Jurnal Polimesin
Department of Mechanical Engineering
State Polytechnic of Lhokseumawe
http://e-jurnal.pnl.ac.id/polimesin

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|---|---|---|---|---|---|
| e-ISSN | : 2549-1999 | No. | : 6 | Month | : December |
| p-ISSN | : 1693-5462 | Volume | : 22 | Year | : 2024 |

Article Processing Dates: Received on 2024-09-19, Reviewed on 2024-11-20, Revised on 2024-11-22, Accepted on 2024-11-28 and Available online on 2024-12-30

# Material and process parameter optimization for dimensional accuracy in Fused Deposition Modeling 3D printing

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## Abstract

The production of complex machine components requires advanced and accurate techniques. Achieving optimal quality through 3D printing involves carefully examining the process parameters. However, many studies have not thoroughly explored the impact of these parameters on parts produced using Fused Deposition Modeling (FDM) 3D printing. This study evaluates how process parameters and material variations affect the dimensional accuracy of printed parts. The study focuses on input variables such as material type, infill density, infill pattern, and raster angle. Using the fractional $L_9$ Taguchi method, the optimal settings identified were PLA+ material, 80% infill density, an infill grid pattern, and a 0° raster angle, resulting in a 1.39%-dimensional deviation and an S/N ratio of -3.29 dB. ANOVA analysis reveals material type as the most significant factor, contributing 49.81% to performance. These findings, complemented by statistical analyses, can guide decision-making in industrial applications and serve as a reference for selecting FDM 3D printing settings related to dimensional accuracy to print components in the industry.

**Keywords:**
3D printing, ANOVA, percentage deviation, signal-to-noise.

## 1 Introduction

Additive Manufacturing (AM) encompasses a range of manufacturing techniques that create components or parts by directly printing from CAD design models without requiring additional tooling [1]. This process involves building products by sequentially layering materials according to CAD designs [2], [3]. Common AM processes include Stereolithography (SLA), Laminated Object Manufacturing (LOM), Selective Laser Sintering (SLS), Selective Laser Melting (SLM), and Fused Deposition Modeling (FDM) [4]. These technologies are constantly evolving to enhance production efficiency and achieve the desired geometric properties in the final products. Consequently, most AM technologies are recognized for their material efficiency [5]. Fused Deposition Modeling (FDM) is one of the most widely adopted extrusion-based AM technologies and is currently among the most popular in the market [6]. FDM is particularly cost-effective for manufacturing certain components, as it eliminates the need for specialized tools when producing thermoplastic parts [7]. In FDM, thermoplastic filaments are fed into a temperature-controlled extruder, where they are converted from solid to semi-liquid form. This semi-liquid material is then deposited layer by layer onto the build platform by the FDM head, which is guided by a Cartesian axis system, and solidified to form a precise laminate [8]. Therefore, achieving geometric precision is vital in determining the quality of products produced by 3D printing machines.

Dimensional accuracy plays a critical role in global trade and commerce, as only products with precise dimensions can perform their intended functions effectively. Therefore, evaluating dimensional accuracy is essential for assessing product quality [9]. In recent years, advancements in Additive Manufacturing (AM), particularly in Fused Deposition Modeling (FDM), have led to significant improvements in print quality. This progress is largely attributed to FDM's ability to produce complex geometries cost-effectively while maintaining high precision [10]. Among the various factors influencing the quality of manufactured components, dimensional accuracy is paramount. The dimensional accuracy of FDM models requires special attention because it directly impacts the outcomes of subsequent studies on printed components [11]. The FDM process is prone to manufacturing errors, as well as variations in accuracy and precision along the x, y, and z axes [12]. Research has shown that dimensional accuracy is affected by numerous process parameters, such as layer thickness, extrusion temperature, raster width, printing speed, and infill pattern [13]. As such, it is crucial to explore different combinations of process parameters to identify the optimal settings that enhance dimensional accuracy in FDM.

Dimensional deviations can occur in 3D-printed components due to variations in operating conditions and process parameter adjustments during printing. Various studies have aimed to identify the optimal process parameters to achieve acceptable Dimensional Accuracy (DA) in 3D printed components. Dhanunjayarao & Naidu [14] conducted nine experiments analyzing the dimensional accuracy of 3D printed parts and found that it significantly influences the shape and size of the components. They used interaction diagrams to pinpoint the parameters affecting accuracy. Zharylkassyn [15] explored different 3D printing process parameters and materials that impact dimensional accuracy, finding that layer thickness had the greatest effect on PLA material. However, other secondary process parameters should also be considered. While layer thickness is a primary factor, other parameters such as print speed, extruder temperature, and infill profile also influence the dimensional accuracy of PLA prints [16], [17]. Research on determining process parameters for dimensional accuracy in PLA components using the Taguchi method is particularly valuable. Key parameters for investigation include layer thickness, printing temperature, infill rate, and infill pattern [18]. Vishwas et al. [19] applied the Orthogonal Taguchi $L_9$ method to examine process parameters like model orientation, layer thickness, and shell thickness, identifying optimal values for dimensional accuracy.

