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Optimization of Process Parameters for Polylactic Acid (PLA) of FDM Using Particle Swarm Optimization (PSO)

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Abstract: Nowadays, more industries across a wide range of sectors are embracing 3D printing because it offers several major benefits over more traditional production processes. However, there are still have issues which will increase the defects in 3D printing parts which may affect the precision of the product. Therefore, this study is carried out to investigate the process parameters which can affect the performance of FDM production and then optimize the selected process parameters by using the Particle Swarm Optimization (PSO) method. The material used in this study is Polylactic Acid (PLA) and the printed model is All-in-one 3D printing tester. The independent variable of this study is layer thickness, print speed, print temperature, retraction distance and infill percentage while the dependent variable is dimensional error. Multiple linear regression (MLR) is used to determine the influence of process parameters on all tests and dimensional accuracy. Besides, the dimensional error model was created and utilized in PSO. The result of minimization of dimensional error by PSO is successfully obtained which are 0.0805mm (layer thickness), 49.7568mm/s (print speed), 195.7164°C (print temperature), 0.8462mm (retraction distance) and 27.5899% (infill percentage). It is not the optimum process parameter value which can be proved by percentage error between the theoretical and experimental optimum process parameters values. The validation model is ranked at 17 out of 25 models which can be concluded that the optimized process parameter value from PSO is confirmed not the optimum value. In conclusion, the optimum process parameter values in this study will be taken from the experimental run model which has the lowest dimensional error, the process parameter values of X_3 are 0.05mm (layer thickness), 50mm/s (print speed), 210°C (print temperature), 1.5mm (retraction distance), and 25% (infill percentage).

Keywords: 3D Printing, Fused deposition modelling (FDM), Process Parameter, Particle Swarm Optimization, Polylactic Acid

1. Introduction

3D printing also known as additive manufacturing (AM) or additive layer manufacturing (ALM), is a method of creating three-dimensional solid products from a digital file. The production of a 3D

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printed product is accomplished via the use of additive manufacturing technologies. An object is built in additive manufacturing technology by laying down successive layers of material until the product is complete. [1] 3D printing makes it possible to create complicated forms with less material than traditional production processes. [2] This manufacturing technology is now utilized in a variety of sectors such as fashion, dentistry, and especially in high-end technical industries such as automotive, aerospace, specialty components, and so on. However, they are no longer as widely employed as they once were due to limits and restraints, such as the high cost of manufacturing processes. [3] The accuracy, efficiency, and characteristics of the created additive are highly influenced by the process parameters. As a result, basic investigations into various process parameters should be incorporated in any attempt to manufacture functionally reliable components using the FDM method. [4]

In addition to the benefits of the FDM method, some uncontrollable production issues need improvement, such as hanging strands, incomplete bottom layers, shifted layers, missing walls, pillowing, unfinished parts, warping syndrome, delamination of layers, burn marks, and irregular walls. [5] Stringing is the most prevalent printer-related issue. It happens when residues of tiny polymer strings are left behind the nozzle while it is not extruding. However, for interior features and joints, this can be difficult to achieve. [6] The mentioned issues will increase the defects in 3D printing parts which may affect the precision of the product.

From the previous study, the optimized process parameter will increase the dimensional accuracy of the 3D printed model, decrease the failure and build time. To improve and spread the advantages of 3D printing technology, the existing problems which may cause the low confidence of consumer to the manufacturing technology of 3D printer should be diminished. This research will aid in 3D printing is far better than conventional industrial technologies for small production runs, prototyping, small business, and educational use.

Since the defects in 3D printing are common, this study is carried out to investigate the process parameters which can affect the performance of FDM production and then optimize the selected process parameters. After the process parameters are adjusted and analysed, we can minimize the 3D printing failures when manufacturing 3D printing models. FDM process parameters are analysed in this study.

2. Materials and Methods

This chapter will cover the model of FDM printer used, the materials utilized, and the design of the experiment. The methodology for determining the best parameters for FDM 3D printing is outlined below. Figure 1 shows the methodology flow chart of the whole study.

