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Optimizing FDM Process Parameters for Efficient Spur Gear Manufacturing

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Abstract:

Gears are critical technological elements present in almost all machines. Plastic gears, therefore, play a crucial role in various objects such as toys, didactical projects, prototypes, etc. For these applications, gear design requires precision, and traditional manufacturing methods prove to be expensive and limited in use. Our study focuses on spur gear production using additive manufacturing, specifically employing Fused Deposition Modeling (FDM). This technology proves to be more efficient in terms of weight, cost, and manufacturing time. To analyze optimal FDM parameters, we considered manufacturing time and the amount of consumed material as the two responses. The optimization of these two responses is based on several parameters (layer thickness, number of shells, infill pattern, and density) related to the FDM process. To achieve this, an optimal experimental plan (D-optimal) was established, and a statistical study was conducted to formulate a suitable mathematical model. The use of the Response Surface Method (RSM) aimed to optimize the model's response and identify ideal values for the printing parameters. In this article, we present the optimal input parameters to reduce manufacturing time and material consumption when printing a spur gear.

Keywords*: Spur Gear, 3D Printing; Fused Deposition Modeling; optimal parameters; Experimental plan (D-optimal).*

1. Introduction

Gears are the most commonly used solution for transmitting mechanical power between shafts in almost all machine designs (Tezel et al., [1]). The increasing adoption of plastic gears in replacement of their metallic counterparts is a current trend that extends to various application areas. In specific sectors such as automotive and aerospace engineering, polymer gears have distinct advantages over metal versions, including reduced production costs, low density, minimal inertia, high efficiency, quiet operation, the ability to absorb shock and vibration through elastic compliance, as well as the ability to operate with minimal or no lubrication. These gears are used in various applications, such as remote-controlled cars and drive mechanisms of electronic components (Senthilvelan and Gnanamoorthy, [2]; Gupta, [3]; Gibson et al., [4]; Maurya et al., [5]). In addition, 3D printed gears can be integrated into scale models, especially in the field of engineering education. These gears, specifically designed for didactic models of mechanisms for educational purposes, are characterized more by a kinematic operation than by a high-power transmission (Buj-Corral et al., [6]). Nevertheless, it is crucial to recognize that the mechanical strength of plastic gears is limited and mainly depends on the type of material selected.

For manufacturing gears, various additive manufacturing processes are available, and the selection depends on factors such as the material, precision requirements, and part volume. Processes like SLS and SLM (selective laser sintering or melting) utilize a powder bed fusion method to produce parts in metal or polymers (Tezel et al., [1]; Gibson and Shi, [7]). SLA (stereo-lithography apparatus) employs light curing to solidify a specific area using various energy sources, including lasers (Chia and Wu, [8]; Melchels et al., [9].

The method employed in our investigation is Fused Deposition Modeling (FDM), given its widespread popularity, making its optimization highly significant. As illustrated in Fig.1, this manufacturing process involves the construction of a part using successive layers with thickness ranging from 0.08 to 3 mm. The material is heated to 200°C and extruded through a nozzle (0.4-1.2 mm), commonly using materials like PLA or ABS (1.75-3 mm diameter). Following the completion of each layer, the platform or extruder ascends along the z-axis to commence printing the subsequent layer (Isksioui et al., [10]).