Despite the progress, there remains a gap in the literature regarding the effects of infill process parameters, patterns, and material types on the percentage change in dimensional accuracy of FDM prints. This study employs the Taguchi method to investigate the main effects of infill process parameters, including percentage, infill pattern, raster angle, and material variation, on the dimensional accuracy of FDM prints. The purpose of this paper is to report on how these process parameters and material variations influence the dimensional accuracy of FDM prints. Understanding the relationship between 3D printing process parameters and dimensional accuracy is crucial for enhancing the quality of 3D printed components. The findings of this study provide important contributions to the manufacturing industry, especially the additive manufacturing field. In its application, this study provides choice for the industry in using FDM 3D print settings in printing components related to dimensional accuracy.

## 2 Materials and Methods

### 2.1 Materials

The filament materials utilized in this study included Polylactic Acid Plus (PLA+), Carbon Fiber-Reinforced Polylactic Acid (PLA-CF), and Glass Fiber-Reinforced Polylactic Acid (PLA-GF). Each filament had a diameter of 1.75 mm and was sourced from Shenzhen Esun Industrial Co., Ltd. The specific characteristics of these filament materials are detailed in Table 1. No additional treatment was applied to the filaments. PLA-based filaments were chosen due to their favorable mechanical properties and their widespread use in structural applications, such as in high-end automotive components, electrical and electronic parts. Furthermore, PLA is commonly employed in the food packaging and medical industries [20].

Table 1. Properties of variations in filament materials

| Property | Value | | | Unit |
|---|---|---|---|---|
| | PLA+ | PLA-CF | PLA-GF | |
| Density | 1.23 | 1.21 | 1.31 | g/cm$^3$ |
| Elongation at break | 20 | 4.27 | 7.99 | % |
| Tensile strength | 60 | 39 | 59.27 | MPa |
| Extruder temperature | 210-230 | 190-230 | 190-230 | $^o$C |
| Bed temperature | 45-60 | 45-60 | 45-60 | $^o$C |
| Printing speed | 40-100 | 50-300 | 40-100 | mm/s |

### 2.2 Specimen Preparations

In this study, a 3D model designed to test dimensional accuracy was created, featuring a square base with various infill methods. The accuracy test involved printing a model with dimensions of 20×20×20 mm. The test specimen's 3D model was designed using CAD software and exported in the Stereolithography (.stl) file format, enabling it to be read by the repeater and slicer software, which configured the selected process parameters. The sliced model was then saved in G-Code format and printed using a 3D printing machine. The machine employed was the Ender 3 v2, a Fused Deposition Modeling (FDM) printer from Shenzhen Creality 3D Technology Co., Ltd. This printer has a frame size of 475×470×620 mm and uses a 0.4 mm nozzle. It can print objects up to 220×220×250 mm along the Cartesian axes, with each axis independently controlled by stepper motors. The dimensions and design of the 3D printing machine are depicted in Fig. 1, while Fig. 2 shows the printed test specimens.

### 2.3 Dimensional Accuracy Measurement

The dimensional accuracy test was performed using a highly precise digital caliper with an accuracy of 0.01 mm (Krisbow Digital Caliper 0-150 mm). Fig. 3 illustrates the dimensional testing tool used in this study. Dimensional accuracy measurements were repeated three times. This is to ensure that the test results have high consistency. Reading measurements were repeated three times on the x, y, and z axes per specimen. The specific locations of these measurements are shown in Fig. 4. Fig. 5 is an example of measuring dimensions using a digital caliper. The average percentage change in accuracy was then calculated using Eq. 1 [21], [22], based on the differences between the CAD model values and the actual measurements, and this was recorded as the output response for each measurement.

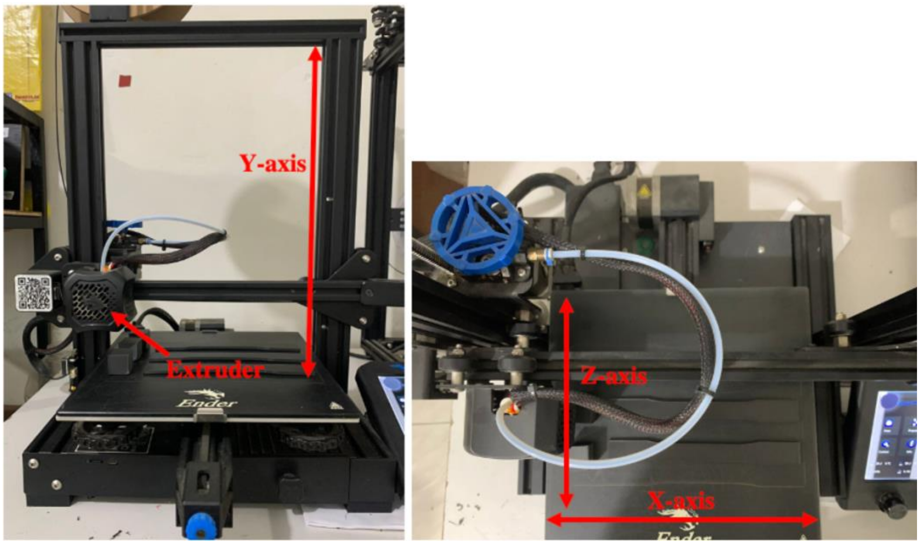



Fig. 1. FDM 3D printer view.

