18,359	3,507
36	50	245	0,25	99	65	114,492	18,479	3,536
37	45	240	0,25	98	60	114,535	18,556	3,448
38	45	250	0,25	98	60	114,526	18,439	3,529
39	45	240	0,25	100	60	114,513	18,341	3,504
40	45	250	0,25	100	60	114,586	18,446	3,517
41	45	245	0,25	99	60	114,452	18,586	3,479
42	45	245	0,25	99	60	114,687	18,348	3,514
43	45	245	0,25	99	60	114,453	18,402	3,458
44	45	245	0,25	99	60	114,602	18,509	3,620
45	45	245	0,25	99	60	114,506	18,569	3,426
46	45	245	0,25	99	60	114,483	18,483	3,471
47	40	240	0,25	99	60	114,506	18,330	3,494
48	50	240	0,25	99	60	114,524	18,482	3,496
49	40	250	0,25	99	60	114,464	18,591	3,505
50	50	250	0,25	99	60	114,514	18,499	3,479
51	45	245	0,2	98	60	114,540	18,526	3,429
52	45	245	0,3	98	60	114,458	18,476	3,470
53	45	245	0,2	100	60	114,461	18,507	3,393
54	45	245	0,3	100	60	114,527	18,434	3,520
55	45	240	0,25	99	55	114,577	18,330	3,373
56	45	250	0,25	99	55	114,451	18,466	3,498
57	45	240	0,25	99	65	114,631	18,418	3,553
58	45	250	0,25	99	65	114,437	18,550	3,484
59	40	245	0,2	99	60	114,516	18,445	3,529
60	50	245	0,2	99	60	114,587	18,358	3,455
61	40	245	0,3	99	60	114,524	18,674	3,522
62	50	245	0,3	99	60	114,464	18,558	3,519
63	45	245	0,25	98	55	114,531	18,481	3,484
64	45	245	0,25	100	55	114,556	18,404	3,513
65	45	245	0,25	98	65	114,538	18,514	3,575
66	45	245	0,25	100	65	114,507	18,388	3,485
67	45	240	0,2	99	60	114,522	18,439	3,391
68	45	250	0,2	99	60	114,415	18,487	3,489
69	45	240	0,3	99	60	114,567	18,452	3,640
70	45	250	0,3	99	60	114,464	18,590	3,387
71	40	245	0,25	98	60	114,458	18,537	3,590
72	50	245	0,25	98	60	114,427	18,501	3,452
73	40	245	0,25	100	60	114,561	18,494	3,491
74	50	245	0,25	100	60	114,453	18,516	3,444
75	45	245	0,2	99	55	114,480	18,419	3,550
76	45	245	0,3	99	55	114,456	18,558	3,495
77	45	245	0,2	99	65	114,481	18,590	3,484
78	45	245	0,3	99	65	114,469	18,450	3,527
79	40	245	0,25	99	55	114,496	18,503	3,610
80	50	245	0,25	99	55	114,526	18,492	3,455
81	40	245	0,25	99	65	114,547	18,504	3,490
82	50	245	0,25	99	65	114,528	18,573	3,667
83	45	240	0,25	98	60	114,506	18,455	3,556
84	45	250	0,25	98	60	114,505	18,638	3,635
85	45	240	0,25	100	60	114,583	18,651	3,583
86	45	250	0,25	100	60	114,474	18,444	3,465
87	45	245	0,25	99	60	114,528	18,514	3,454
88	45	245	0,25	99	60	114,422	18,562	3,366
89	45	245	0,25	99	60	114,479	18,534	3,439
90	45	245	0,25	99	60	114,580	18,751	3,526
91	45	245	0,25	99	60	114,521	18,528	3,481
92	45	245	0,25	99	60	114,496	18,499	3,377

b) ANOVA Analysis for RSM

The Analysis of Variance (ANOVA) was conducted to evaluate the statistical significance of the Response Surface Methodology (RSM) models for the three-dimensional responses: Length, Width, and Thickness. The results are summarized below:

- **Length**

The ANOVA analysis for the Length response revealed that the overall model was not statistically significant, as indicated by an F-test p-value of 0.917 (>0.05). None of the individual process parameters or their interaction terms showed significant effects on the length, with all p-values exceeding the conventional threshold of 0.05. Furthermore, the adjusted R-squared value was 0.00%, indicating that the model failed to explain any variability in the length measurements under the current experimental design.