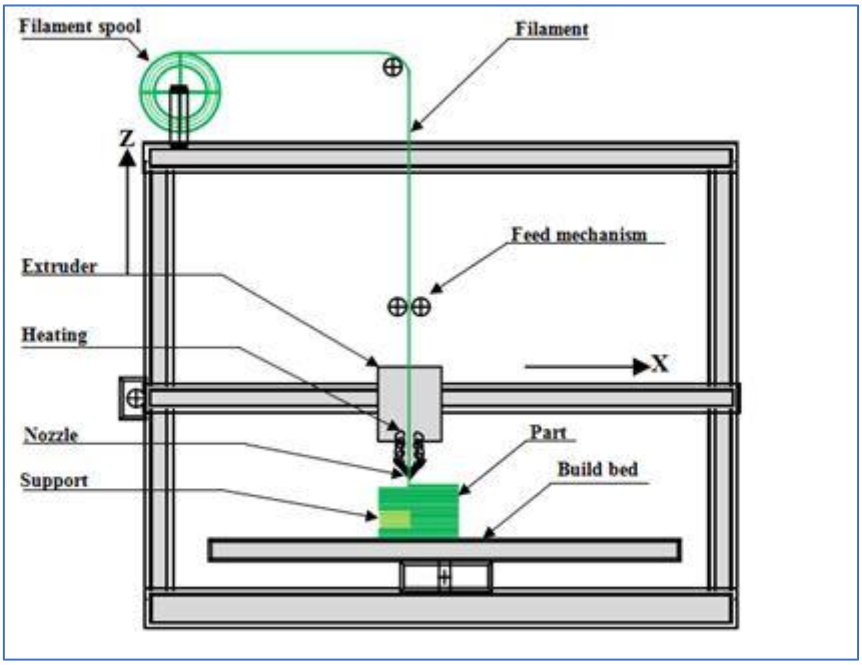

Fig.1. FDM manufacturing process.

Few researches have studied the effect of FDM process parameters on the manufacturing time of gears. But for test specimens we cite the study carried out by Nancharaiah [11], using the Taguchi design matrix (the L9 orthogonal matrix) and ANOVA (analysis of variance) technique, it examined the relationship between manufacturing time and FDM printing parameters. This study was able to demonstrate that the parameters which have the most influence on the manufacturing time are the thickness of the layer and the gap between the nozzle and the platform. Also the experimental study by Kumar and Regalla [12], based on a factorial experimental design, analyzed the influence of parameters (layer thickness, orientation and angle of the frame) on the manufacturing time and the consumption of support material. The investigation revealed that changing the layer thickness and strategic orientation of the sample during printing results in a decrease in manufacturing time. Eryildiz [13] studied the impact of printing orientation on manufacturing time and tensile strength. The findings indicate that the printing orientation influences the tensile properties and printing time of parts produced by FDM, with a reduction in printing time observed for a flat orientation. Another study (Le et al., [14]) sought to optimize process parameters to achieve the shortest printing time while minimizing ultimate strength loss. The study results indicated that nozzle diameter, infill percentage, and number of outer shells were key factors in reducing printing time. The study conducted by Wu [15] investigates the impact of layer thickness on the printing time of PLA cylinders, material consumption, and dimensional accuracy. It concludes that an optimal layer thickness of 0.14 mm achieves the shortest print time while maintaining good print quality.

The materials used in the production of polymer gears vary widely, including PLA, ABS, nylon and others. According to a study by Buj-Corral and Zayas-Figueras [16], PLA offers better dimensional precision for spur gears compared to nylon. Vasilescu and Fleser [17], recommend PLA as the first choice for 3D printed spur and helical gears due to its higher compressive strength and lower elongation at break than ABS and PETG. In our study, we opted for PLA as the gear material.

To improve the production rate of parts (notably gears) produced by additive manufacturing, this study uses a D-optimal experimental design to analyze the influence of printing parameters on manufacturing time and material consumption. A mathematical model linking these influential parameters is developed, leading to the determination of optimal process parameters.

2. Research Strategy and Gear Specifications

The 3D printing process for a gear involves four steps (Gupta, [3]): initiation through the design of the CAD model using Catia V5 Software (Fig.2a.) (The detailed specifications of the gear wheel are listed in Tab.1.), conversion of the CAD model into an STL (Standard Triangle Language) file, transfer of the STL file to the machine (G-code generated by Ultimaker Cura), and ultimately, printing the gear model. (Fig.2b.) depicts a gear wheel in the process of being printed using the FDM printing process.

The printing parameters held constant include part orientation (horizontal), printing temperature (200 °C), bed temperature (50 °C) and printing speed (50 mm/s). The decision to maintain a horizontal part orientation is based on studies by (Eryildiz, [13]; Corapi et al., [18]) demonstrating that 3D printed PLA specimens exhibit superior mechanical properties when oriented horizontally. Therefore, opt for an orientation that minimizes support needs, as the removal and cleaning of supports will increase processing time.

