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Experimental Analysis of the Effect of Printing Parameters of 3D Printer FDM Machine on Dimensional Error and Surface Hardness of PLA+ Material

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ABSTRACT

PLA material is one of the most commonly used materials in Fused Deposition Modelling 3D printers for various purposes. The quality of the printed part can be assessed from its dimensional accuracy and surface hardness. The method used to determine the appropriate parameters for achieving optimal results is the 2k factorial design method. The parameters studied include BTT, WT, and FP. The levels for BTT were set at 1 mm and 3 mm, WT were 1 mm and 2 mm, and FP consists of concentric and lines. Statistical analysis revealed that several parameters significantly influence the response. The statistical analysis results show factors with a P-value < 0.05 (α = 0.05). The WDE response shows an interaction between BTT, WT, and FP. The HDE response indicates that the interactions between BTT and WT, BTT and FP, WT and FP, and WT affect HDE. In the SH response, the factors BTT, WT, and the interaction between WT and PT affected SH. Meanwhile, in the LDE response, all factors had P-values > 0.05. This study also found that WT individually affects HDE, WDE, and SH. On the other hand, the WT factor interacts with BTT and FP to affect SH.

1. INTRODUCTION

One of the materials commonly used in additive manufacturing processes is polymer material. PLA material is one of the thermoplastic polymer materials used in additive manufacturing processes (Prihadianto et al, 2022). PLA material can be used in various fields, including research (Sukiman & Tontowi, 2018) and healthcare (Bose et al., 2013; Ferretti et al., 2021). PLA can be used on Additive Manufacturing Technology. Additive manufacturing processes can also be referred to as 3D printing (Bose et al., 2013; Rusianto & Huda, 2019; Tay et al., 2017), layer manufacturing (Yan et al., 2018), or rapid prototyping (Eguren et al., 2020; Rusianto & Huda, 2019). The formation of workpieces in additive manufacturing technology uses a layer-by-layer process (Shashi et al., 2017), unlike subtractive manufacturing processes, which involve creating products by removing or eliminating parts of the workpiece. AM technology continues to evolve, from its initial application in prototype production (Rusianto & Huda, 2019). FDM machines are one type of 3D printing technology (Pettalolo et al., 2022; Prihadianto et al., 2022; Yakout et al., 2018). FDM works by melting thermoplastic material extruded through a nozzle at a semi-liquid viscosity. The nozzle is moved to form the workpiece. The material that comes out of the nozzle changes viscosity until it becomes more solid, so that the workpiece can be formed (Prihadianto et al., 2022).

Pratama et al. (2021) researched PLA material used in FDM 3D printers. The research optimized machine parameters using several parameters, namely printing speed, nozzle temperature, layer thickness, cooling speed, and printing orientation. The method used was the Taguchi method with tensile strength as the response. The optimal parameters obtained in the study were a layer thickness of 1 mm, a printing speed of 40 mm/s, and a nozzle temperature of 190°C. In the study by Seprianto et al. (2021), parameter optimization for PLA material was conducted using nozzle diameter and layer thickness parameters, with a 2-level factorial design experimental method. In this study, the tolerance values consistent with the design were obtained, namely, a layer thickness of 0.1 mm and a nozzle diameter of 0.2 mm. The ANOVA approach was used to determine the significance of the parameters on the response. Research conducted by Sukiman & Tontowi (2018) investigated the optimization of parameters in PLA material to obtain optimal print flexibility using the Response Surface Method (RSM). In this study, the parameters used were moment and thickness. The experiment results showed that L1 to L5 produced the best flexibility. In the study conducted by Pratama (2021) on PLA+ material optimized using the Taguchi Method, several printing parameters were used,

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including printing speed, nozzle temperature, layer thickness, cooling speed, and orientation.