- **Width**

Similarly, the ANOVA for the Width response also indicated that the RSM model was not statistically significant, with an F-test p-value of 0.901 (>0.05). No main effects or interaction terms were found to have a significant influence on the width, as all p-values were greater than 0.05. The adjusted R-squared value was also 0.00%, suggesting that the model did not capture any meaningful variation in the width response.

- **Thickness**

For the Thickness response, the ANOVA results showed that the overall model was again not statistically significant, with an F-test p-value of 0.193 (>0.05). Similar to the other responses, none of the process parameters or their interactions exhibited significant effects on thickness, as all p-values were above 0.05. The adjusted R-squared value was 0.00%, reinforcing the conclusion that the model lacked explanatory power for this response.

- **Summary**

In summary, the ANOVA analyses for all three-dimensional responses (Length, Width, and Thickness) consistently demonstrated that the RSM models were not statistically significant. None of the process parameters or their interactions showed meaningful influence on the responses, and the adjusted R-squared values were all 0.00%, indicating that the models failed to explain any variability in the data. These findings suggest that either the relationships between the process parameters and the dimensional responses are more complex than captured by the current model structure, or additional factors outside the scope of this study may be influencing the outcomes. Further investigation or refinement of the experimental design may be necessary to improve model performance and identify key influential parameters.

c) Response Optimization Analysis

In this study, response optimization was performed to determine the values of process parameters consisting of print speed, nozzle temperature, layer thickness, infill rate, and bed temperature. The composite desirability (D) is calculated as 0.2951, which indicates the overall performance of the system across all three responses. The current desirability (Cur) suggests that the current settings are close to the optimal conditions.

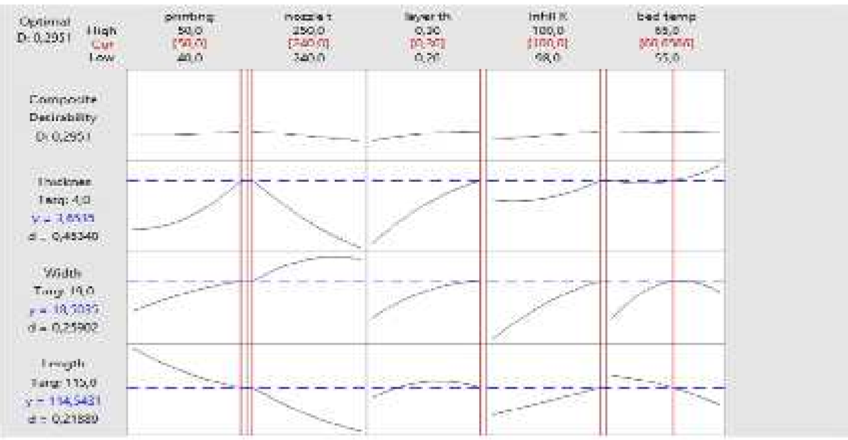


Figure 5: Response Optimization

Based on the Figure 5 response optimization graph, it shows that the response variables for the parameters of printing speed, nozzle temperature, layer thickness, infill rate, and bed temperature that are most optimal are 50 mm/s, 240°C, 0,30 mm, 100%, and 60,65°C.