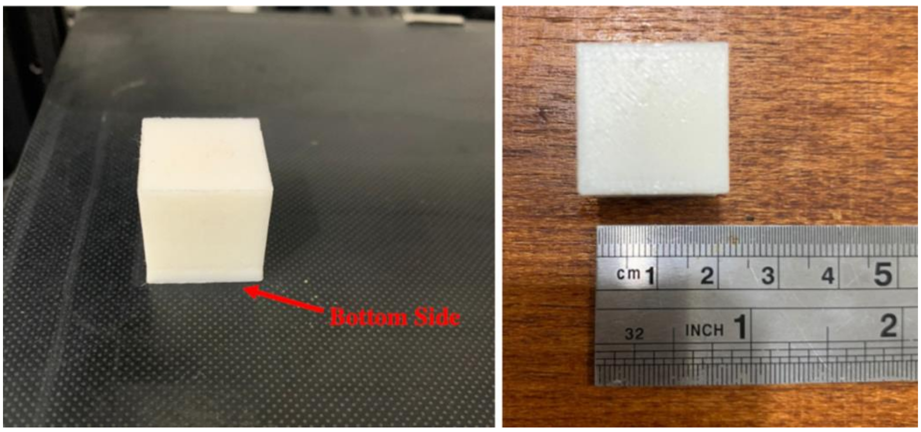



Fig. 2. 3D Printed dimensional test specimen.

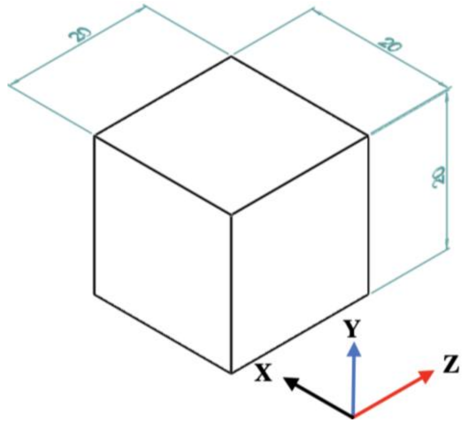



Fig. 3. The direction of the axis is visible on the specimen.

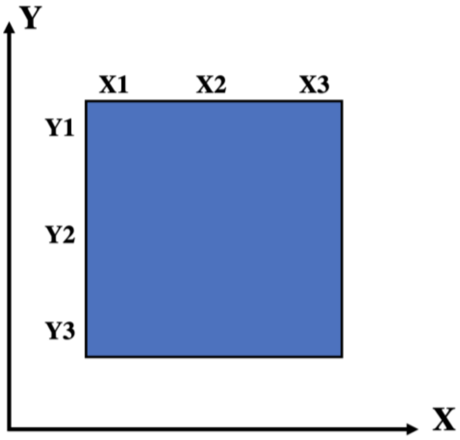



Fig. 4. Dimension measurement location.

$$\Delta D = \left|\frac{D_{EXP} - D_{CAD}}{D_{CAD}}\right| \times 100 \quad (1)$$

where ΔD is the percentage change in the experimental dimension (D), $D_{EXP}$ is the experimental length measurement value, and $D_{CAD}$ is the length measurement value designed by the CAD model.


Fig. 5. Dimensional measurements on test specimens.

## 2.4 Design of Experimental

The print quality in FDM technology is heavily influenced by various printing parameters. In this study, four process parameters were analyzed to evaluate their impact on the accuracy of the printed surfaces. These parameters can be adjusted through the 3D printing software's user interface. Table 2 outlines the printing parameters and their respective levels, while Table 3 lists additional parameters that were kept constant throughout the experiments. Several statistical methods were applied for ranking, modeling, and optimizing the printing parameters. The Design of Experiments (DOE) method was utilized as a statistical tool to identify, optimize, test the significance, and analyze the sensitivity of the parameters. Due to the extensive experimental and physical measurements required to evaluate the dimensional and geometric variations of the printed parts, the DOE method was selected to reduce the number of necessary experiments while determining the significance and sensitivity of the parameters [1].

Table 2. Process parameters and materials with their levels [23], [24], [25], [26], [27]

| Parameter | Level | | | Unit |
|---|---|---|---|---|
| | 1 | 2 | 3 | |
| Material (A) | PLA+ | PLA-CF | PLA-GF | - |
| Infill density (B) | 80 | 90 | 100 | % |
| Infill pattern (C) | Grid | Triangular | Trihexagonal | - |
| Raster angle (D) | 0 | 45 | 90 | Degree |

Table 3. Fixed parameters FDM 3D printing

| Parameter | Value | Unit |
|---|---|---|
| Layer height (thickness) | 0.1 | mm |
| Temperatur | 240 | Degree |
| Bad temperatur | 80 | Degree |
| Printer speed | 80 | m/s |
| Fan speed | 100 | % |

An Orthogonal Array (OA) was used to choose combinations of parameter control levels for each experiment. Based on the study's experimental design, an $L_9$ OA was employed to investigate four parameters, each with three control levels. The $L_9$ OA consists of nine rows, each representing a unique experiment with different combinations of controlled parameter levels. The printing process parameters, including the materials used (PLA+, PLA-CF, and PLA-GF), infill densities (80%, 90%, and 100%), infill patterns (Grid, Triangular, and Trihexagonal), and raster angles (0, 45, and 90 degrees), had significant effects on the 3D printing outcomes. All nine experiments were conducted according to the experimental design detailed in Table 4. On average, each component required approximately nine hours to print. Table 5 shows the infill pattern and raster angle.

