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THE USE OF INTELLIGENT SYSTEMS AND INNOVATION TO MODEL AND OPTIMIZE FUSED DEPOSITION MODELING PROCESS PARAMETERS FOR TIME MANUFACTURING AND MATERIAL CONSUMPTION

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ABSTRACT

Additive manufacturing processes, especially the FDM process (Fused Deposition Modeling), are used for prototyping or manufacturing complex geometries. The ease of using 3D scanners and printers made FDM process a must have in every tech-house or laboratory. To optimize it, the prototyping cost, the manufacturing time and the material consumption must be reduced. Thus, the process parameters that intervene in the quantity of material and the manufacturing time (platform and extruder temperature, layer thickness, number of shells and solid layers, infill pattern and density, print speed) have been analyzed. An experimental study using a statistical analysis and an optimal experimental plan Design-optimal have been made. In addition, a mathematical model adapted to the experimental results has been designed. The RSM (response surface method) has been used to optimize the model response and find the most suitable set of process parameters. Those inputs have been validated with the developed mathematical model.

Keywords: *Additive Manufacturing; Fused Deposition Modeling; Parameters Optimization; response surface method*

1. INTRODUCTION

Additive manufacturing [1] processes produce parts by adding material, layer-by-layer [2], until obtaining a complete design. The first step in the production chain is designing a 3D part using an adequate software. The file must be saved as an stl format [3]. The stl format has been developed for the stereo lithography process. This process represents the origin of additive manufacturing; it has been developed by Dimitri Decoudu in the 80s. It is the most used file format in AM (additive manufacturing). It contains the information about the geometry and the part dimension, without taking into account the color, nor the texture or the other casual parameters found in other design formats. The file is then modified by a specific software that generates a g-code corresponding to the machine input format. This file contains the information about the machining process. Then the machine starts operating following the given data. The process is similar to 2D printers; the difference is in the third dimension that constitutes the part layer by layer. Many materials can be implemented in AM processes, such as plastics (PLA or ABS) [4-6] and metals (aluminum, titanium, steel, wax, ceramics or even glass).

AM allows the rapid manufacturing of complex parts. With the high concurrence that characterizes our era, the need of cost effective and fast manufacturing processes is predominant. That is why many industries use AM to manufacture complex parts [7-10] in a short time notice, such as biomedical or automotive fields.

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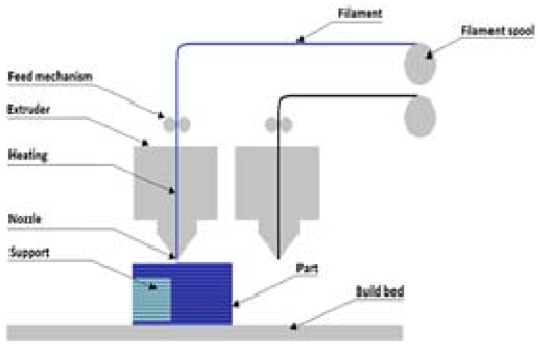

Figure 1: FDM manufacturing process

There is a wide range of AM processes, depending on the material, the precision or the volume parts. There are SLS and SLM (selective laser sintering or melting) that fusion a powder bed to manufacture parts in metal or polymers [11-13]. There is SLA (stereo lithography apparatus) that uses a light cure to harden a local zone using different energy sources, such as laser [14,15]. The most used process is the FDM (fused deposition modeling) that producesparts in polymers [16-18].

The scope of our study is the FDM process, because it is the most used one, thus, the need of its optimization is of high importance. Figure 1 shows the manufacturing process; successive layers between 0.08 and 3 mm thickness constitute the part. The material is heated around 190°, then it is extruded from a nozzle with a diameter ranged between 0.4 and 1.2 mm. The used material is PLA or ABS with a diameter between 1.75 and 3mm. Once a layer is printed, the platform or the extruder moves following the z axis, to start printing the next layer.

The FDM parameters play a predominant role in the finish surface, the dimension precision, the fabrication time and the mechanical properties of the produced part. Many studies have been made to optimize those parameters and achieve the most effective quality.