The four printing parameters (Layer thickness, Infill density, Infill pattern and Number of shells) analyzed in this study is based on a previous study (Isksioui et al., [10]). Table 2 provides detailed information on these parameters (or factors) and their levels. Figure 3 illustrates the four levels of each parameter while keeping the other parameters constant (these illustrations were produced using Ultimaker Cura software, after the fifteenth printing layer).

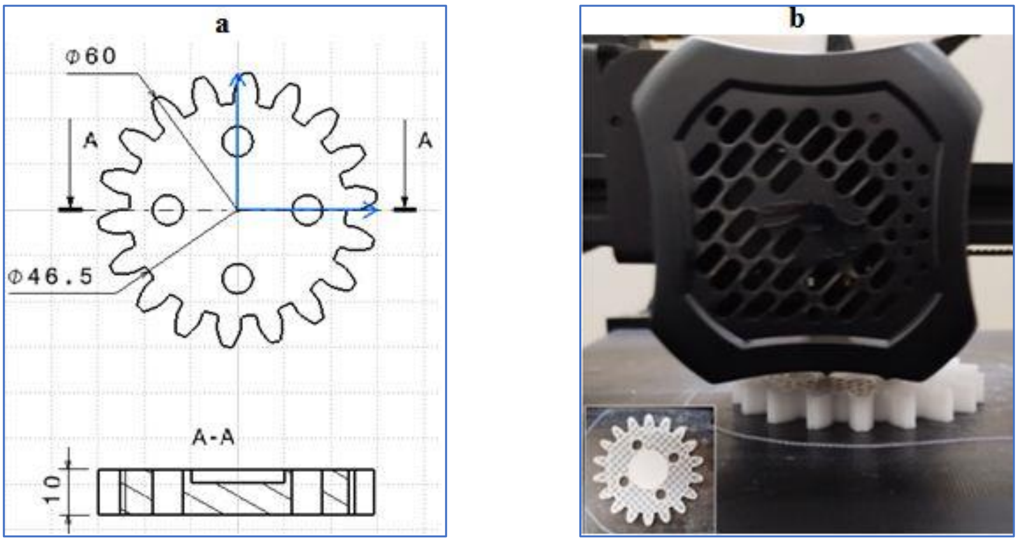

Fig.2. a. The technical drawing of the gear wheel created by Catia V5. b. Sample undergoing the FDM printing process

Table 1. Specifications of gears.

Parameter	Value or type	Units
Type	Spur gear	--
Module	3	mm
Number of teeth	18	--
Pressure angle	20	degree
Tooth and gear width	10	mm
Root fillet	0.75	mm

Table 2. Variations in Processing Parameters and their respective levels.

Symbols	Factors	Units	Levels

A	Layer thickness	mm	0.12-0.16-0.2-0.24
B	Infill density	%	25-50-75-100
C	Infill pattern	--	T-G-C-L
D	Number of shells	–	1-2-3-4