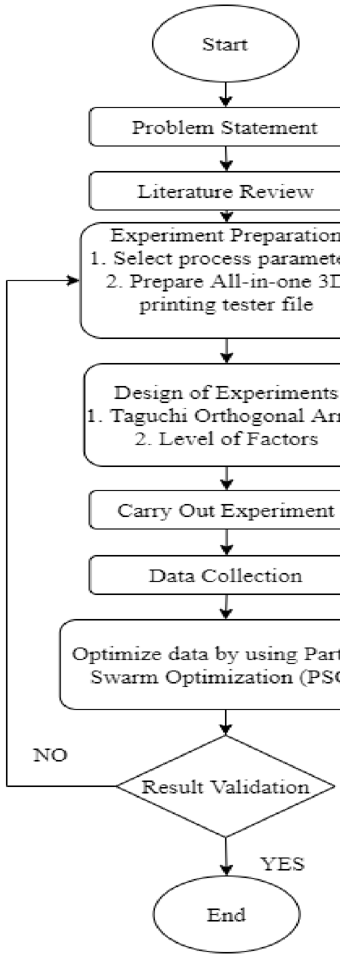

Figure 1: Methodology Flowchart

2.1 Materials and Equipment

The Anycubic Chiron 3D Printer, which has advantages on multi-material compatibility, accurate printing, and high-performance extruder is used to print model during this study. The raw material utilized in the study is Polylactic Acid Resins (PLA) with a diameter of 1.75mm, which is one of the most common filaments used in 3D printing. It is very usual that PLA specimens undergo sudden brittle fracture at the elastic limit and lower failure loads. [7] The All-In-One 3D printing tester is a test model that includes overhang, bridges, stringing, extrusion, temperature, belt tension, and other tests. This model is chosen for use in this study, which will contribute to the stringing, overhang, hole, bridge, and diameter tests.

2.2 Data Preparation

The process parameter od this study are selected. Table 1 and Table 2 show the fixed factors and controllable factors respectively.

Table 1: Fixed Factor

Factor	Value	Unit
Nozzle Diameter	0.4	mm
Filament Diameter	1.75	mm
Bed Temperature	60	°C
Infill Geometry	Rectangular	-

Table 2: Controllable Factor

Factor	Symbol	Level					Unit
		1	2	3	4	5	
Layer Thickness	A	0.05	0.10	0.15	0.20	0.25	mm
Print Speed	B	40	45	50	55	60	mm/s
Print Temperature	C	190	200	210	220	230	°C
Retraction Distance	D	0.5	1.0	1.5	2.0	2.5	mm
Infill Percentage	E	15	20	25	30	35	%

The Taguchi Orthogonal Array (OA) is a highly fractional orthogonal design based on a design matrix is a sort of broad fractional factorial design which is applicable to consider a selected subset of various factor combinations at various levels by using OA. [8] The levels of parameters have been determined as the framework of the experiment. To provide more accurate results, the level of each control factor has been set to 5 whereas the 25 sets of the experimental run will consist of the different factors with different levels. Table 3 displays the Taguchi Orthogonal Array with level of factors.

Table 3: Taguchi Orthogonal Array with Level of Factors

Run	Taguchi P=5, L=5					Experimental Run, X
	Level of Factors					
	Layer Thickness	Print Speed	Print Temperature	Retraction Distance	Infill Percentage	
1	0.05	40	190	0.5	15	X_1
2	0.05	45	200	1.0	20	X_2
3	0.05	50	210	1.5	25	X_3
4	0.05	55	220	2.0	30	X_4
5	0.05	60	230	2.5	35	X_5
6	0.10	40	200	1.5	30	X_6
7	0.10	45	210	2.0	35	X_7
8	0.10	50	220	2.5	15	X_8
9	0.10	55	230	0.5	20	X_9
10	0.10	60	190	1.0	25	X_{10}
11	0.15	40	210	2.5	20	X_{11}
12	0.15	45	220	0.5	25	X_{12}
13	0.15	50	230	1.0	30	X_{13}
14	0.15	55	190	1.5	35	X_{14}
15	0.15	60	200	2.0	15	X_{15}
16	0.20	40	220	1.0	35	X_{16}
17	0.20	45	230	1.5	15	X_{17}
18	0.20	50	190	2.0	20	X_{18}
19	0.20	55	200	2.5	25	X_{19}
20	0.20	60	210	0.5	30	X_{20}

Table 3: Taguchi Orthogonal Array with Level of Factors (cont.)