3. Grey Relational Analysis (GRA)

Based on GRA calculations for the Taguchi method, the Grey Relational Grade (GRG) value was obtained from two replications with a total of 27 experimental combinations in each replication. The GRG values show a fairly wide variation, with the GRG range in replication 1 between 0.389 and 0.942, while in replication 2 it ranges from 0.487 to 0.887.

Based on the GRA calculations for the RSM method, the Grey Relational Grade (GRG) values were obtained from two replications with a total of 92 experimental combinations in each replication. The GRG values showed considerable variation, ranging from 0.482 to 0.952 in the first replication and from 0.517 to 0.906 in the second replication.

4. Regression Analysis

In the Taguchi method regression results, the Taguchi method passed the multicollinearity test (VIF), autocorrelation test (Durbin Watson), normality test (Kolmogorov Smirnov), heteroscedasticity test (Glejser), multiple linear regression, F test, and coefficient of determination. In the hypothesis test (T-test), replication 1 had significant parameters, namely printing speed and bed temperature, while replication 2 had significant parameters, namely printing speed and layer thickness. Meanwhile, the RSM method passed the multicollinearity test (VIF), autocorrelation test (Durbin Watson), normality test (Kolmogorov-Smirnov), heteroscedasticity test (Glejser), multiple linear regression, hypothesis testing (T-test), and coefficient of determination, replication 1 and 2 had no significant effect or no effect on the dependent variable.

III.2. Discussion

The results of this study demonstrate that the Taguchi method successfully identified optimal parameters at a printing speed of 45 mm/s, nozzle temperature of 240°C, layer thickness of 0.30 mm, infill rate of 100%, and bed temperature of 55°C. In contrast, the RSM method yielded different optimal parameters: printing speed of 50 mm/s, nozzle temperature of 240°C, layer thickness of 0.30 mm, infill rate of 100%, and bed temperature of 60.65°C. In addition, (Nugraha & Wahyujati, 2022) Demonstrated that printing temperature and layer thickness significantly influence mechanical properties, which aligns with this study's finding that layer thickness notably affects dimensional accuracy, as confirmed by both the significant p-value (0.022) in the ANOVA results and the regression model of the Taguchi experiments.

The regression analysis performed on the RSM experimental data did not yield statistically significant results. None of the individual process parameters showed significant p-values, indicating that within the ranges investigated, no single factor had a dominant influence on dimensional accuracy. Additionally, the regression models generated from the RSM data exhibited low R^2 values, reflecting a poor fit between the predicted and actual measurements. This suggests that the selected parameter ranges or experimental design in RSM were insufficient to capture the underlying relationships influencing dimensional accuracy, ultimately limiting the model's predictive capability. This outcome supports (Alenezi et al., 2022), who emphasized that RSM requires homogeneous and stable data for effective modeling.

The study's limitations may have led to the low R^2 values in the RSM models. Future research should examine a broader range of parameters and include variables like cooling fan speed or nozzle diameter to build a better predictive model. Additionally, exploring other multi-response optimization methods, such as TOPSIS, could help assess their effectiveness compared to GRA in improving print quality.

IV. CONCLUSIONS

Based on research findings related to the effects of process parameters in 3D printing on dimensional accuracy through the application of the Taguchi method and Response Surface Methodology (RSM), the analysis shows that the optimal parameters in the Taguchi method are printing speed of 45 mm/s, nozzle temperature of 240°C, layer thickness of 0.30 mm, infill rate of 100%, and bed temperature of 55°C. Meanwhile, using the RSM method, the optimal parameters were obtained at a printing speed of 50 mm/s, nozzle temperature of 240°C, layer thickness of 0.30 mm, infill rate of 100%, and bed temperature of 60.65°C.

Based on regression analysis, in the Taguchi method, the variables that have a significant effect are printing speed, layer thickness, and bed temperature, while in the RSM method, there are no variables that have a significant effect.

This indicates that the Taguchi method is more robust against data variability and remains capable of producing a valid regression model, while the RSM method is more sensitive to data stability and the form of relationships between variables.

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