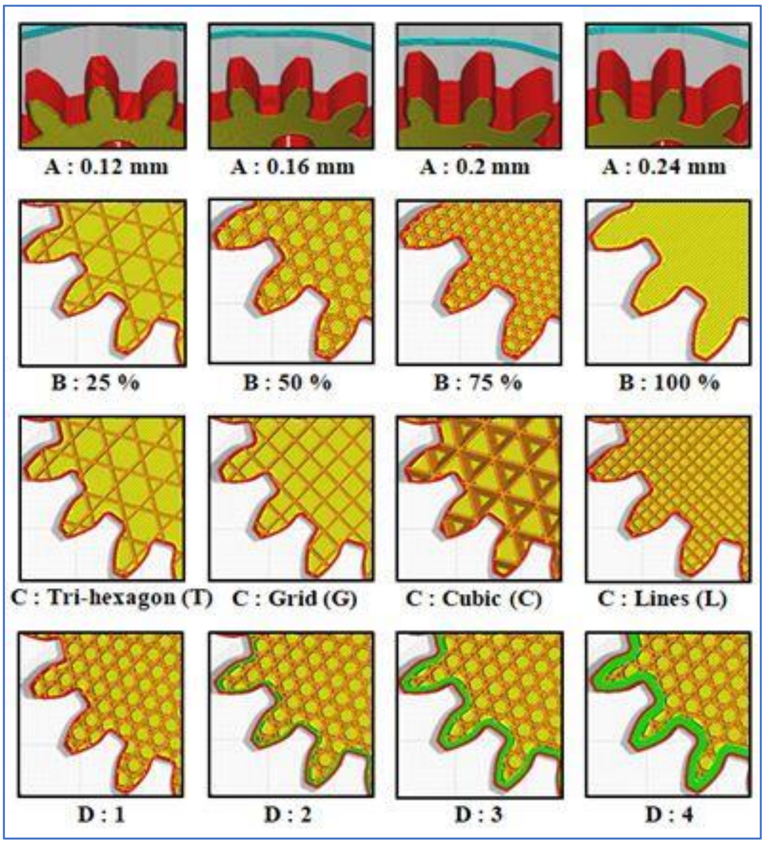

Fig.3. Illustrations for each factor according to the four levels in Tab.2.

3. Analysis

To optimize the number of experiments, an experience plan was established. With four factors at four levels, a D-Optimal experience plan was used with only 20 experiences. Table 3 presents the adopted design matrix, allowing for a precise estimation of the response variation based on the studied parameters, along with the test results.

The selected responses to analyze the variation of the factors in the D-optimal matrix are material consumption and manufacturing time. Four mathematical models were derived from the 20 experiments (linear, interactions, pure quadratic, and quadratic). The MATLAB software is used to analyze the four models and choose the most suitable one based on the experimental results. Table 4 summarizes the different statistical parameters for the four models and for each response (T: manufacturing time and M: material consumption). The quadratic model exhibits the most favorable outcomes with the lowest p-value and root mean squared error among the various models, suggesting a superior fit with a minimized error distribution. Furthermore, both R^2 and adjusted R^2 values are higher, indicating the model's appropriateness for our response variables. Hence, the quadratic model stands out as the optimal choice for capturing the relationship between the selected parameters and the two responses.

3.1. Mathematical models

The statistical method used to define the relationship between the four factors and the two responses is the Response Surface Methodology (RSM). This method is used to optimize the two outputs (T and M). The quadratic regression model adopted for this study is generally described by Eq.(3.1):

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ij} X_i + \sum_{i<1}^{k} \beta_{ij} X_i X_j + \varepsilon \tag{3.1}$$

Where: Y: The response variable;
k: The number of factors;
X_i and X_j: The encoded factors;
β_0 : The constant in the regression formula;
β_{ii} : The interaction parameter;
β_{ij} : The second power term for each variable;
ε: The unpredictable measurement deviation

Drawing from the statistical outcomes and Eq.(3.1), we present the quadratic model formulation in this study for manufacturing time (T) and material consumption (M) through the following Eqs (3.2)–(3.3):

$$T = 255.89 - 1874.5A + 1.5221B + 16.807C - 8.607D - 8.2806AB - 0.29983BC - 0.4463BD + 4435.6A^2 + 0.028036B^2 + 9.4084D^2 \tag{3.2}$$

$$M = -0.16572 + 15.734A + 0.29501B + 0.42046C + 1.9082D - 0.25263AB - 0.014902BD - 0.13526CD - 0.00044812B^2 \tag{3.3}$$

3.2. Model Validation

To confirm the accuracy of the previously discussed mathematical model, we generated normal probability curves. The charts in Figures (4a–4b) illustrate that the deviations conform well and follow a normal distribution. This affirms the suitability of the mathematical models presented in Eqs (3.2)–(3.3) to the experimental outcomes.

Figures (5a–5b) presents another test for the chosen mathematical model. The comparison between the experimental values and those predicted by the model demonstrates a good agreement. These results confirm the validity of the mathematical model in establishing the correlation between the two variables (manufacturing time and material consumption) and the four parameters under investigation.

Table 3. The optimal experimental plan and its Responses.

N° RUN	Factors				Responses	
	A	B	C	D	M (g)	T (mn)
1	0.12	25	T	3	13	175
2	0.16	50	G	1	16	139
3	0.12	50	G	1	16	175
4	0.2	25	L	3	14	111
5	0.16	100	G	4	25	287
6	0.24	25	T	1	12	75
7	0.12	75	T	3	22	235
8	0.24	50	G	3	18	114
9	0.12	75	G	2	21	224
10	0.2	100	C	1	25	222

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11	0.16	75	C	4	22	201
12	0.2	75	T	4	22	162
13	0.2	50	T	3	18	127
14	0.12	100	G	1	25	367
15	0.24	25	L	3	14	98
16	0.24	75	C	2	21	121
17	0.16	25	G	1	11	104
18	0.16	25	T	2	12	120
19	0.2	50	L	4	19	149
20	0.16	75	L	2	21	177

Table 4. Statistical Overview Analysis.

