The transformation of 3D printing parameters under sustainable manufacturing

Ching-Chia Huang[1], Hua-Chen Shih[1], Tim de Ancos[2], Cheng-Jung Yang[1]*

[1]*Program in Interdisciplinary Studies, National Sun Yat-sen University, Kaohsiung, Taiwan*

[2]*Industrial Engineering, Technische Hochschule Mittelhessen, Friedberg, Germany*

*Corresponding author. Tel.: +886-7-5252000 ext.5740

E-mail: cjyang0521@mail.nsysu.edu.tw

ABSTRACT: Three-dimensional (3D) printing is a novel product creation process. Although it is convenient for human life, it generates large amounts of greenhouse gases and air pollutants, which cause global warming and harm human health. This study used fusion deposition molding technology as an example to investigate the multi-target optimization results of mechanical properties (dimensional accuracy and surface roughness), manufacturing costs, CO_2 emissions (electricity consumption generation), and air pollution (PM2.5), which represent the quality of manufactured products to achieve a win-win situation for both economic and environmental aspects in the process of mechanical manufacturing. The multi-target optimization results obtained by desirable analysis are without heat bed and fan, 185 ℃ of extrusion temperature, 10 mm/s of printing speed, 50% filled Tri-hexagon pattern, lying flat on the printing platform, two-layer shell with 0 mm height per layer, two outer shells with a layer height of 0.2 mm each, and blue filament.
Keywords: 3D printing, fusion deposition molding, multi-target optimization, desirable analysis

1 INTRODUCTION

Fusion deposition molding (FDM) is a popular 3D printing manufacturing technology with advantages such as low cost, ease of operation, and ease of equipment maintenance. Numerous studies conducted in the past investigated the mechanical properties (e.g., surface roughness and dimensional accuracy), manufacturing costs, and air pollution (including PM2.5 and VOCs) of plastic filaments.

Different printing planes (XY, YZ, and XZ) affect the energy consumption and dimensional accuracy of the sample thickness. (Carmita Camposeco-Negrete. 2020) The printing speed has a smaller effect on the mechanical properties of polylactic acid (PLA) parts. (Farazin, A., & Mohammadimehr, M. 2022) Regarding manufacturing costs, energy consumption decreased when the printing speed increased. (Vincenzo Lunetto, Paolo C. Priarone, Manuela Galati and Paolo Minetola. 2020) When the filament width increased, the percentage change in length and width in dimensional accuracy increased, however, the percentage change in thickness decreased. (Omar Ahmed Mohamed, Syed Hasan Masood and Jahar Lal Bhowmik. 2016) Regarding cost, the larger the layer thickness, the shorter the printing time and the lower the energy consumption. (Carmita Camposeco-Negrete. 2020) The power consumption is strongly related to heating (bed and extrusion temperatures), which is considerably higher than the power consumption of the stepper motor. Therefore, the power consumption is primarily related to the printing time rather than the complexity of printing; therefore, the shorter the printing time, the lower the power consumption. (Hunter James Hinshaw, Shane Terry and Ismail Fidan.2020) The higher the infill density and extrusion temperature, the higher the number of PM particles emitted. (Shirin Khaki, Emer Duffy, Alan F. Smeaton, Aoife Morrin. 2021) During 3D printing, PLA released VOCs in the liquid state, and these compounds condensed upon contact with air. (Timothy R. Simon, Wo Jae Lee, Benjamin E. Spurgeon, Brandon E. Boor, Fu Zhao. 2018) In addition, different filament colors produce different amounts of suspended PM particles for the same printed item. Therefore, 3D printing emits air pollutants such as PM particles and VOCs during the manufacturing process, and the amount of these pollutants is affected by different factors such as printing parameters and filament color. (Haejoon Jeon, Jihoon Park, Sunju Kim, Kyungho Park, Chungsik Yoon. 2020)

However, most of these studies were conducted on a single target, and comprehensive analysis results are missing. Therefore, this study aims to determine the best parameters for optimizing the total performance of FDM while simultaneously considering the mechanical properties, manufacturing cost, and air pollution. This study will conduct experimental planning using the Taguchi method; 36 sets of experiments will be designed using 10 factors, each set of experiments will be conducted three times; the best results of the single target will be analyzed by the S/N ratio and ANOVA after the experiments. In addition, this study investigates the best combination of printing parameters of 10 factors for multiple targets by a desirable analysis, and the optimization of the best combination is measured empirically.