FDM technology is among the various fields' most commonly used AM technologies (Ford & Despeisse, 2016). PLA material can be used in FDM machines (Prihadianto et al., 2022; Rusianto & Huda, 2019; Tappa & Jammalamadaka, 2018). Dimension error parameters (Almy & Tontowi, 2018; Arief et al., 2024; Latif et al., 2024; Rosid & Tontowi, 2021) and mechanical properties can be one of the success parameters in the additive manufacturing process (Espino et al., 2020; Nowacki et al., 2021). The approach for parameter optimization that can be used is the design of experiments with a 2k factorial design (Latif et al., 2024; Rosid & Tontowi, 2021; Tontowi et. al., 2017; Tontowi & Putra, 2015).

From the research that has been conducted, no analysis has been carried out on mechanical properties such as surface hardness, and some parameters have not been analyzed as research factors. Therefore, this study analyzed FDM 3D printer machine parameters to achieve the highest surface hardness and dimensional accuracy for PLA material. The method used was an experiment employing a 2^k factorial design. The parameters analyzed were bottom and top thickness, wall thickness, and fill pattern.

2. RESEARCH METHODS

The material used is PLA+ with a diameter of 1.75 mm and a printing temperature of 210°C - 220°C. The dimensions of the specimens are determined based on the ASTM D2240 test standard.

Fig. 1. Vernier calipers

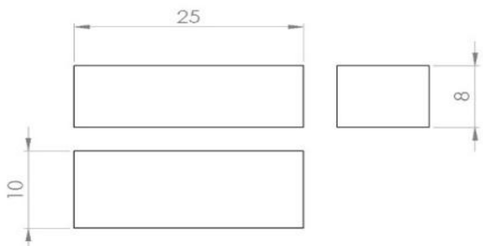

Fig. 2. Speciment dimension

Measurements were taken using a vernier caliper with an accuracy of 0.02 mm. Measurements were taken at several points (Fig. 1). Calculations were performed on the length, width, and height dimensions. Measurements were taken several times for each dimension (Fig. 2).

The measurement results are calculated using equation (1) from the difference between the measured results of the specimen and the design dimensions divided by the design dimensions (Rosid & Tontowi, 2021). The measurement results are then averaged for each measurement dimension, namely dimension x, dimension y, and dimension z.

$$Err.Dim. = \frac{D_{speciment} - D_{design}}{D_{design}} \, x \, 100 \, \% \qquad (1)$$

The surface hardness testing device used is a Shore Type D Durometer Test (Fig. 3a), and the standard used is ASTM D2240 (American Society of Testing and Materials, 2015). The machine is a Fused Deposition Modeling (FDM) 3D printer with x, y, and z motion systems. Print volume capacity of 235x235x250 mm, hot end capacity of 260°C and hot bed capacity of 100°C (Fig. 3b).

Fig. 3. Durometer shore test (a) and FDM 3D Printer (b)

The DoE method used in the experiment was a 2k Full Factorial Design, using 3 parameters and 1 response, with 2 levels for each parameter (Table 1). The parameters used are bottom and top thickness, wall thickness, and fill pattern. The values for BTT and WT are obtained from the default settings for low to high quality in the slicer, ranging from 1 mm to 3 mm. Meanwhile, the WT level values vary between 1 mm and 2 mm. The Fill Pattern levels used are Concentric and Lines.

Table 1. Printing parameters

Parameters	Units	Explanations
Bottom and Top Thickness (BTT)	mm	Thickness of the upper and lower surface layers of the specimen
Wall Thickness (WT)	mm	Specimen wall thickness
Fill Pattern (FP)	-	Fill pattern on specimens

The measurement results were analyzed using Minitab 22 software. Several results were analyzed, including analysis of variance or ANOVA with a 95% confidence level, R^2 values, and Pareto charts for standardized effects. The combination of parameters obtained using a 2^k factorial design yielded 24 run times (RT) (Table 2).