Thrimurthulu et al. [19] conceived a mathematical model to optimize the manufacturing time. The predominant parameter in this model is the orientation of the part during the fabrication. The results have been compared to other published solutions, thus, the model has been validated. Vijay.B.Nidagundi [26] have studied the optimization of FDM process parameters (Layer thickness, Orientation angle and fill angle) using Taguchi's L9 orthogonal array and Taguchi's S/N ratio. Analysis of variance has been used to check parameters effectiveness. Nancharaiah [20] studied the relationship between the manufacturing time and the process parameters using the design matrix of Taguchi (the orthogonal matrix L9) and the ANOVA (variance analysis) technique. The result is that the layer thickness and the gap between the nozzle and the platform are the most important parameters influencing the manufacturing time. Those parameters influences are 30.77% for the air gap and 66.57% for the layer thickness. The study also concluded that the optimal parameters are a layer thickness of 0.33mm and an air gap of 0.02mm with a frame angle of 30°. Kumar and Regalla [21] made a factorial experience plan to analyze every parameter influence on the manufacturing time and the support material consumption. The studied parameters are the layer thickness, the orientation and the frame angle. The experimental study also showed that the most influencing parameters for time reduction are the layer thickness and the orientation of the part during the machining. However, the study did not conclude on the optimal parameters for time and material reduction.

In this article, the parameters influences on the FDM process were studied using the D-optimal methodology for the experience plan. A mathematical model that links the influencing parameters has been formulated to verify the results. Then, the optimal parameters have been determined.

2. METHODOLOGY

Figure 2 shows the studied sample dimensions. Those dimensions are defined from the ASTM D5418-07 [22] standard. Figure 3 shows the fabricated samples. The 3DP workbench (figure 4) has been used with a 0.6mm nozzle diameter and a 2.85mm filament diameter of PLA (Polyacttic acid). The workbench is characterized by a 1000*1000*500mm print volume and a 0.07mm resolution. The samples have been fabricated in the center of the building platform. The design software used is Catia V5. After converting the designed part into the STL format, Simplify3d software was used to generate the nozzle path and define the building parameters.

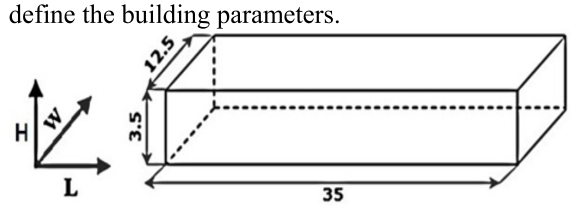

Figure 2: Sample dimensions

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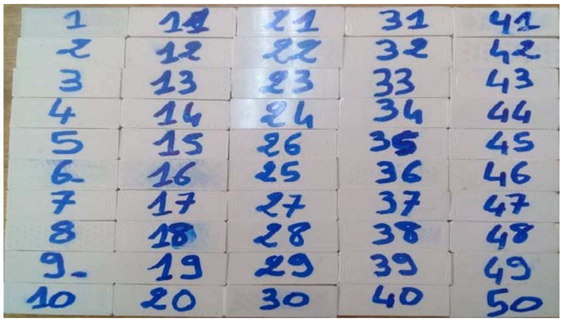

Figure 3: Printed samples

Eight parameters have been analyzed in this study. The choice and levels of these parameters were defined from literature and experiences made at a preliminary investigation [23-25]. Table 1 shows the range limits. Due to the number of the studied parameters, an experience plan has been determined to limit the number of experiences. Design-Optimal experience plan was used due to its high precision with only 50 experiences at three levels for each one of the eight parameters (irregular experimental matrix). The efficiency of an experimental model depends on the precise measurements and the detailed plan of the experimental process. Design Optimal betters the model and lowers the influence of the design on the adjustment regression. This gave us a valid estimation on the variation response to develop an adequate relationship between studied parameters and the outputs. Table 2 shows the final design matrix.


Figure 4: 3DP workbench used

Table 1: Parameters and levels of varying Processing Parameters

Symbols	Factors	Units	Levels
A	Platform temperature	°C	70 75 80
B	Extruder temperature	°C	190 200 210
C	Layer thickness	mm	0.15 0.3 0.45
D	Number of shells	–	1 2 3
E	Infill density	%	25 50 75
F	Print speed	mm/s	50 65 80
G	Infill pattern 'H=1 D=2 L=3'	–	H D L
H	Number of solid layers 'U/L'	–	2 3 4

- ✓ (A) Platform temperature is the bed temperature.
- ✓ (B) Extruder temperature is the necessary temperature to melt the material.
- ✓ (C) Layer thickness is the thickness of the extruded layer. It is based on the filament and the nozzle diameters (figure5-a).
- ✓ (D) Number of shells is the number of outlines built around the outer and inner pattern (figure 5-b).
- ✓ (E) Infill density: is the percentage of the infill of the printed part.
- ✓ (F) Print speed: is the printing velocity in mm/s.
- ✓ (G) Infill pattern: is the internal structure of the print H: Honeycomb; D: Grid; L: Rectilinear (figure 5-c).
- ✓ (H) Number of solid layers 'U / L': is the number of upper and lower layers (figure 5-d)