Response	**Model**	**P-value**	**R2**	**R2 Adj**	**RMSE.**	**Accuracy**	**Decision**
T	Linear	$4.2*10^{-8}$	0.896	0.877	25	Insufficient	
	Interactions	$3.65*10^{-7}$	0.919	0.890	23.7	Insufficient	
	Purequadratic	$1.62*10^{-7}$	0.989	0.976	11	sufficient	
	Quadratic	$8.36*10^{-8}$	0.99	0.979	10.3	sufficient	Selected
M	Linear	$1.25*10^{-16}$	0.996	0.995	0.322	sufficient	
	Interactions	$1.24*10^{-16}$	0.996	0.995	0.321	sufficient	
	Purequadratic	$1.76*10^{-15}$	0.998	0.997	0.189	sufficient	
	Quadratic	$1.75*10^{-15}$	0.999	0.998	0.188	sufficient	Selected

4. Results and discussion

The process adopted to assess the degree of influence of the four parameters on the two studied responses involves fixing two parameters while varying the other two. Subsequently, the observation of the impact of the varying parameters on the two responses (T and M) is carried out through 3D graphical representations. These curves were generated using scripts from the MATLAB software.

Minimizing manufacturing time and material consumption is synonymous with optimization. Subsequently, the goal is to identify the optimal level of each parameter leading to the minimum value of each response, T and M.

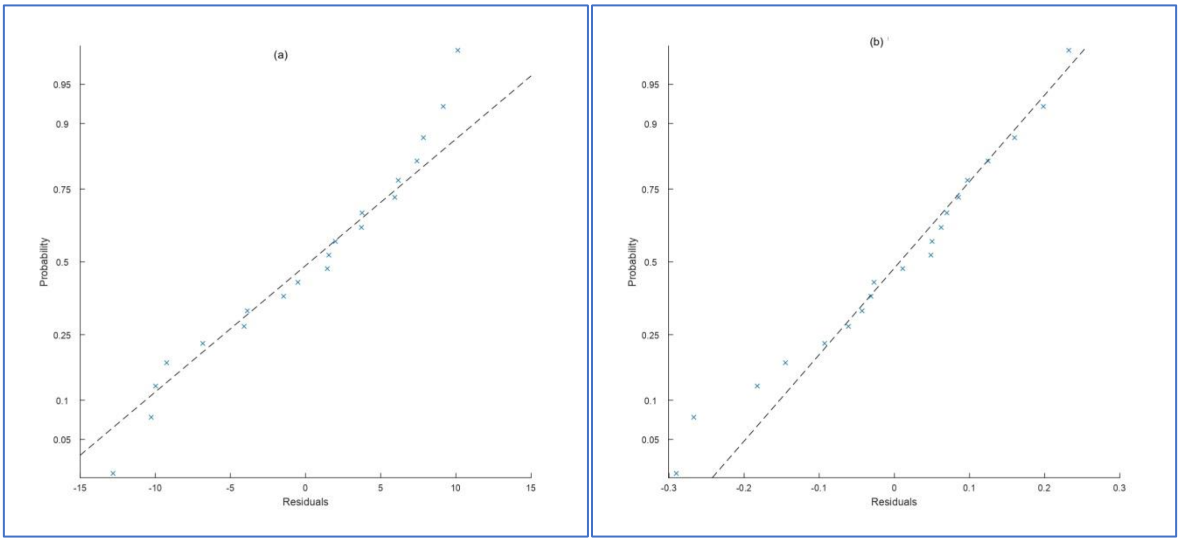


Fig.4. Normal probability curves for: a: T (manufacturing time); b: M (material consumption)