Run	Taguchi P=5, L=5					Experimental Run, X
	Level of Factors					
	Layer Thickness	Print Speed	Print Temperature	Retraction Distance	Infill Percentage	
21	0.25	40	230	2.0	25	X_{21}
22	0.25	45	190	2.5	30	X_{22}
23	0.25	50	200	0.5	35	X_{23}
24	0.25	55	210	1.0	15	X_{24}
25	0.25	60	220	1.5	20	X_{25}

2.3 Data Collection

There are result from six outputs should be recorded which are the number of stringing, Angle A, Angle B, dimension of holes, dimension of the bridge and diameter of the cylinder will be measured and observed. The results will be recorded and rated in a data collection sheet. The data recorded of overhang test, hole test, bridging test and diameter test will refer to the rating scale. Table 4 shows the result range of the output response, meanwhile Table 5, 6, 7, 8 show the rating scale of overhang test, hole test, bridging test and diameter test. The design rating scale for all tests is based on the smaller the better concept.

Table 4: The Result Range of the Output Response

Angle A (°)	Angle B(°)	Hole (mm)	Bridge Length (mm)	Diameter (mm)
15	10	4	2	4
30	20	6	5	6
45	30	8	10	8
60	40		15	10
75	50		20	
	60		25	
	70			
	80			

Table 5: Rating Scale of Overhang Test

Angle A (°)	Rating	Angle B (°)	Rating
15	5	10	5
30	4	20	4.375
45	3	30	3.75
60	2	40	3.125
75	1	50	2.5
		60	1.875
		70	1.25
		80	0.625

Table 6: Rating Scale of Hole Test

Hole (mm)	Rating
4	1.666
6	3.332
8	5

Table 7: Rating Scale of Bridging Test

Bridge Length (mm)	Rating
2	5
5	4.165
10	3.332
15	2.499
20	1.666
25	0.833

Table 8: Rating Scale of Diameter Test

Diameter (mm)	Rating
4	1.25
6	2.5
8	3.75
10	5

2.4 Multiple Linear Regression

Multiple linear regression (MLR) is used to observe that how strong the relationship is between the layer thickness, print speed, print temperature, retraction distance and infill percentage and affect dimensional error.

$$\mathrm{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \quad \text{Eq. 1}$$

Where Y = Dependent Variable, β_0= Intercept, β_i = Slope for X_i, X= Independent Variable (layer thickness, print speed, print temperature, retraction distance and infill percentage)

2.5 Particle Swarm Optimization

The optimization of data will be done by using Particle Swarm (PSO). Position parameters, speed parameters, and fitness parameters of each particle can be used to determine the ideal position.

Step 1: Initialize a particles population, n

The PSO approach parameters utilized in the proposed mathematical model are listed below. PSO optimization will be carried out using the MATLAB R2022a software.

Table 9: Parameter Setting of PSO

Parameter	Setting Value
Number of iterations	80
Number of particle population	50
Dimension (number of process parameter)	5
C_1 (acceleration constant for the cognitive parameter)	1.49

C_2 (acceleration constant for the social parameter)	1.49
W (inertia weight)	1.0

Step 2: Calculate fitness value, $fx_i^{(t)}$ for each particle.
If the fitness value is better than the best fitness value (p_{best}) in history, set current value as the new p_{best}. This step will be repeated until all the particles in the population have been processed.