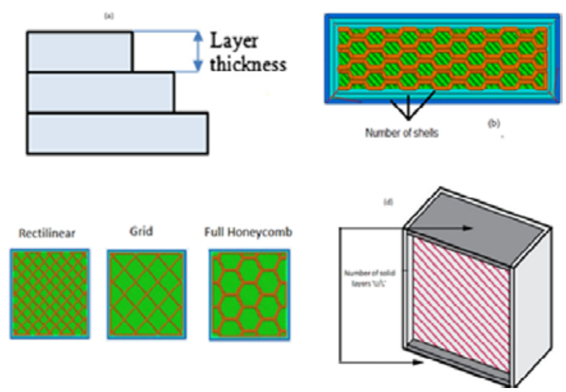

Figure 5: Input parameters, (a) Layer thickness, (b) Number of shells, (c) Infill pattern, (d) Number of solid layers 'U / L'

3. ANALYSIS

The material consumption and the manufacturing time have been analyzed following the variation of the parameters defined by D-optimal matrix. Table 2 shows the response of the two outputs according to the parameters levels. Using the results of the 50 experiences, the most adequate mathematical model, was determined. The graphical analysis and the regression have been studied with the MATLAB software. Four models (linear, interactions, purequadratic, and quadratic) have been analyzed to determine the most suitable model for our experimental results. Table 3 shows the resulted stats of the model. The quadratic one has the lower p-value and the lower Root mean squared error, which means that the error distribution is lower than the other models. In addition, the R^2 and the adjusted R^2 are higher and are adapted to our response. Thus, the quadratic model is most suitable to show the relationship between the studied parameters and the outputs.

3.1 Mathematical models:

RSM (response surface methods) is a set of mathematical and statistical technics used to enhance and develop process variables. In our case, it was used to outline the relationship between the eight studied parameters and the two selected outputs. Here, the goal of the RSM is to optimize the outputs. Equation 1 shows the quadratic regression model used in this study.

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i<j}^{k} \beta_{ij} X_i X_j + \varepsilon \quad (1)$$

Table 2: D-Optimal Design Matrix And Collected Data

RUN	Factors								Responses	
	A	B	C	D	E	F	G	H	T	M
1	80	210	0.45	3	25	80	L	4	3	2.27
2	80	210	0.45	1	75	50	L	4	4	2.28
3	70	190	0.15	3	75	65	H	4	7	1.78
4	70	210	0.15	1	75	50	H	3	8	1.66
5	80	190	0.15	3	25	80	H	4	5	1.5
6	80	210	0.45	1	75	80	H	2	2	1.99
7	80	190	0.45	3	75	50	D	4	3	2.27
8	80	190	0.15	1	75	80	H	2	5	1.61
9	70	210	0.15	3	25	50	L	4	8	1.52
10	70	210	0.45	3	25	80	H	4	3	2.27
11	70	200	0.45	1	25	50	D	4	4	2.28
12	80	190	0.45	1	25	50	L	4	4	2.28
13	70	210	0.15	1	75	80	L	2	5	1.74
14	80	190	0.45	1	75	80	L	2	2	2.08
15	80	190	0.45	1	75	50	H	2	3	1.99
16	70	190	0.15	1	25	65	L	2	4	1.08
17	70	190	0.45	2	25	50	H	3	3	2.02
18	70	190	0.45	3	50	80	L	4	3	2.27
19	70	190	0.15	3	75	50	L	2	8	1.83
20	80	190	0.45	1	75	80	H	4	3	2.28
21	80	190	0.3	3	25	50	L	2	4	1.64
22	80	210	0.15	1	25	50	L	2	5	1.08
23	80	190	0.15	1	50	50	H	4	7	1.48
24	80	210	0.15	1	50	80	L	4	5	1.55
25	70	210	0.45	2	75	80	D	4	3	2.28
26	70	210	0.45	1	25	80	L	3	2	1.97
27	70	210	0.45	1	25	50	H	2	3	1.65
28	70	200	0.15	1	25	80	H	4	4	1.28
29	70	200	0.15	3	75	80	L	3	6	1.86
30	80	210	0.15	3	25	80	L	2	5	1.38
31	70	190	0.45	3	25	80	L	2	2	1.84
32	70	210	0.3	3	75	65	D	2	4	2.1
33	75	190	0.15	2	25	80	L	4	5	1.42
34	70	190	0.45	1	75	80	H	2	2	1.99
35	70	200	0.45	2	50	50	L	2	3	1.93
36	80	210	0.15	3	75	50	H	2	8	1.71
37	80	200	0.15	2	75	65	L	4	7	1.85
38	80	210	0.45	3	25	50	D	2	3	1.89
39	70	210	0.45	3	75	50	H	4	3	2.27
40	75	210	0.45	1	50	65	H	4	3	2.28
41	75	200	0.15	3	25	50	H	2	7	1.35