2 EXPERIMENTAL

In this experiment, an XYZ-type FDM 3D printer (Original Prusa i3 MK3S) and a 1.75 mm diameter filament of PLA were used for printing; all three filament colors were produced by the same factory. The surface roughness was measured using a Mitutoyo surface roughness meter (SJ-210), and the dimensional accuracy was measured using a Vernier caliper (TESA - CCMA-M - 0.01 mm). The energy consumption and air quality data of the printer were collected using Python (Figure 1). When the program detected that the printer was printing, it automatically collected the values of energy consumption, PM 2.5, VOCs, and CO2 and saved the data as CSV files after printing was completed.

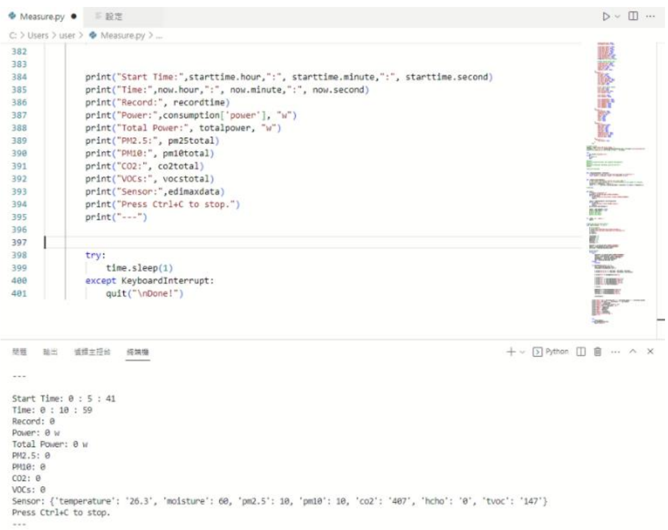

Figure 1. Python Data Collection

The experiment had different objectives for different aspects. The first is the total weight and power consumption of the prints for manufacturing costs. Second, manufacturing emissions of PM2.5, CO2, and VOCs affect human health. Finally, the surface roughness and dimensional accuracy (Wi, Wo, OL, and T in Figure 2) for the mechanical properties of the prints. Ten single objectives were summarized from these three aspects. The main factors affecting these objectives are the manufacturing parameters: bed temperature, fan speed, extrusion temperature, print speed, infill density, infill pattern, color, layer height, number of contours, and build orientation. The print object specification standard is ASTM-1708, as shown in Figure 2. Referring to the orthogonal arrays invented by Dr. Taguchi, L36 was selected for the experimental design, and the ten factors are in the order of A–J in Table 1. Three experiments were performed for each group, and the average calculation was used to understand the influence of each parameter on different single objectives using the S/N ratio. The S/N ratio was used to determine the influence of each parameter on the different single targets. The results of the ANOVA were used to determine whether the influence of each parameter was significant. Finally, a desirable analysis and Taguchi's prediction were used to obtain the optimal combination of all the single objectives. The improvement rate of the difference between Taguchi's prediction and the actual value was calculated.

As shown in Figure 2, the dimensional accuracies of Wi (inner width of the specimen), Wo (outer width of the specimen), OL (length of the specimen), and T (thickness of the specimen) were 5 cm, 15 cm, 38 cm, and 3 cm, respectively, according to ASTM-1708. Wi and T are the averages of three measurements (1 to 3), and Wo is the average of Wo1 and Wo2.