Table 4. Orthogal Taguchi array with fractional $L_9$

| Eks. | Material (A) | Infill density (B) | Infill pattern (C) | Raster angle (D) |
|---|---|---|---|---|
| 1 | PLA+ | 80 | Grid | 0 |
| 2 | PLA+ | 90 | Tiangular | 30 |
| 3 | PLA+ | 100 | Trihexagonal | 45 |
| 4 | PLAC-F | 80 | Tiangular | 45 |
| 5 | PLAC-F | 90 | Trihexagonal | 0 |
| 6 | PLAC-F | 100 | Grid | 30 |
| 7 | PLAG-F | 80 | Trihexagonal | 30 |
| 8 | PLAG-F | 90 | Grid | 45 |
| 9 | PLAG-F | 100 | Tiangular | 0 |

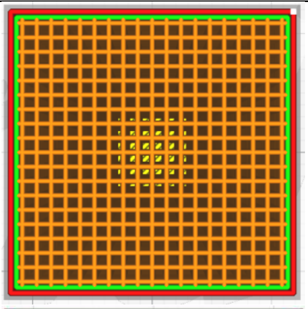
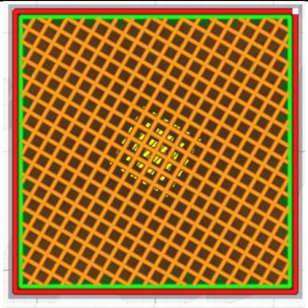
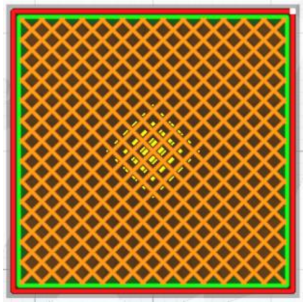
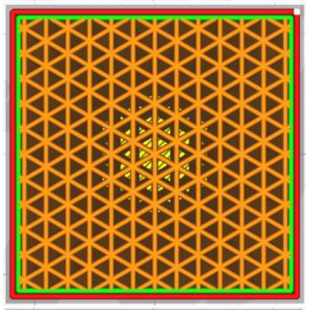
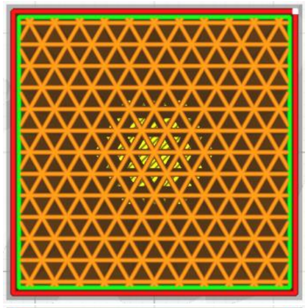
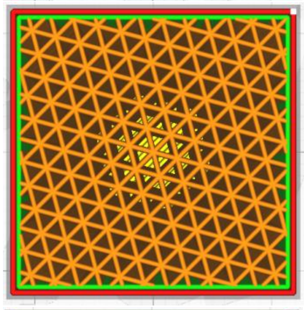
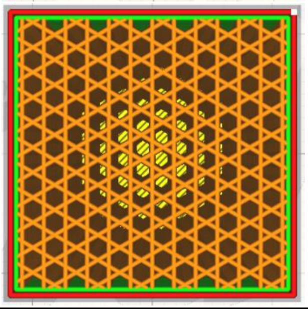
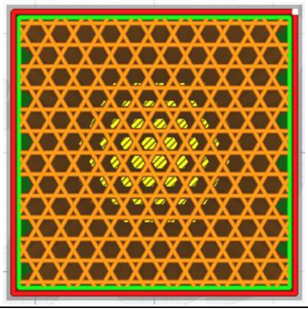
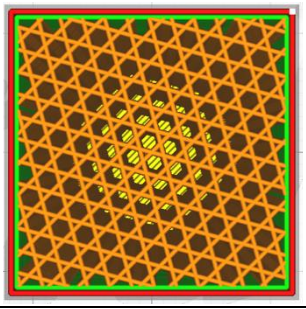
## 2.5 Taguchi Method

Taguchi categorizes the factors influencing parameters into two types: control factors and noise factors. Control factors are those that are set by the research design, whereas noise factors are variables that are difficult or nearly impossible to control, such as environmental temperature or humidity. Due to the challenges posed by noise factors, the Taguchi method employs the signal-to-noise (S/N) ratio, which is particularly sensitive to variations in noise factors, with the goal of achieving a stable system. The S/N ratio can be classified into three types: "smaller is better," "nominal is better," and "larger is better."