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42	70	210	0.15	2	50	80	H	2	5	1.47
43	75	210	0.45	3	75	50	L	2	3	2.13
44	80	210	0.15	1	25	65	H	3	4	1.18
45	75	200	0.3	3	50	80	D	3	3	1.97
46	75	210	0.15	3	75	80	H	4	6	1.78
47	80	190	0.45	3	75	80	H	2	2	2.06
48	70	190	0.3	1	75	50	L	4	5	2.08
49	80	190	0.45	1	25	80	H	2	2	1.65
50	80	210	0.3	2	25	50	H	4	4	1.87

Table 3: The Statistical Summary Of The Models.

Response	Model	P-value	R2	R2 Adj	Root Mean Squared Error	Precision	Remarks
T	Linear	$5.4*10^{-7}$	0.67	0.624	0.0385	Adequate	
	Interactions	$7.32*10^{-6}$	0.887	0.809	0.0275	Adequate	
	Purequadratic	$6.33*10^{-5}$	0.628	0.576	0.0409	Adequate	
	Quadratic	4.34*10^-[illegible]	0.976	0.937	0.0157	Adequate	Selected
M	Linear	5.14*10^-[illegible]	0.861	0.821	0.0265	Adequate	
	Interactions	5.14*10^-[illegible]	0.861	0.821	0.0265	Adequate	
	Purequadratic	3.31*10^-[illegible]	0.906	0.865	0.023	Adequate	
	Quadratic	5.14*10^-[illegible]	0.984	0.957	0.013	Adequate	Selected

- ✓ Y is the predicted response
- ✓ k is the number of variable
- ✓ Xi and Xj are the coded variables
- ✓ β_0 is the constant of the regression equation
- ✓ β_{ii} is the interactive coefficient
- ✓ β_{ij} is the square term of each variable
- ✓ ε is the random measurement error

Equation 2 shows the formulation of the quadratic model:

$$Y=\beta_0+\beta_1A+\beta_2B+\beta_3C+\beta_4D+\beta_5E+\beta_6F+\beta_7G+\beta_8H+\beta_{12}AB+\beta_{13}AC+\beta_{14}AD+\beta_{15}AE+\beta_{16}AF+\beta_{17}AG+\beta_{18}AH+\beta_{23}BC+\beta_{24}BD+\beta_{25}BE+\beta_{26}BF+\beta_{27}BG+\beta_{28}BH+\beta_{34}CD+\beta_{35}CE+\beta_{36}CF+\beta_{37}CG+\beta_{38}CH+\beta_{45}DE+\beta_{46}DF+\beta_{47}DG+\beta_{48}DH+\beta_{56}EF+\beta_{57}EG+\beta_{58}EH+\beta_{67}FG+\beta_{68}FH+\beta_{78}GH+\beta_{11}A^2+\beta_{22}B^2+\beta_{33}C^2+\beta_{44}D^2+\beta_{55}E^2+\beta_{66}F^2+\beta_{77}G^2+\beta_{88}H^2 \quad (2)$$

After defining the coefficients, the mathematical model has been developed. Here are the final models for the manufacturing time T and the material consumption M.

$$T=-16.531+0.42601A+0.1887B-37.791C+1.2665D+0.063384E-0.24913F-0.44118G-1.0382H-0.0024403AB+0.00066847AF-1.8801CD-0.098161CE+0.15123CF-0.0072853DE+0.0044167DF+0.05601DG-0.16019DH-0.00207EH+0.13463GH+42.585C^2+0.00072023F^2+0.25699H^2 \quad (3)$$

$$M=-26.204+0.19509A+0.17006B+3.3746C+0.2755D+0.027298E+0.030265F+0.064142G+0.3953H-0.00021704AB-9.2303\times10^{-5}AE-0.00087213BH-0.16239CD-0.019614CE-0.060593CG+0.38923CH-0.0012944DE-0.010487DG-0.026238DH+2.3579\times10^{-5}EF-0.0024997EH-0.00065703FH-0.0009813A^2-0.00037701D^2-1.9718C^2-0.00022656F^2 \quad (4)$$