Table 1. Factors and their corresponding levels and codes

Code	Factors	Levels		
		1	2	3
A	Bed temperature	25°C	50°C	-
B	Fan speed	0%	100%	-
C	Extrusion temperature	185°C	195°C	205°C
D	Print speed	10 mm/s	20 mm/s	40 mm/s
E	Infill density	20%	50%	80%
F	Infill pattern	Grid	Triangles	Tri-hexagon
G	Color	Green	Blue	Black
H	Layer height	0.1 mm	0.2 mm	0.3 mm
I	Number of contours	1	2	3
J	Build orientation	0°	45°	90°

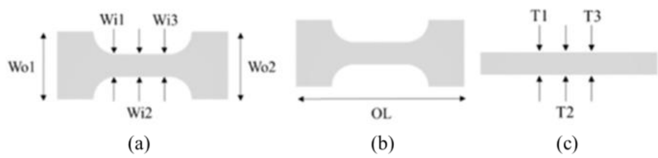

Figure 2. ASTM-1708

The better the accuracy of the single target size in this experiment, the better the actual geometry is close to the ideal geometry, which belongs to the Taguchi method. (Vincenzo Lunetto, Paolo C. Priarone, Manuela Galati and Paolo Minetola. 2020) The smaller the measured value is, the better it belongs to the Taguchi method. The relevant analytical formula for Signal Noise Ratio (SNR), standard deviation, sum of squares, and contribution rate is sequentially described as equation (1) to (5).

$$\mathrm{SNR} = -10 \cdot \log(\sum Y^2/n) \tag{1}$$

$$\mathrm{SNR} = 10 \cdot \log(1/(\bar{Y}^2 * S^2)) \tag{2}$$

$$S = (\sum_{i=1}^{n}(y_i - \bar{y})^2/n)^{0.5} \tag{3}$$

$$SS_A = \frac{(A_1)^2}{m} + \frac{(A_2)^2}{m} + \cdots + \frac{(A_p)^2}{m} - CF \tag{4}$$

$$\rho\,(\%) = (SS/TSS) \times 100\% \tag{5}$$

Note: k is the constant of proportionality, y is the measurement value of product quality characteristics, n is the number of measurement values, S is the standard deviation, $\bar{y}$ is the average of n measurements, $CF = (\sum \eta_I)^2/N$.

The Desirability Function calculates the best reconciliation result for multiple targets. The target value is the value of the smallest of the 36 groups for the lookahead characteristics. However, for the lookahead characteristics, the target value is the value defined in Figure 2. Equations (6) to (8) can be used to minimize response desirability. The targets of the response desirability are (9) to (12). Composite desirability is given by Equation (13).

Minimize the Response Desirability：

Di=0	if	yi > Ui	(6)
Di=((Ui– yi)/(Ui - Ti))ri	if	Ti ≤ yi ≤ Ui	(7)
Di=1	if	yi<Ti	(8)

Target the Response Desirability：

Di = ((yi –Li)/(Ti –Li))ri	if	Li ≤yi ≤ Ti	(9)
Di = ((Ui – yi)/(Ui - Ti))ri	If	Ti ≤ yi ≤ Ui	(10)
Di=0	if	yi < Li	(11)
Di=0	if	yi > Ui	(12)

Composite desirability：

$$D = (d1\times d2\times d3\times\ldots\ldots\times dn)^{1/n} \tag{13}$$

Note: Di = Desirability of individual responses, D = Composite desirability, n = the total number of responses, yi = experimentally produced value, Ti = Target value of response under consideration, Li = Lowest value of response under consideration, Ui = Highest value of response under consideration, and ri = weight value.

3 RESULTS AND DISCUSSION

Through the S/N ratio and ANOVA analysis, this study found that the build orientation parameter had a significant effect on all single targets except for Wi and Wo. The second most significant parameter affecting most of the single targets was the layer height, except for Wi and OL. The bed temperature parameter had no significant effect on dimensional accuracy, total grammage, and PM2.5 but had a significant effect on surface roughness, energy consumption, CO2, and VOCs. Table 2 shows the detailed correlation of all the parameters with each target. Figure 3 shows the contributions of different factors to each objective.