In this study, all dimensions of the nine produced specimens were measured, and the dimensional deviation was calculated as the difference between the experimental and design values. This dimensional deviation was then used to calculate the signal-to-noise ratio (S/N) to assess the 3D printer's performance. The "smaller is better" S/N response characteristic was chosen to analyze the effect of parameters on dimensional accuracy, and the analysis was conducted using Eq. 2.

$$S/_N = -10 \log \left[\frac{1}{n} \sum_{i=1}^{n} Y_i^2\right] \quad (2)$$

Table 5. Infill model parameters

| Infill pattern | Raster angle | | |
|---|---|---|---|
| | 0º | 30º | 45º |
| Grid |  |  |  |
| Tiangular |  |  |  |
| Trihexagonal |  |  |  |

## 3 Results and Discussion

### 3.1 Dimensional Deviations Result in Measurement

Dimensional deviation measurements were conducted by calculating the average deviation along the print axes of the 3D printing machine [28]. Table 6 presents the percentage of dimensional deviation and the S/N ratio of the measurement results for the three print axes. Based on the average measurements, experiment number 1 exhibited the smallest percentage deviation of 1.39%, indicating the highest dimensional accuracy, while experiment number 8 showed the largest percentage deviation of 2.41%. A smaller percentage deviation signifies better dimensional accuracy, which is influenced by various printing parameters and is linked to residual thermal stress during the 3D printing process [29]. The heating and cooling cycles during printing can lead to issues such as distortion, delamination, fracture, and failure due to residual thermal stress [30], [31]. These dimensional variations in 3D printing are influenced by the type of material used and the geometry of the infill. Filament extrusion can result in uneven temperature distribution, leading to geometric distortions [32].

Table 6. Experimental result of dimensional percentage deviation

| Eks. | Material (A) | Infill density (B) | Infill pattern (C) | Raster angle (D) | Percentage deviation | | | | S/N ratio | Standard deviation |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | X | Y | Z | Average | | |
| 1 | PLA+ | 80 | Grid | 0 | 0.82 | 1.50 | 1.87 | 1.39 | -3.29 | 0.53 |
| 2 | PLA+ | 90 | Tiangular | 30 | 1.22 | 2.73 | 1.02 | 1.66 | -5.22 | 0.94 |
| 3 | PLA+ | 100 | Trihexagonal | 45 | 2.63 | 1.23 | 2.75 | 2.21 | -7.27 | 0.84 |
| 4 | PLAC-F | 80 | Tiangular | 45 | 2.07 | 0.92 | 2.37 | 1.78 | -5.53 | 0.77 |
| 5 | PLAC-F | 90 | Trihexagonal | 0 | 2.45 | 0.98 | 2.22 | 1.88 | -5.98 | 0.79 |
| 6 | PLAC-F | 100 | Grid | 30 | 2.17 | 0.78 | 2.52 | 1.82 | -5.89 | 0.92 |
| 7 | PLAG-F | 80 | Trihexagonal | 30 | 2.95 | 0.92 | 2.47 | 2.11 | -7.17 | 1.06 |
| 8 | PLAG-F | 90 | Grid | 45 | 3.15 | 1.35 | 2.73 | 2.41 | -8.07 | 0.94 |
| 9 | PLAG-F | 100 | Tiangular | 0 | 3.45 | 0.72 | 3.35 | 2.51 | -8.97 | 1.55 |

The statistical analysis revealed the S/N ratio values for each experiment, with experiment 1 having the smallest value (-3.29) and experiment 9 the largest (-8.97). This study employs the "smaller is better" principle to minimize deviations from the target dimensions during the 3D printing process [33], [34]. According to the data, the optimal process parameters for minimizing deviation are A1B1C1D1, corresponding to PLA+ material, 80% infill density, a grid infill pattern, and a 0° raster angle. Material variation significantly impacts both the percentage deviation and the S/N ratio because it affects the filament's fluidity and the extent of dimensional deviation. An optimal infill density and pattern, specifically a grid pattern with fewer and simpler configurations, help reduce excessive fluidity and geometric distortions [35], [36]. The raster angle also plays a crucial role in dimensional accuracy, with angles of 0° and 90° generally resulting in lower deviations compared to other angles [37]. The 0° raster angle is advantageous due to its perpendicular movement to the Y-axis, whereas raster angles of 30° and 45° may introduce skew, leading to less precise dimensional control [38].

The effects of the process parameters and their levels are summarized in Table 7, showing the average performance or main effects on percentage deviation. The graphs in Fig. 6 illustrate the main effect plots for percentage deviation and the S/N ratio. The most influential parameters on dimensional deviation are material, infill density, infill pattern, and raster angle, in that order. Material choice is the most critical factor, followed by infill density, infill pattern, and raster angle. Variations in material can cause contraction due to internal stresses, which reduces the dimensions along each axis direction [39].