3.2 Checking out the data and the developed model adequacy:

Normal probability curves have been used to check the regression model validity. Figure 6 a-b shows the normal probability curves for T

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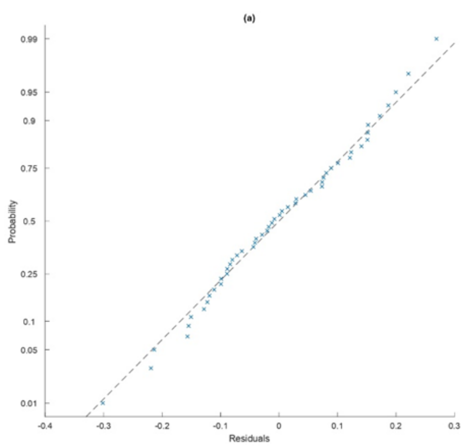
(manufacturing time) and M (material consumption). Results indicate that the residuals are aligned and follows a normal distribution. In addition, the errors are distributed normally. Thus, the developed model used in equations 3-4 is adapted to the experimental values.

As shown in figure 7 a-b, the model predicted values which are in total correlation with the experiments results. This means that the model is highly reliable to determine the relationship between T, M and the eight studied parameters.

4. RESULTS AND DISCUSSION

To determine the relationship between the eight studied parameters and the two outputs (T and M), the followed process is to fix six inputs at the middle value, and check the graphical 3D response of the manufacturing time and the material consumption, while varying the studied parameter and the platform temperature. In the pre-study, the less influencing parameter was determined as the bed temperature, thus, a "platform temperature" was chosen as the varying input used in the seven parameters 3D graphs.



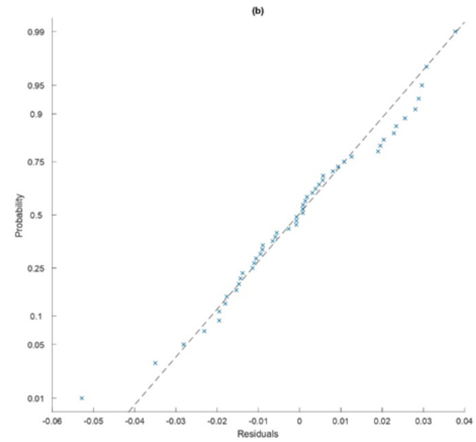


Figure 6: Normal probability curves for T and M

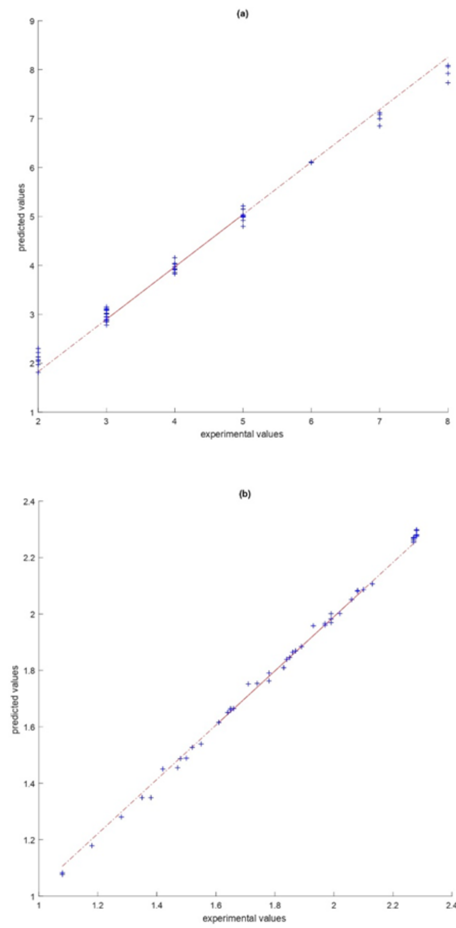


Figure 7: Models predicted values

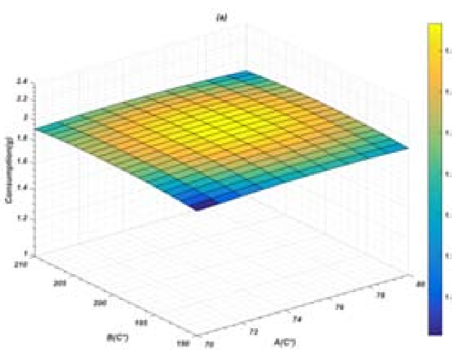
On the other hand, the 3D response allows determining the optimal inputs for a low T and M.