Step 3: Choose particle with the best fitness value of all the particles considered so far as the g_{best}.
If the new x is better than the current g_{best}, then the new value of x will become the g_{best} .

Step 4: Calculate and update the particle velocity and position for each particle by using Eqs. (2) and (3).
Velocity update equation,

$$V_i^{(t+1)} = wV_i^{(t)} + c_1 r_1 \times \left(p_i^{best} - x_i^{(t)}\right) + c_2 r_2 \times (g_{best} - x_i^{(t)}) \qquad \text{Eq. 2}$$

And position update equation,

$$x_i^{(t+1)} = x_i^{(t)} + V_i^{(t+1)} \qquad \text{Eq. 3}$$

Step 5: If the maximum number of iterations is reached, the program should be ended. Otherwise, proceed to Step 2.

Step 6: End.

3. Results and Discussion

The data are first rated and normalized, then the data and the results are used in multiple linear regression to create a model which can be used for optimization. The result is further analysis by optimizing it through Particle Swarm Optimization (PSO). After optimizing, we can get the minimize dimensional error result and the optimized combination of parameter values. The printed models are sized down to the ratio of 1:2. The printing process comes to a successful result since all the 25 models are printed completely.

3.1 Results

Table 10 shows the results for the selected tests by referring designed rating scale. The linear regression model for each test was generated using MATLAB R2022a software. For the stringing model, layer thickness and infill percentage are major controlled variables for the stringing test. R^2 and adjusted R^2 also given, and the values are 0.754 and 0.689 respectively. For the overhang test, layer thickness and print temperature are major controlled variables for the overhang test, the value of R^2 and adjusted R^2 are 0.685 and 0.602 respectively. For the hole test, that layer thickness, print temperature, retraction distance and infill percentage are major controlled variables and the values of R^2 and adjusted R^2 are 0.712 and 0.636 respectively. For the bridging test, layer thickness is the only significant controllable variable and the values of R^2 and adjusted R^2 are quite low, which are 0.242 and 0.043 respectively. For the diameter test, only layer thickness is significant and the values of R^2 and adjusted R^2 are 0.561 and 0.445 respectively. From Figure 2, the dimensional error model obtained the value of R^2 and adjusted R^2, which are 0.828 and 0.783 respectively show a high level of correlation. Moreover, the root mean squared error is 0.108, which is the lower the better a given model can fit the dataset. However, there is only one independent variable which has a p-value less than 0.05, the layer thickness is significant for dimensional accuracy. The linear regression model for dimensional accuracy is given in the equation as stated below:

$$Dimensional\ Error = -0.59395 + 2.8521x_1 + 0.0022329x_2 + 0.001339x_3 - 0.00043696x_4 + 0.0047388x_5 \quad \text{Eq. 4}$$

```
mdl =


Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5

Estimated Coefficients:
                    Estimate         SE          tStat        pValue
                   __________    _________    _________    __________

    (Intercept)      -0.59395      0.36811      -1.6135       0.12312
    x1                 2.8521      0.30413       9.3778     1.466e-08
    x2              0.0022329    0.0030413      0.73418        0.4718
    x3               0.001339    0.0015206      0.88052       0.38958
    x4            -0.00043696     0.030413    -0.014368       0.98869
    x5              0.0047388    0.0030413       1.5582        0.1357


Number of observations: 25, Error degrees of freedom: 19
Root Mean Squared Error: 0.108
R-squared: 0.828,  Adjusted R-Squared: 0.783
F-statistic vs. constant model: 18.3, p-value = 1.1e-06
```