Table 7. Response signal-to-noise ratio the smaller is better of dimensional percentage deviation

| Level | Material (A) | Infill density (B) | Infill pattern (C) | Raster angle (D) |
|---|---|---|---|---|
| 1 | -5.26 | -5.33 | -5.75 | -6.08 |
| 2 | -5.80 | -6.42 | -6.57 | -6.09 |
| 3 | -8.07 | -7.38 | -6.81 | -6.96 |
| Delta | 2.80 | 2.05 | 1.06 | 0.88 |
| Rank | 1 | 2 | 3 | 4 |

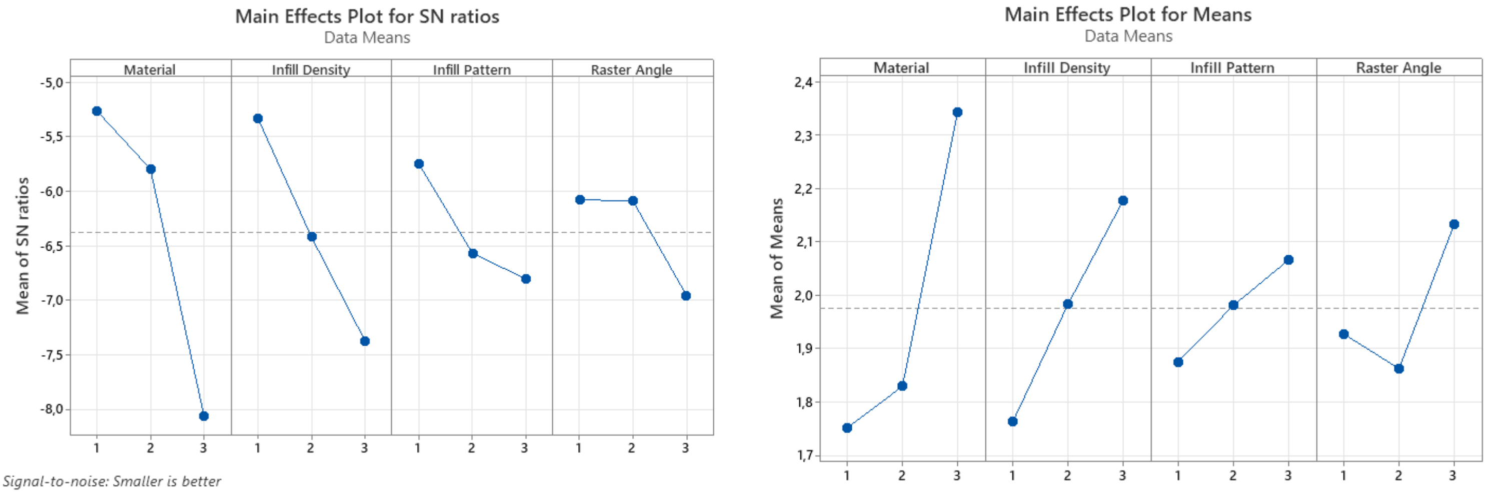



Fig. 6. Main effect plot for SN Ratio and percentage deviation means of all process parameter.

## 3.2 Analysis of Variance

The relative influence of factors and their interactions in the experiment can be analyzed using ANOVA. Table 8 presents the total Degrees of Freedom (DOF) for four factors at three levels, along with their interactions, within an experiment that has 8 DOF. The ANOVA results show that the material has the largest contribution to the deviation in results, accounting for 49.81%. Other contributions include infill density at 24.56%, infill pattern at 5.19%, and raster angle at 6.03%. These findings indicate that the material is the dominant factor statistically influencing the print results, with a p-value less than 0.05, confirming its significant impact on the FDM print outcomes at a 95% confidence level [40]. The amount of contribution is determined by the overall Sum of Squares (SS), where the material factor has the highest value of 0.52. Factors with smaller contributions are considered insignificant to the print results [41].

Table 8. Analysis of variance in the result of dimensional percentage

| Source | DF | Seq SS | Contribution | Adj MS | F-value | P-value |
|---|---|---|---|---|---|---|
| Material (A) | 1 | 0.52 | 49.81% | 0.52 | 13.83 | 0.02 |
| Infill density (B) | 1 | 0.26 | 24.56% | 0.26 | 6.82 | 0.06 |
| Infill pattern (C) | 1 | 0.05 | 5.19% | 0.05 | 1.44 | 0.30 |
| Raster angle (D) | 1 | 0.06 | 6.03% | 0.06 | 1.67 | 0.27 |
| Error | 4 | 0.15 | 14.41% | 0.04 | | |
| Total | 8 | 1.05 | 100% | | | |

The percentage of dimensional deviation varies according to the type of material used, suggesting that the filament material type significantly affects the dimensional accuracy of FDM printing. The cooling process, from the melting temperature to the glass transition temperature, causes shrinkage in the thermoplastic material deposited by the 3D printing machine [39]. The deposited material can undergo varying degrees of deformation during this cooling phase. As the material cools from the melting temperature to the glass transition temperature, its capacity to withstand forces may decrease, leading to internal stress and shrinkage. Dimensional accuracy in printing reflects the relationship between the dimensions of the print and the original design specifications [42]. During cooling from the transition temperature to room temperature, stress may develop. Uneven temperature gradients can cause stress that negatively impacts the dimensional precision of the print, potentially resulting in deformation, delamination of inner layers, and failure of the supporting structure in the print.