Table 2. Combination of print parameters

Run Time	Bott. and Top Thick. (mm)	Wall Thick. (mm)	Fill Pattern	Run Time	Bott. and Top Thick. (mm)	Wall Thick. (mm)	Fill Pattern
1	1	1	C	13	1	1	L
2	3	1	C	14	3	1	L
3	1	2	C	15	1	2	L
4	3	2	C	16	3	2	L
5	1	1	L	17	1	1	C
6	3	1	L	18	3	1	C
7	1	2	L	19	1	2	C
8	3	2	L	20	3	2	C
9	1	1	C	21	1	1	L
10	3	1	C	22	3	1	L
11	1	2	C	23	1	2	L
12	3	2	C	24	3	2	L

R^2 (R-Sq) or the coefficient of determination determines how well the model explains the dependent variable, with R^2 values ranging from 0 to 1. A higher R^2 value indicates that the model is better able to explain the dependent variable (Natoen et al., 2018). Analysis of Variance (ANOVA) testing is one of the tools used to analyze various experimental studies (Septiadi & Ramadhani, 2020). A P-value in the ANOVA results that is less than the alpha value ($\alpha < 0.05$) can be interpreted as statistically significant, indicating that the factor influences the predetermined response (Winarni et al., 2019).

3. RESULTS AND DISCUSSION

The printout results were by design (Fig. 4). The specimens were identified on the printout to obtain specimen value information according to the run time.

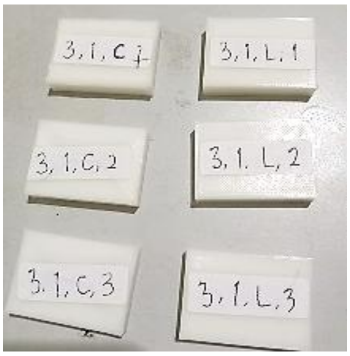

Fig. 4. Print results

The study results obtained 24 run times consisting of 8 combinations with 3 replications. The values obtained were Length Dimension Error (LDE), Width Dimension Error (WDE), Height Dimension Error (HDE), and Surface Hardness (SH) (Table 3). The results of the calculations of the dimensional error and surface hardness measurements showed an average LDE value of 0.040, WDE of 0.168, HDE of 0.092, and SH of 78.9. The R-Square (R-Sq) analysis yielded an R-Sq value of 23.87%. This result indicates that the model is still low in explaining the data obtained. (Table 4).

Table 3. Experiment results

RT	LDE	WDE	HDE	SH
1	0.020	0.060	0.032	82.5
2	0.193	0.108	0.020	82.4
3	0.040	0.060	0.040	83.3
4	0.060	0.080	0.068	77.9
5	0.080	0.048	0.080	83.0
6	0.060	0.080	0.040	82.6
7	0.080	0.180	0.020	81.9
8	0.080	0.092	0.040	70.5
9	0.040	0.080	0.020	82.7
10	0.040	0.056	0.020	80.0
11	0.040	0.060	0.028	83.1
12	0.080	0.080	0.092	77.6
13	0.060	0.040	0.080	83.1
14	0.080	0.080	0.020	83.3
15	0.080	0.120	0.020	75.7
16	0.020	0.040	0.064	70.9
17	0.020	0.080	0.020	82.3
18	0.020	0.064	0.044	62.8
19	0.020	0.040	0.060	83.1
20	0.020	0.080	0.132	76.3
21	0.080	0.080	0.060	84.1
22	0.040	0.084	0.020	81.3
23	0.020	0.068	0.020	77.2
24	0.020	0.100	0.072	66.0

Table 4. R-Square value response error length dimension

S	R-sq	R-sq(adj)	R-sq(pred)
0.0405061	23.87%	0.00%	0.00%

The Pareto chart results for the LDE response show that no factors or interactions exceed the significance threshold at $\alpha = 0.05$ (value 2.120) (Fig. 5). Although not statistically significant, this graph still

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provides a clear picture of which factors most influence dimensional changes in the PLA+ FDM printing process. The graph shows that the AC interaction (BTT × FP) has the most significant effect, indicating that the combination of base/top layer thickness, as well as infill pattern, plays the most significant role in triggering dimensional error variation. The WT (B) factor also appears to be quite dominant as a single factor, indicating that wall thickness has a significant impact on the stability of the print size. Meanwhile, the AB interaction (BTT × WT) and the A factor (BTT) have a moderate influence, followed by FP (C), which contributes less. The ABC and BC interactions show the lowest influence.