The optimal combination of multiple targets obtained by Desirable analysis and Taguchi's prediction is indicated by the code A1B1C1D3E2F3G2H2I2J1, which stands for no hot bed, no fan, 185 degrees of extrusion temperature, 10 mm/s of printing speed, 50% filled Tri-hexagon pattern, lying flat on the printing platform, and a two-layer shell with 0 mm height per layer, two outer shells with a layer height of 0.2 mm each, and blue filament. This Taguchi-derived best solution was not included in L36, so additional experiments were required. Analyzing the results of the best solution experiments revealed that, the performance of the derived best solution for multiple targets was indeed the best when compared to the original 36 sets of experiments. The improvement rate compared with the best combination of multiple targets in the original 36 groups, was 0.6%.

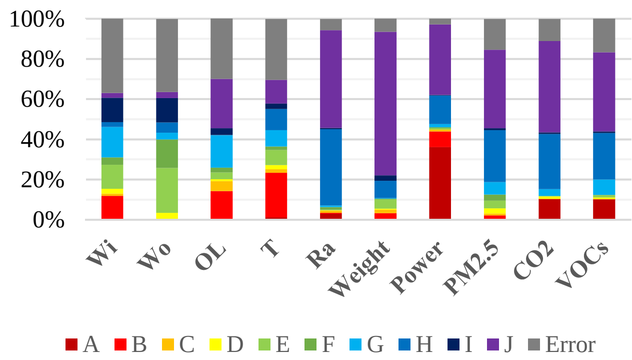

Figure 3. The contribution of different factors to each single objective

Table 2. Optimal combination of single objectives and ranking of the influence of each factor

Response	Optimal factors	Factor importance
Wi	A1,B2,C3,D1,E3,F3,G1,H2,I2,J1	G>I>E>B>F>D>J>H>C>A
Wo	A1,B2,C1,D2,E3,F2,G3,H1,I1,J1	E>F>I>H>G>J>D>C>B>A
OL	A1,B2,C3,D3,E1,F3,G1,H3,I3,J3	J>G>B>C>E>I>F>D>A>H
T	A2,B2,C2,D2,E1,F3,G2,H2,I3,J3	B>J>H>G>E>I>D>C>F>A
Ra	A2,B1,C3,D3,E2,F3,G3,H1,I3,J1	J>H>A>F>C>G>I>B>E>D
Weight	A1,B1,C1,D3,E1,F3,G2,H1,I1,J1	J>H>E>B>I>C>D>F>A>G
Power	A1,B1,C1,D1,E1,F3,G1,H3,I1,J1	A>J>H>B>G>C>E>F>I>D
PM2.5	A2,B2,C1,D1,E1,F3,G1,H3,I3,J1	J>H>G>E>F>D>B>C>I>A
CO2	A1,B1,C3,D1,E3,F1,G2,H3,I3,J1	J>H>A>G>D>I>E>B>C>F
VOCs	A1,B1,C3,D1,E1,F2,G1,H3,I1,J1	J>H>A>G>E>I>D>B>F>C

Table 3. The top three composite desirability values(CDI) of L36, and the best solution CDI

Group	Composite Desirability	Rank
Best	0.988434	-
1	0.982454	1
8	0.974883	3
33	0.980556	2

4 CONCLUSION

This study investigated the effects of various parameters on the mechanical properties, manufacturing cost, and air pollution of FDM 3D printing through a multi-objective analysis and used the Taguchi method to determine the best formulation for the combined manufacturing parameters. In addition, this study also analyzed the influence of every single objective and found that three parameters–orientation, layer height, and bed temperature–play key roles in weight, power, and surface roughness. In the future, obtaining good product quality while reducing energy use and environmental pollution should be a priority when setting printing parameters. In terms of environmental impact, future research can focus on the life-cycle assessment of 3D printing and explore the possibility of optimizing carbon emissions while optimizing energy consumption, air quality, and mechanical properties.

5 REFERENCES

M Heidari-Rarani, N Ezati, P Sadeghi and MR Badrossamay. 2020. Optimization of FDM process parameters for tensile properties of polylactic acid specimens using Taguchi design of experiment method. Journal of Thermoplastic Composite Materials.1–18.