## 3.3 Interaction between each Parameter

Fig. 7 illustrates the interaction between each parameter analyzed in this study. The interaction diagram reveals that material 1 (PLA+) exhibits a distinct interaction compared to other material levels. Additionally, the trends for other factors show more dynamic variations. This suggests that the material at level 1 is a sensitive factor influencing the percentage deviation of printed dimensions. As the PLA+ material factor increases, there are corresponding increases in other factors such as infill density, infill pattern, and raster angle. Consequently, PLA+ experiences a rise in the percentage of dimensional deviation as these factors increase. Therefore, further analysis is required to better understand the interactions between parameters on the 3D printing machine and other process factors [14], [43].

The Pareto diagram, shown in Fig. 7, illustrates the effects in order of magnitude from largest to smallest, with a reference line indicating statistically significant effects at a value of 2.776. According to Fig. 8, factor A (material) is statistically significant, while the other factors have not surpassed the predetermined reference line [44]. Factors that cross the reference line on the Pareto diagram are considered significant [14]. Thus, material is identified as a significant factor influencing the percentage value of dimensional deviation.

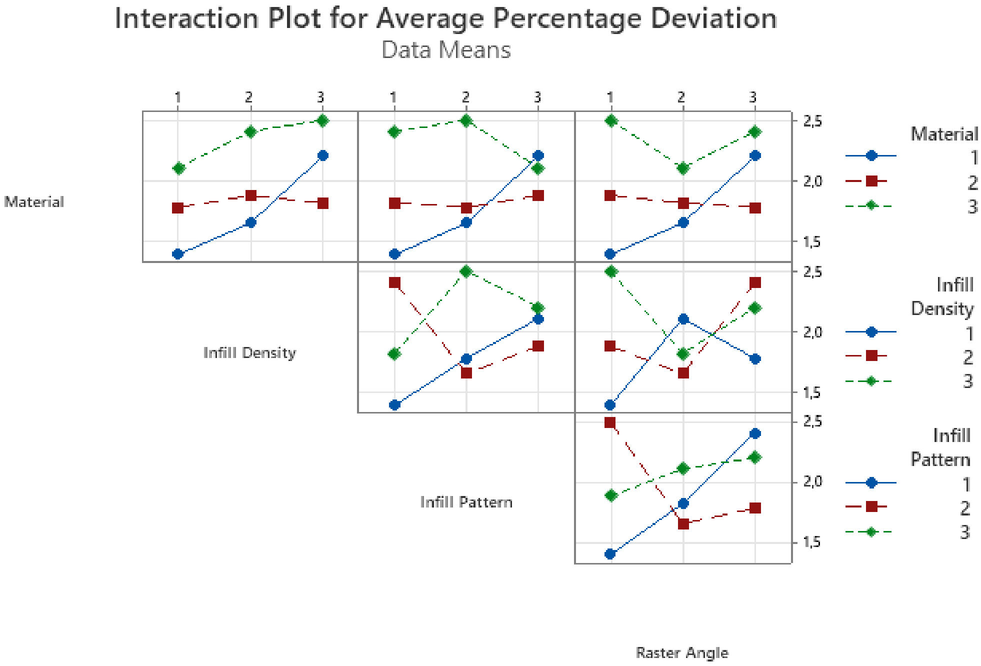



Fig. 7. Interaction plot between process parameters.

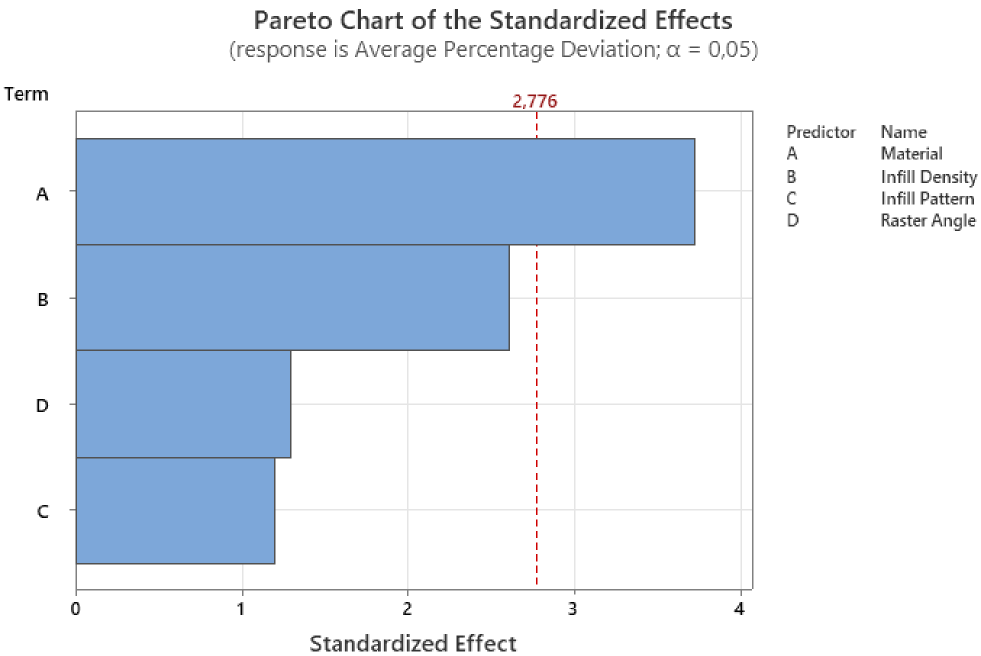



Fig. 8. Pareto chart of the standardized effect for percentage deviation.