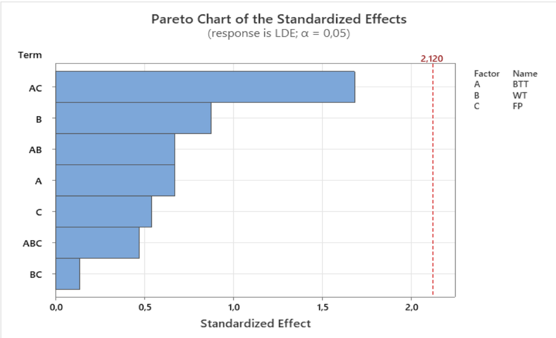

Fig. 5. Pareto chart of the standardized effect for LDE

In the ANOVA results, statistically, no parameters or combinations of parameters were found to have a significant relationship with the response in the form of Length Dimension Error (Table 5).

Table 5. ANOVA response error length dimension

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	0.00823	0.00118	0.72	0.660
Linear	3	0.00247	0.00082	0.50	0.687
BTT	1	0.00074	0.00074	0.45	0.511
WT	1	0.00125	0.00125	0.76	0.395
FP	1	0.00047	0.00047	0.29	0.598
2-Way Int.	3	0.00540	0.00180	1.10	0.379
BTT*WT	1	0.00074	0.00074	0.45	0.511
BTT*FP	1	0.00463	0.00463	2.82	0.112
WT*FP	1	0.00003	0.00003	0.02	0.895
3-Way Int.	1	0.00036	0.00036	0.22	0.644
BTT*W *FP	1	0.00036	0.00036	0.22	0.644
Error	16	0.02625	0.00164		
Total	23	0.03448			

The R-Sq analysis yielded an R-Sq value of 45.11% in terms of width. This result indicates the model's suitability for obtaining data is still low (Table 6).

Table 6. R-Square value response error width dimension

S	R-sq	R-sq(adj)	R-sq(pred)
0.0267083	45.11%	21.10%	0.00%

The Pareto Chart results for WDE responses show that the interaction of three factors, namely ABC (BTT × WT × FP), is the only effect that exceeds the significance line at α = 0.05 (Fig. 6). This indicates that the combination of BTT, WT, and FP greatly influences changes in WDE. Meanwhile, other effects, such as the BC interaction, the single factor C (FP), and the AC and AB interactions, show an influence but are not statistically significant. Factors B (WT) and A (BTT) have the least influence on WDE.

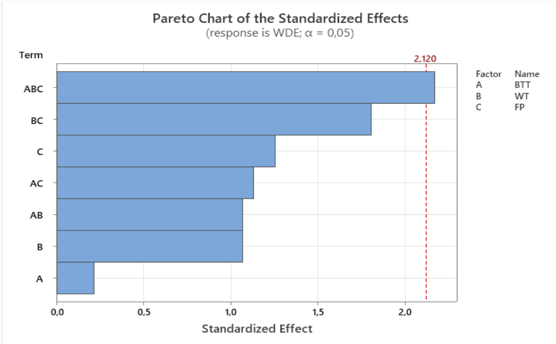

Fig. 6. Pareto chart of the standardized effect for WDE

In the ANOVA results, statistically, most individual parameters and two-way combinations showed no significant relationship with the response in the form of width dimension error. However, the three-way combination of BTT, WT, and FP parameters showed a statistically significant relationship with the width dimension error (p = 0.045) (Table 7).