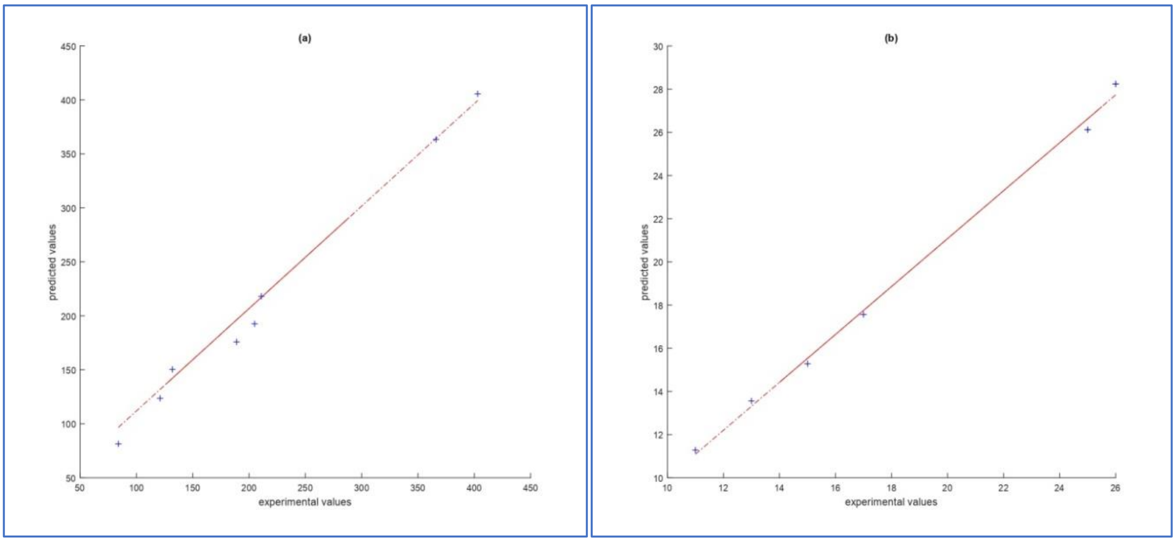
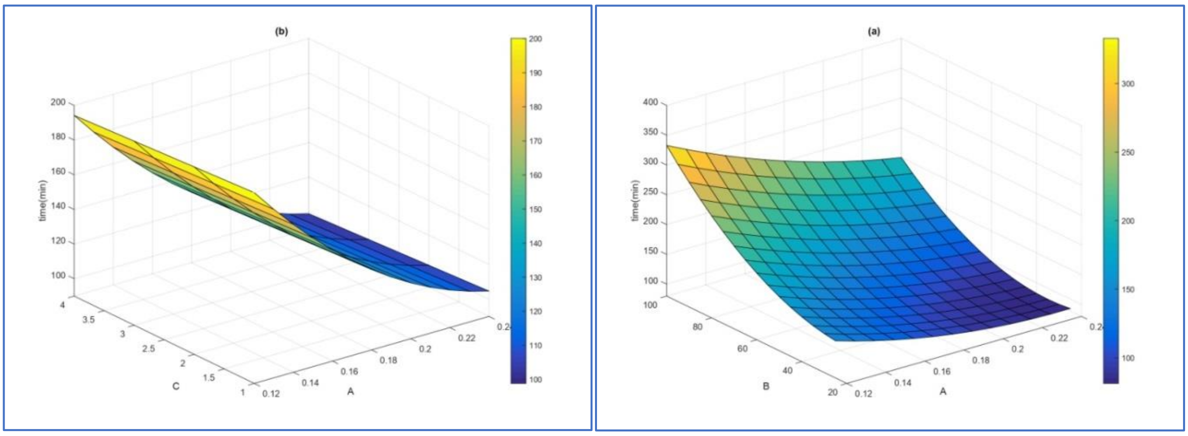


Fig.5. Model predictions vs. experimental results for:(a) Manufacturing Time. (b) Material Consumption.