Figure 2: Regression Result of Dimensional Error

Table 11: Result in Rating

Run	Count of string	Angle A	Angle B	Hole	Bridging	Diameter	Experimental run, X
1	2	2	1.25	1.666	2.499	2.5	X_1
2	1	1	0.625	1.666	3.332	2.5	X_2
3	0	1	2.5	1.666	3.332	1.25	X_3
4	3	1	1.25	3.332	3.332	1.25	X_4
5	2	1	3.75	5	2.499	2.5	X_5
6	4	1	1.875	3.332	2.499	1.25	X_6
7	7	3	1.875	5	1.666	1.25	X_7
8	1	1	2.5	5	2.499	2.5	X_8
9	2	1	3.125	3.332	2.499	1.25	X_9
10	2	1	1.875	1.666	2.499	1.25	X_{10}
11	3	1	2.5	3.332	1.666	2.5	X_{11}
12	3	1	1.875	3.332	3.332	2.5	X_{12}
13	5	1	3.125	5	1.666	2.5	X_{13}
14	10	1	2.5	3.332	2.499	1.25	X_{14}
15	10	1	2.5	3.332	3.332	2.5	X_{15}
16	11	1	3.125	5	1.666	2.5	X_{16}
17	7	3	3.125	3.332	4.165	2.5	X_{17}
18	6	2	1.875	5	2.499	2.5	X_{18}
19	5	2	2.5	5	4.165	1.25	X_{19}
20	8	3	3.75	5	3.332	2.5	X_{20}
21	9	4	4.375	5	5	5	X_{21}
22	11	2	2.5	5	4.165	5	X_{22}
23	19	4	3.75	5	2.499	3.75	X_{23}
24	10	4	3.75	5	3.332	5	X_{24}
25	9	4	3.75	5	3.332	5	X_{25}

The regression result of stringing, overhang, hole, bridging and diameter tests are obtained from MLR. From the Table 12, we can conclude that the most significant independent variable is layer thickness, follow by infill percentage, print temperature and retraction distance, lastly the print speed.

Table 12: Significant Rank for Independent Variables

	Layer Thickness	Print Speed	Print temperature	Retraction Distance	Infill Percentage
Stringing Test	Significant	-	-	-	Significant
Overhang Test	Significant	-	Significant	-	-
Hole Test	Significant	-	Significant	Significant	Significant
Bridging Test	Significant	-	-	-	-
Diameter Test	Significant	-	-	-	-
Rank from MLR	1	5	2	4	2
Rank from MEP	1	5	4	3	2

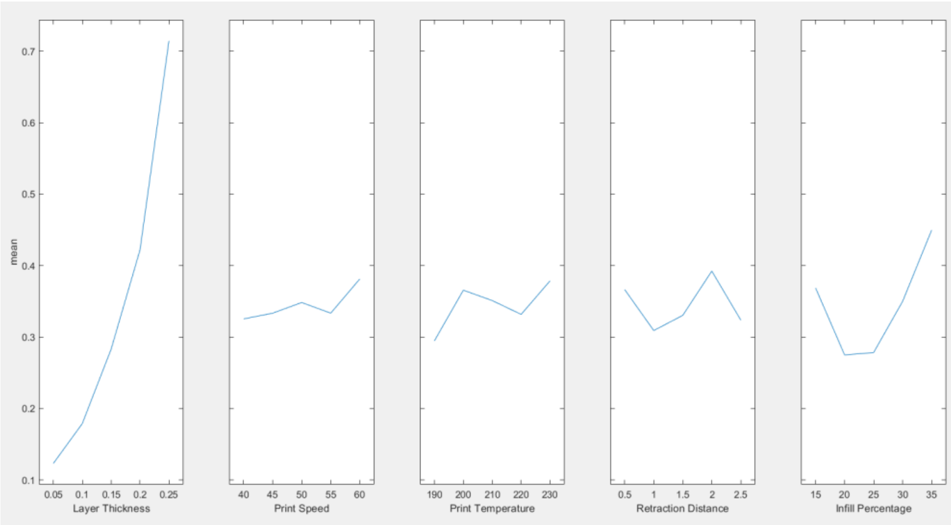

Figure 3: Main Effects Plot of Dimensional Error

Since the dependent variable is the dimensional error with the smaller-the-better scale, we should take the lowest mean as the best point. From this plot, we can obtain the optimum process parameters by taking the lowest mean of level among all factors. From the Figure 3, the optimum parameter will be A1-B1-C1-D2-E2.