Table 7. ANOVA response error width dimension

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	0.009381	0.001340	1.88	0.140
Linear	3	0.001970	0.000657	0.92	0.453
BTT	1	0.000033	0.000033	0.05	0.833
WT	1	0.000817	0.000817	1.14	0.301
FP	1	0.001121	0.001121	1.57	0.228
2-Way Int.	3	0.004050	0.001350	1.89	0.172
BTT*WT	1	0.000817	0.000817	1.14	0.301
BTT*FP	1	0.000913	0.000913	1.28	0.275
WT*FP	1	0.002321	0.002321	3.25	0.090
3-Way Int.	1	0.003361	0.003361	4.71	0.045
BTT*WT*FP	1	0.003361	0.003361	4.71	0.045
Error	16	0.011413	0.000713		
Total	23	0.020794			

The R-Sq analysis yielded an R-Sq value of 79.52% for height, which indicates that the model fits the data well (Table 8).

Table 8. R-Square value response error height dimension

S	R-sq	R-sq(adj)	R-sq(pred)
0.0161658	79.52%	70.56%	53.91%

The Pareto Chart for HDE responses reveals three effects that exceed the significance threshold (α = 0.05), namely the AB interaction (BTT × WT), the BC interaction (WT × FP), and the AC interaction (BTT × FP) (Fig. 7). These three interactions indicate that the relationships between these parameters influence HDE variation. The most significant effects, namely the AB and BC interactions, indicate that WT affects the response when combined with other parameters. The BTT and FP interactions are also significant, albeit with a slightly lower effect. Meanwhile, single factors such as B (WT) and A (BTT), as well as the ABC and C effects, make a smaller contribution and are not statistically significant.

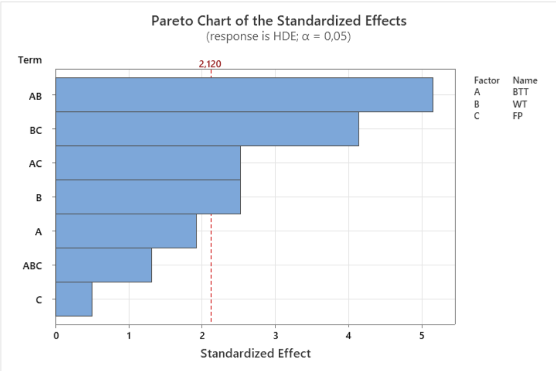

Fig. 7. Pareto chart of the standardized effect for HDE

In the ANOVA results, the WT parameter was found to have a statistically significant relationship with the response in the form of height dimension error ($p = 0.022$). In addition, the two-way interactions between BTT and WT, BTT and FP, as well as WT and FP, also showed significant effects on the height dimension error ($p < 0.05$). However, the three-way interaction among BTT, WT, and FP did not show a statistically significant relationship with the response ($p = 0.208$) (Table 9).

Table 9. ANOVA response error height dimension

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	0.016232	0.002319	8.87	0.000
Linear	3	0.002696	0.000899	3.44	0.042
BTT	1	0.000963	0.000963	3.68	0.073
WT	1	0.001667	0.001667	6.38	0.022
FP	1	0.000067	0.000067	0.26	0.620
2-Way Int.	3	0.013085	0.004362	16.69	0.000
BTT*WT	1	0.006936	0.006936	26.54	0.000
BTT*FP	1	0.001667	0.001667	6.38	0.022
WT*FP	1	0.004483	0.004483	17.15	0.001
3-Way Int.	1	0.000451	0.000451	1.72	0.208
BTT*WT*FP	1	0.000451	0.000451	1.72	0.208
Error	16	0.004181	0.000261		
Total	23	0.020413			

Meanwhile, the R-Sq analysis results for factors affecting surface hardness yielded an R-Sq value of 66.36%. These results indicate that the model fits the data well (Table 10).

Table 10. R-Square value response surface hardness

S	R-sq	R-sq(adj)	R-sq(pred)
4.09801	66.36%	51.64%	24.31%

The Pareto Chart for SH response indicates that three effects exceed the significance line ($\alpha = 0.05$): factor A (BTT), interaction BC (WT × FP), and factor B (WT). This indicates that BTT and WT, both individually and when interacting with FP, have a significant effect on the SH of PLA+ material. Meanwhile, other effects such as the ABC interaction, AB, factor C (FP), and AC (BTT × FP) are below the significance threshold, so their contribution to SH is relatively small. (Fig. 8).