4.1. Effect of process variables on manufacturing time (T)

Figure 6 illustrates how every manufacturing parameter affects the production duration. Initial scrutiny reveals that B (infill density) stands out as the most influential factor, as shown in (Fig.6a). The second parameter is layer thickness (graphs b and c). According to graph a, the optimal values for a minimal time (Tmin = 81.36 mn) are A = 0.24 mm and B = 25%. Additionally, there is limited influence from the infill pattern C. Figure 6b indicates that for a minimal time (Tmin = 98.84 mn), the optimal infill pattern is Grid, C = 2, and the optimal layer thickness is 0.24 mm, demonstrating that a thicker layer requires less printing time. Figure 6c confirms that the number of shells minimally impacts (T). The shortest time (Tmin = 102.7 minutes) is achieved with a double shell (D = 2). This can be logically attributed to the fact that a decreased number of shells leads to a reduction in printing time.

These results are in agreement with those obtained by Le et al., [14], where lower filling rates and a minimum number of shells will contribute to reducing the printing time. The findings of the study (Wu, [15]) support our results regarding the influence of layer thickness, demonstrating that a thicker layer results in a reduction in printing time.



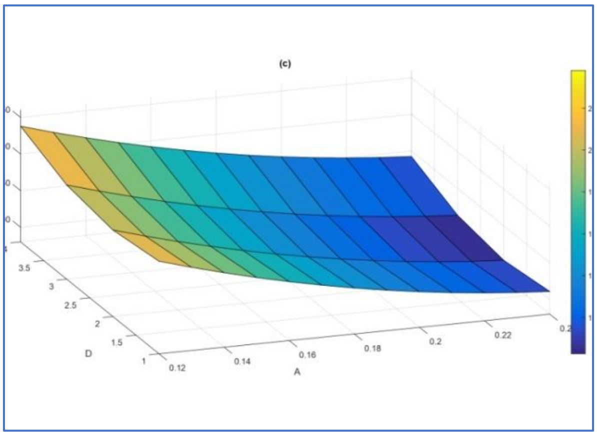
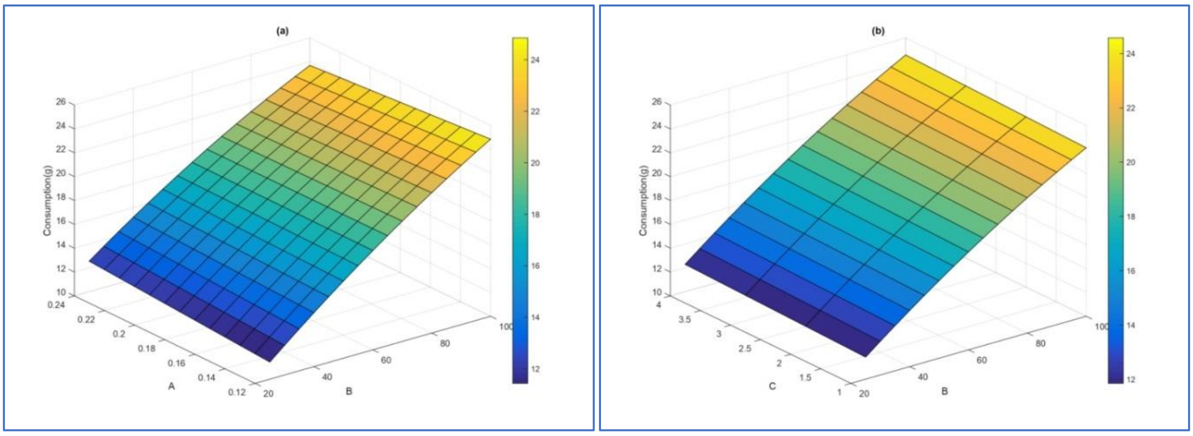


Fig.6.Three-dimensional representation of how parameters impact manufacturing time.

4.2. Effect of processing variables on the Material consumption (M)

The curves in Fig.7. shows how each manufacturing factor affects the result of material consumption. A first analysis reveals that the filling density (factor B) has the most significant influence (Fig. 7a – 7b – 7c). The second factor is the number of contours (Fig. 7c).

According to (Fig. 7a), the optimal values for minimal material consumption (Mmin = 11.43 g) are A = 0.12 mm and B = 25%. This explains that the amount of material consumed is inversely proportional to the layer thickness. Additionally, we can note a limited influence of the fill pattern C. Graph b indicates that the (Mmin = 11.84 g) is achieved for a tri-hexagonal pattern C = 1 and a fill density B = 25%. This explains that material consumption decreases with a reduction in fill density. Figure 7c indicates that the number of contours minimally affects material consumption (M). The optimal condition is a single contour (D = 1) with a minimum material consumption of 10.73 g, aligning with the logic of less material usage. Wu [15] also noted a reduction in material consumption for low layer thicknesses.