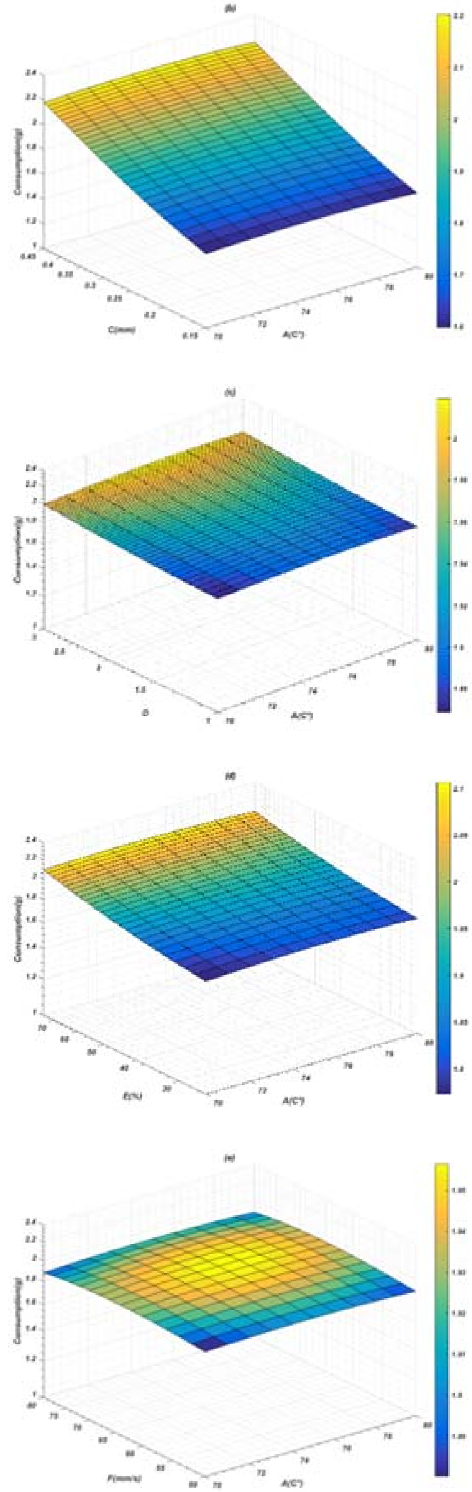
Figures 8 and 9 show the interactive effect of the parameters effect on the studied outputs.

4.1 Influence of process parameters on the M (Material consumption):

Figure 8 shows the effect of each process parameter on the material consumption response. The first observation is that the most influencing parameter is the C (layer thickness) of the graph b. The second parameter is the print speed (graph e).

From graph a, the optimal inputs to reduce the M are A = 70°C and B = 190°C. In addition, it can be observed that the influence of the extruder temperature is low. Graph b indicates that the optimal condition is at a layer thickness of 0.15mm. It can be observed that the thicker the layer, the more material is consumed. Secondly, due to the negligible effect of the platform temperature, the graph shows that the C is a lot more influencing on the M rather than the A. Graph c shows that the number of shells has a low influence on the M. Also, the optimal condition is at one shell. This is logical because the less contour is done, the less material is consumed. Graph d outlines that the infill density at 25 % and 80°C is optimal to reduce M. Less density means less material. Graph e proves the small influence of the printing speed on the material consumption. The optimal conditions are at 50mm/s and 70°C. Graph f indicates that the optimum infill pattern is the honeycomb (H) at 70°C. Graph g shows the less upper and lower solid layers are printed, the less material is spent for manufacturing. The optimum is then at 2 layers, which is the minimum in this study.