D'Addona, D. M., Raykar, S. J., Singh, D., & Kramar, D. 2021. Multi Objective Optimization of Fused Deposition Modeling Process Parameters with Desirability Function. Procedia CIRP. 99:707–710.

Farazin, A., & Mohammadimehr, M. 2022. Effect of different parameters on the tensile properties of printed Polylactic acid samples by FDM: experimental design tested with MDs simulation. The International Journal of Advanced Manufacturing Technology, 118(1), 103-118. doi:10.1007/s00170-021-07330-w

Omar Ahmed Mohamed, Syed Hasan Masood and Jahar Lal Bhowmik. 2016. Optimization of fused deposition modeling process parameters for dimensional accuracy using I-optimality criterion. Measurement. 81:174–196

Carmita Camposeco-Negrete. 2020. Optimization of printing parameters in fused deposition modeling for improving part quality and process sustainability. Advanced Manufacturing Technology.108:2131–2147

Table 4. Comparison between the results achieved using the desirability analysis and the Taguchi methodology

Response	Scenarios										
	Best	1	2	3	4	5	6	7	8	9	10
Wi(mm)	5.03	5.00									
Wo(mm)	15.14		15.07								
OL(mm)	38.05			37.99							
T(mm)	3.00				3.18						
Ra(μm)	8.062					4.474					
weight(g)	1.50						1.2				
Power(W)	15911							10904			
PM2.5(ug/m3)	3943								334		
CO2(g)	231963									148400	
VOCs(ppb)	84129										50036
Difference between scenarios	-	0.67%	0.44%	0.17%	-5.77%	45.92%	80.19%	25.00%	1080.44%	56.31%	68.14%

Vincenzo Lunetto, Paolo C. Priarone, Manuela Galati and Paolo Minetola. 2020. On the correlation between process parameters and specific energy consumption in fused deposition modeling. Manufacturing Processes.56:1039–1049

Carmita Camposeco-Negrete. 2020. Optimization of FDM parameters for improving part quality, productivity, and sustainability of the process using Taguchi methodology and desirability approach. Progress in Additive Manufacturing.5:59–65

Hunter James Hinshaw, Shane Terry and Ismail Fidan.2020. Power consumption investigation for fused filament fabricated specimen. Rapid Manufacturing.9.Nos.2/3.

Shirin Khaki, Emer Duffy, Alan F. Smeaton, Aoife Morrin. 2021. Monitoring of Particulate Matter Emissions from 3D Printing Activity in the Home Setting. Sensors (Basel). 21(9): 3247.

Timothy R. Simon, Wo Jae Lee, Benjamin E. Spurgeon, Brandon E. Boor, Fu Zhao. 2018. An Experimental Study on the Energy Consumption and Emission Profile of Fused Deposition Modeling Process. Procedia Manufacturing. 26:920–928.

Haejoon Jeon, Jihoon Park, Sunju Kim, Kyungho Park, Chungsik Yoon. .2020. Effect of nozzle temperature on the emission rate of ultrafine particles during 3D printing. Indoor Air, 2020 Mar; 30(2): 306-314.

Original Prusa i3 MK3S+, https://www.prusa3d.com/category/original-prusa-i3-mk3s.

EDIMAX AI-2002W Smart Wireless Indoor Air Quality Detector with 7-in-1 Multi-Sensor, https://www.edimax.com/edimax/merchandise/merchandise_detail/data/edimax/tw/air_quality_monitoring_indoor/ai-2002w.

TP-LINK HS110 Kasa Smart Wi-Fi Plug with Energy Monitoring, https://www.tp-link.com/us/home-networking/smart-plug/hs110.

TESA - CCMA-M - 0.01mm (n.d.). Greatest Idea Strategy Co., Ltd., http://www.gch-lab.com.tw/web/product/product_in.jsp?pd_no=PD1532427574593

Mitutoyo SJ-210 Portable Surface Roughness Tester. (n.d.). https://www.mitutoyo.com/products/form-measurement-machine/surface-roughness/sj-210-portable-surface-roughness-tester-2/