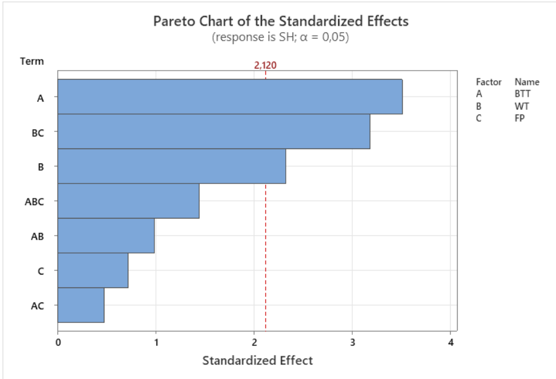

Fig. 8. Pareto chart of the standardized Effect for SH

The ANOVA results showed that both BTT and WT parameters had a statistically significant relationship with the response in the form of surface hardness ($p < 0.05$). In addition, the two-way interaction effects were significant overall ($p = 0.032$), indicating that certain parameter combinations may influence the response. However, the three-way interaction among BTT, WT, and FP did not show a statistically significant relationship with surface hardness ($p = 0.167$) (Table 11).

Table 11. ANOVA response surface hardness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	530.087	75.727	4.51	0.006
Linear	3	305.287	101.762	6.06	0.006
BTT	1	206.272	206.272	12.28	0.003
WT	1	90.326	90.326	5.38	0.034
FP	1	8.688	8.688	0.52	0.482
2-Way Int.	3	189.662	63.221	3.76	0.032
BTT*WT	1	16.401	16.401	0.98	0.338
BTT*FP	1	3.872	3.872	0.23	0.638
WT*FP	1	169.389	169.389	10.09	0.006
3-Way Int.	1	35.138	35.138	2.09	0.167
BTT*WT*FP	1	35.138	35.138	2.09	0.167
Error	16	268.698	16.794		
Total	23	798.786			

The results of this study indicate that variations in the Bottom and Top Thickness (BTT), Wall Thickness (WT), and Fill Pattern (FP) parameters in the FDM printing process affect the dimensional accuracy and surface hardness of PLA+ material. ANOVA analysis shows that the interaction between BTT and WT has a significant effect on Height Dimension Error, while the combination of WT and FP affects Surface Hardness. An increase in BTT is related to layer formation, both on the top and bottom, in line with previous studies, which explain that wall thickness formation affects the mechanical strength of printed workpieces. In this study,

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the mechanical strength referred to is surface hardness. This study builds upon previous findings by demonstrating that fill patterns also play a significant role through their interaction with other parameters. Therefore, the results of this study can be used as a basis for further research related to parameter analysis to obtain print results with maximum surface hardness.

4. CONCLUSION

The results of statistical analysis on the print results of PLA+ material using an FDM 3D printer yielded several conclusions regarding the effect of parameter usage on the response. The analysis results showed that for Length Dimension Error and Width Dimension Error, no parameters had a significant relationship. Regarding Height Dimension Error, parameters with a significant relationship were identified, specifically Wall Thickness, Bottom and Top Thickness with Wall Thickness, Bottom and Top Thickness with Fill Pattern, and Wall Thickness with Fill Pattern. Meanwhile, parameters with a significant relationship were identified for surface hardness, namely Bottom and Top Thickness, Wall Thickness, and the combination of Wall Thickness with Fill Pattern. The main finding of this study is that wall thickness individually affects the response accuracy of height dimension (HDE), width dimension (WDE) and surface hardness (SH). On the other hand, WT interacts with BTT and FP to affect surface hardness. Although this study successfully identified several significant parameters affecting dimensional accuracy and surface hardness, future research should expand parameter variation to reduce bias and improve the generalization of the findings, explore wider parameter ranges, additional print settings (e.g., temperature, speed, infill density), and include more complex factorial or Response Surface Methodology models to improve generalization and strengthen the predictive capability of the findings.

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