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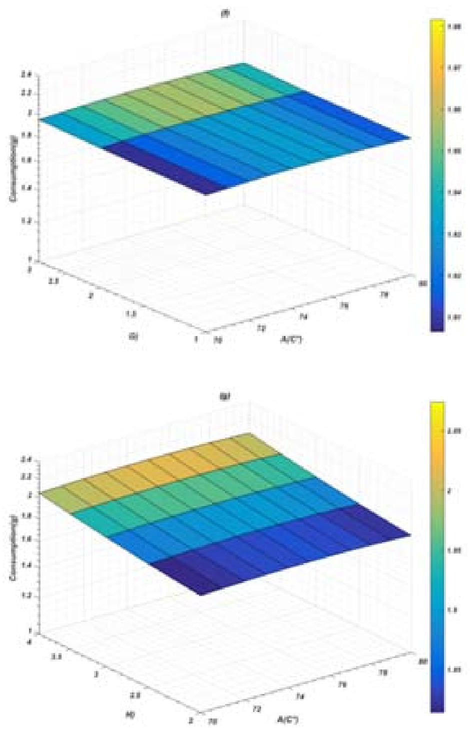
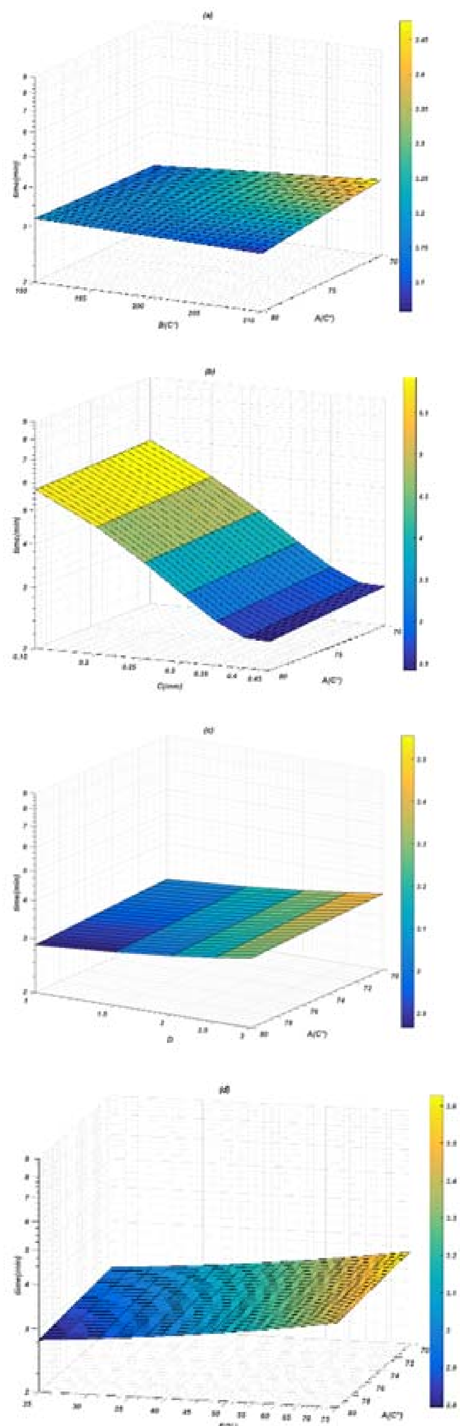


Figure 8: Parameters influence on the Material consumption

4.2 Influence of process parameters on the T (manufacturing time):

Figure 9 shows the effect of each process parameter on the manufacturing time response. The first observation is that the most influencing parameter is the C (layer thickness) as seen in the graph b. The second parameter is the print speed (graph e). From graph a, the optimal inputs to reduce the T are A = 80°C and B = 210°C. In addition, it can be observed that the influence of the nozzle temperature is low. Graph b indicates that the optimal condition is at a layer thickness of 0.45mm. It can also be observed that the thicker the layer, the less printing time is necessary. Secondly, the graph shows that the C is a lot more influencing on the T than the platform temperature A. Graph c proves that the number of shells has a low influence on the T, and the optimal condition is at one shell and a bed temperature of 80°C. This is logical because the less contour is done; the less time is spent for printing. Graph d shows that the infill density at 25 % and 80°C is optimal to reduce T. Graph e indicates an absence of influence of the bed temperature when compared to the F (printing speed); this indicates the high influence of the F on manufacturing time. The more velocity is used, the less time is spent. The optimum condition is at the higher speed which is 80 mm/s. Graph f outlines that the optimum infill pattern is the honeycomb (H) at 80°C. Graph g shows the less upper and lower solid layers are printed, the less time is spent manufacturing. The optimum is then at 2.