Table 13: Theoretical Optimum Process Parameter

Factors	Symbols	Optimized Level	Parameters of Level
Layer Thickness	A	1	0.05
Print Speed	B	1	40
Print Temperature	C	1	190
Retraction Distance	D	2	1
Infill Percentage	E	2	20

In this study, Particle Swarm Optimization (PSO) is used to determine the optimum parameters for FDM 3D printing based on the result of stringing test, overhang test, hole test, bridging test and diameter test.

Table 14: Optimized Process Parameter Value from PSO

Process Parameter	Value
Layer Thickness	0.0805
Printing Speed	49.7568
Printing Temperature	195.7164
Retraction Distance	0.8462
Infill percentage	27.5899

3.2 Discussions

From the optimization, the data collected from the validation model does not obtain the best result. We can observe that the stringing problem have not decrease and the part of hole, bridge and diameter test are not printed perfectly. It can be concluded that the validation printing does not improve more than the best experimental run. Table 15 shows that the validation model is ranked at 17 out of 25 models.

Table 15: Ranked Result of Experimental Run

Rank	Experimental Run	Count of String	Sum of Rate	Dimensional Error (cos+sor)/2
1	3	0	0.096652	0.048326
2	10	0.10526	0	0.05263
3	2	0.052632	0.05522	0.053926
4	1	0.10526	0.10772	0.10649
5	4	0.15789	0.12423	0.14106
6	9	0.10526	0.1933	0.14928
7	6	0.21053	0.11044	0.160485
8	11	0.15789	0.17952	0.168705
9	8	0.052632	0.34531	0.198971
10	12	0.15789	0.24853	0.20321
11	5	0.10526	0.42817	0.266715
12	13	0.26316	0.33152	0.29734
13	7	0.36842	0.29838	0.3334
14	14	0.52632	0.15187	0.339095
15	18	0.31579	0.37017	0.34298
16	19	0.26316	0.43918	0.35117
17	Validation	0.52632	0.24853	0.387425
18	15	0.52632	0.28996	0.40814
19	17	0.36842	0.51919	0.443805
20	16	0.57895	0.33152	0.455235
21	20	0.42105	0.61598	0.518515
22	22	0.57895	0.68777	0.63336
23	25	0.47368	0.84799	0.660835
24	24	0.52632	0.84799	0.687155
25	21	0.47368	1	0.73684
26	23	1	0.70991	0.854955

Table 16: Percentage Error Result of Optimum Process Parameter Value

Factors	The Best Experimental Run	Main Effects Plot (theoretical)	Particle Swarm Optimization (experimental)	Error (%)
Layer Thickness	0.05	0.05	0.0805	61
Print Speed	50	40	49.7568	24.39
Print Temperature	210	190	195.7164	3.01
Retraction Distance	1.5	1	0.8462	15.38
Infill Percentage	25	20	27.5899	37.95

From the Table 17, there is only the print temperature obtained the percentage error less than 5%, means that the optimized print temperature value is very close to the accepted value. From the previous regression results, we obtained that the layer thickness is the most significant process parameter for the printing performance improvement. However, the error of the layer thickness is 61% which indicates that there is apprehension that the optimized layer thickness value from PSO is the main reason that makes the validation model a bad printing. Besides, the percentage of error of the print speed, retraction distance and infill percentage are also having a quite long way off from the theoretical optimum value.

From the comparison between theoretical and experimental optimum process parameter value, we can conclude that the high error obtained is the main factor of the bad performance occurred on the validation model. Since the optimized process parameter values obtained from PSO is not the optimum result, therefore the validation model had more defects compared to the best printing (X3). The stringing problem had not been improved since it had 10 strings which is considered a high value among all printing. The overhang result from the validation model is considered optimum results meanwhile the result of the hole test, bridging test, and diameter test are considered lower-middle.

A model named XYZ 20mm Calibration Cube which is a basic 20-mm cube with the faces X, Y, and Z labeled. The objective is to obtain a length of 20 mm for each side that corresponds to the axis they test with the huge letters. Since the validation model had contributed to bad performance, the calibration cube is used to identify the dimensional accuracy of our printing by using the optimized process parameter values by PSO.