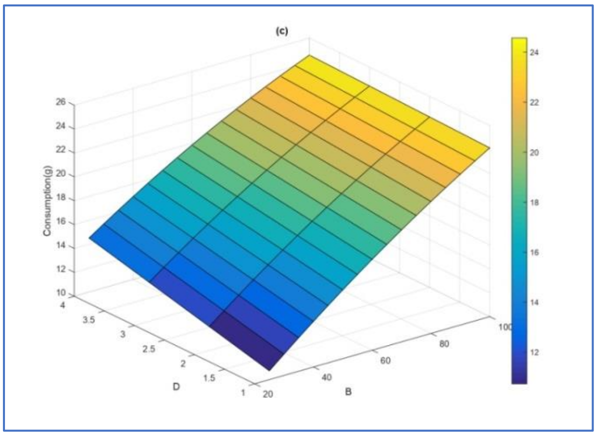


Fig.7. Three-dimensional representation of how parameters impact the Material consumption

4.3. Optimal Parameters for the FDM Process

From the experimental plan, we have identified optimal parameters aimed at minimizing the manufacturing costs associated with producing a gear using the Fused Deposition Modeling (FDM) process. The following provides a summary of the achieved results. Concerning manufacturing time, the optimum is achieved at: A = 0,24 mm;B = 25 %; C = 2 and D = 2.

Utilizing the mathematical model (Eq. (3.2)), the optimal parameters yielded a minimum manufacturing time of (Tmin = 84.11 minutes). These optimized parameters were applied to produce five samples, validating the accuracy of our model. Details of the printing time for the generated samples can be found in Table 5.

The average manufacturing time for samples using the optimal parameters is (Tavg = 84.2 mn). Thus, the experimental validation confirms the results of the mathematical model.

By employing the mathematical model (Eq.(3.3)), the optimal parameters leading to the minimum material consumption (Mmin = 9.88 g) are determined as follows:A = 0.12 mm;B= 25 %; C = 1 and D= 1.

Table5.Printing Time for Fabricated Samples.

Sample	Time (mn)
1	85
2	85
3	84
4	84
5	83
Average	84.2

The optimal parameters were implemented for the production of five samples to validate the outcomes of the mathematical model. The weights of the printed samples are outlined in Table 6.

Table 6.Weight of Printed Samples.

Sample	Weight (g)
1	10.2
2	10.3
3	10
4	10
5	9.9
Average	10.08

The optimal parameters yielded an average material consumption of (Mavg = 10.08 g) by the samples, thus validating the experimental confirmation of the mathematical model results.

5. Conclusion

The additive manufacturing of gears, particularly through the Fused Deposition Modeling (FDM) process, requires optimization to compete with other manufacturing methods. Achieving a gear at minimal cost involves minimizing both the manufacturing time and the amount of consumed material, the two responses selected for this study. Critical factors considered in the study comprised selected process parameters, encompassing layer thickness, pattern, infill density, and the number of contours. In pursuit of optimization objectives, a D-Optimal experimental plan was devised to evaluate the response of output variables. Following this, a tailored mathematical model was created to identify optimal parameter values aligned with the experiment. Leveraging the Response Surface Method (RSM), efforts were directed toward minimizing both manufacturing time and material consumption. The outcomes were subsequently validated through a new series of experiments.

- The gears' minimum manufacturing time was achieved using a grid infill pattern with two contours.
- The most impactful parameter was the layer thickness, reaching a maximum value of 0.24 mm. The infill percentage, set at a minimum of 25%, played a significant role.
- The minimum material consumption was optimized with a tri-hexagonal infill pattern and a single contour.
- For material consumption, the critical factor was the infill percentage at its minimum of 25%, coupled with a layer thickness of 0.12 mm.

This article presents optimal input parameters for the Fused Deposition Modeling (FDM) process to produce a cylindrical spur gear. The goal is to lower printing costs by minimizing both manufacturing time and material consumption.

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