Contour plots were generated to examine the interactions between material and infill density, as these two factors are the most influential. The contour plot, shown in Fig. 9, depicts the relationship between the output sizes of these two continuous variables in a 2D view. The maximum and minimum response values are plotted as factor contours on the x and y axes, helping to visualize the distribution range of the experimental results. Areas with the same response value are connected to form contour lines [14]. The light green area represents the minimum response value, while the dark green area indicates the maximum response value obtained [45]. According to the contour plot, a higher material level (3) PLA glass fiber results in a greater percentage dimensional deviation and lower dimensional accuracy of the print results. Similarly, a higher infill density level corresponds to a higher percentage of dimensional deviation. The area of interest is the light-colored region, specifically material 1 (PLA+) with an infill density of 1 (80%).

### 3.4 Linier Regresion

Regression analysis is employed to estimate the relationship between process parameter variables and the responses observed in the study [46]. Linear regression is used to examine how the values of the response variable change as the predictors vary [43]. In this study, the regression parameters are utilized to estimate the average percentage deviation results with a 95% confidence level (CI) [7]. The confidence interval is defined as $p < 0.05$ [47]. The primary goal of applying linear regression is to estimate the relationship between the parameters and the response of the 3D printing results. Consequently, a linear regression model was developed in this study to predict the average percentage deviation concerning the dimensional accuracy of the printed outcomes. The linear regression equation is presented in Eq. 3.

$$\begin{aligned}&\text{Average Percentage Deviation} = \\ &0.573 + 0.2954 \text{ materials} + 0.2074 \text{ infill density} \\ &+ 0.0954 \text{ infill pattern} + 0.1028 \text{ raster angle}\end{aligned} \tag{3}$$

Based on the linear regression results, a summary of the confidence level or coefficient of determination is provided, with an average R-squared ($R^2$) value shown in Table 9. This value reflects the percentage of total variation in the response that the model explains. The analysis indicates that an $R^2$ value of 85.59% suggests a satisfactory level of confidence in the linear regression model's reliability [40].

Table 9. Regression model summary

| S | R-sq | R-sq (adj) | PRESS | R-sq (pred) |
|---|---|---|---|---|
| 0.1946 | 85.59% | 71.19% | 1.1107 | 0.00% |

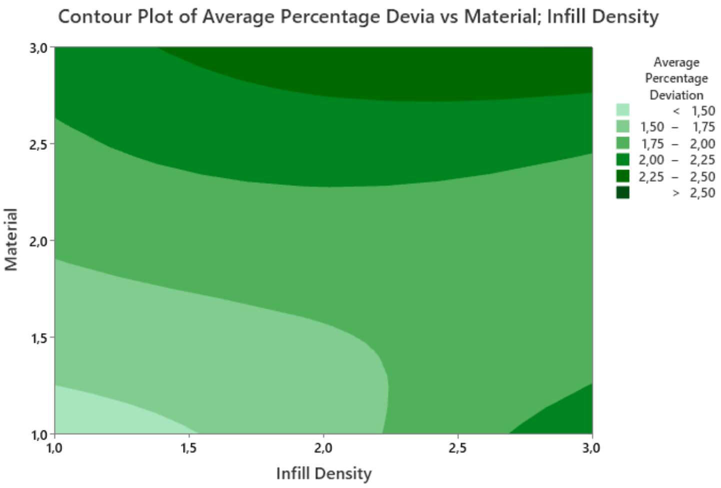



Fig. 9. Contour plot of process parameter.

## 4 Conclusion

The aim of this study was to identify the optimal process parameters and materials for achieving high dimensional accuracy in FDM 3D printing using the Taguchi method. The $L_9$ fractional design revealed that the best settings were PLA+ material, 80% infill density, a grid infill pattern, and a 0° raster angle, resulting in a deviation percentage of 1.39% and an S/N ratio of -3.29 dB. ANOVA analysis showed that material type was the most significant factor, contributing 49.81% to performance, while infill pattern had the least impact at 5.19%.

Although the contribution of individual factors to dimensional accuracy was moderate, the results confirmed the critical role of material choice in print quality. These findings can guide the selection of FDM 3D printing settings for both individual and industrial applications. Further research is recommended to explore additional factors, such as layer thickness, nozzle and bed temperature, print orientation, and speed, for a more comprehensive understanding of parameter optimization.


## Acknowledgements

This research was founded by a grant from Basis Informasi Penelitian dan Pengabdian kepada Masyarakat, Kementerian Kelautan dan Perikanan (BIMA KKP), Pusat Pendidikan Kelautan dan Perikanan, Badan Penyuluhan dan Pengembangan Sumber Daya Manusia Kelautan dan Perikanan, Ministry of Marine Affairs and Fisheries (Number: 393/PPK.PUSDIK/PL.430/V/2024).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