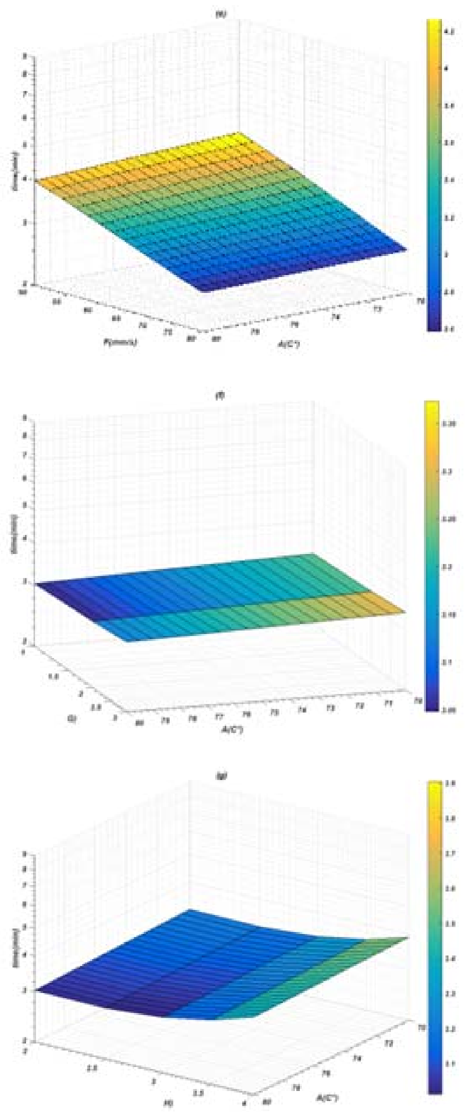


Figure 9: Parameters influence on the manufacturing time

4.3 Optimal conditions:

From the experience plan the optimum inputs have been determined to lower the Manufacturing cost of the FDM process. Here is a summary of the retrieved data. For the Material consumption, the optimum is at:

- A=70°C
- B=190°C
- C=0.15mm
- D= 1
- E= 25%
- F= 50mm/s
- G=1
- H=2

Using the mathematical model, the minimum material consumption obtained with these inputs is 0.94g. The optimum inputs have been used to print five samples and check the validity of the mathematical model result. Table 4 shows the printed samples weight.

Table 4: printed samples weight.

Sample	Weight (g)
1	0.935
2	0.939
3	0.948
4	0.951
5	0.932
Average	0.941

The average samples weight using the optimum inputs is 0.941g. Therefore, the mathematical model results have been validated experimentally.

For the Manufacturing time optimum, the inputs are:

- A=80°C
- B=210°C
- C=0.45mm
- D= 1
- E= 25%
- F= 80mm/s
- G=1
- H=2

Using the mathematical model, the minimum manufacturing time obtained with these inputs is 1min40s (1.66min).

The optimum inputs have been used to print five samples and check the validity of the mathematical model result. Table 5 shows the printed samples manufacturing time.

Table 5: printed samples manufacturing time

Sample	T (min)
1	1.62
2	1.64
3	1.7
4	1.67
5	1.71
Average	1.67

The average samples manufacturing time using the optimum inputs is 1.67min. Therefore, the mathematical model results have been validated experimentally.

5. CONCLUSION

The most used Additive manufacturing process is the fused deposition modeling. In this study, the process parameters optimization has been studied to benefit at the most from the process advantages at a low cost. The cost of machining is directly linked to material

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consumption and manufacturing time. Therefore, those have been the principal outputs of our system. On the other hand, the influent process parameters (platform and extruder temperature, layer thickness, number of shells and solid layers, infill pattern and density, print speed) have been the variables of the study. First of all, samples have been printed following the appropriate standard. Then, a D-optimal experience plan has been set and carried on to check the output response of variables. Secondly, a mathematical model adapted to the experiment has been developed to find the best inputs. The response surface method has been used to find the lower possible manufacturing time and material consumption. The results have been checked out with a new set of experiments.

The lower achievable sample weight is 0.94g; this optimum has been reached using a bed temperature of 70°C and an extruder heated at 190°C. The most influent parameter was logically the layer thickness at its lower value, which is 0.15mm. One shell was used with a 25% infill percentage and a 50mm/s speed, following a honeycomb pattern with a minimum number of solid layers (2).

The lower achievable sample manufacturing time is 1min40s; this optimum has been reached using a bed temperature of 80°C and an extruder heated at 210°C. The most influent parameter was logically the layer thickness at its biggest value, which is 0.45mm. One shell was used with a 25% infill percentage and 80mm/s speed, following a honeycomb pattern with a minimum number of solid layers (2).

This article offers optimal data input for FDM process parameters to lower the printing cost, by lowering the manufacturing time and the material consumption.

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