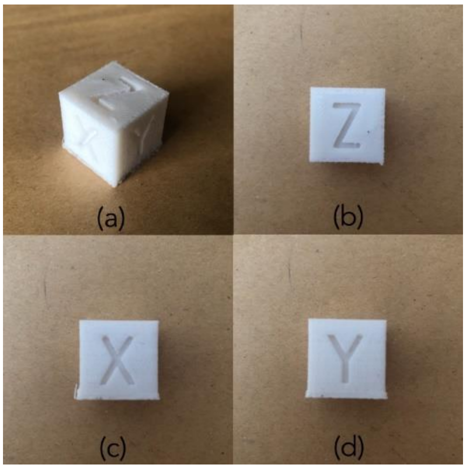

Figure 4: The printed model of XYZ 20mm Calibration Cube set in (a) isometric view, (b) top view, (c) side view, (d) front view

Figure 4 shows the printing of XYZ 20mm calibration cube. The length of the side X, Y and Z are measured by using a digital Vernier caliper. The length measured of the side X, Y, and Z are 20mm, 19.99mm and 19.98mm respectively. Since the results are all in a deviation of 0.05mm, it can be said that the printing using the optimized process parameter values by PSO is considered a precise product. Besides, there is no incomplete printing problem, but the stringing problem occurred on this printing calibration cube. Therefore, it can be concluded that the optimized process parameter values by PSO can produce a low dimensional error product but it cannot diminish the stringing problem.

4. Conclusion

In conclusion, the objective of the study has been achieved as the optimized parameters have been successfully determined although the result is not the optimum. Since the optimum result is failed to achieve, therefore the defect of 3D printing did not reduce with the optimized process parameter. The percentage error of the theoretical and experimental optimum process parameters values is obtained and there is a high error which can be considered as the failure reason of the validation model. Therefore, we can conclude that the optimized process parameter value from PSO is confirmed not the optimum value. In conclusion, the optimum process parameter values in this study will be taken from the experimental run model which has the lowest dimensional error, the process parameter values of X3 are 0.05mm (layer thickness), 50mm/s (print speed), 210°C (print temperature), 1.5mm (retraction distance), and 25% (infill percentage).

Acknowledgement

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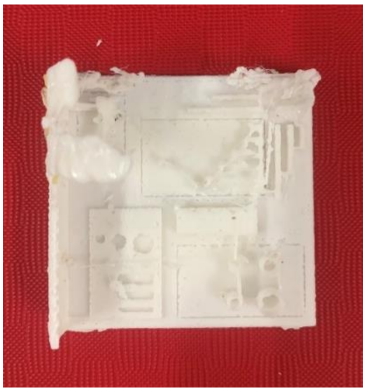
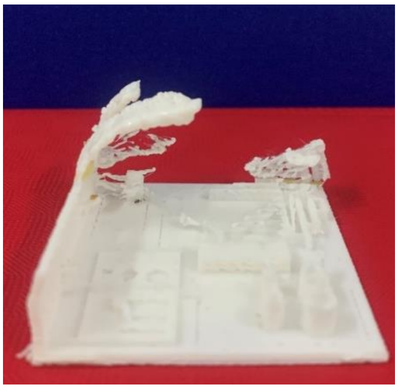
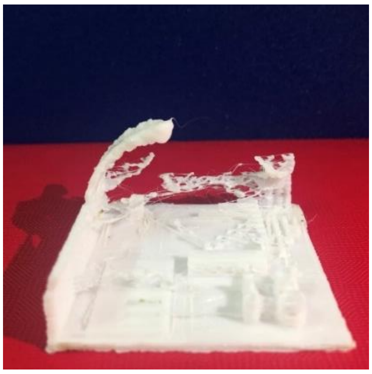
Appendix A

1. Top and side view of X_3

2. Top and side view of Validation Model

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