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A decision support system for the selection of FDM process parameters using MOORA

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A B S T R A C T

Additive Manufacturing (AM) is an automated process of fabricating three-dimensional (3D) physical objects from a 3D-CAD data by adding layers of materials one upon another through a print head or nozzle without using any tooling components or machining environments. Due to freedom in design, any complex shape can be produced using this process. Fused Deposition Modeling (FDM) is one such AM technology that is commonly used for its simplicity, environment friendliness and low requirement for process monitoring. However, this technology is limited only to small-scale production due to high cost and high build time. The present work focuses on the development of a framework for parametric optimization of the FDM process using multi-objective optimization based on ratio analysis (MOORA). A CAD model of the cam follower mechanism has been prepared in the Solidworks platform and used in this experiment for optimization of build time and cost which have been considered as response variables of the experiment. The experiment has been conducted following the full factorial design of experiment (DoE) method.

1. Introduction

Additive Manufacturing (AM) technology was first introduced in 1987 and at that time it was called Generative Manufacturing or Rapid Prototyping, as it was used for making prototypes and porous structures (Gebhardt, 2005; Nadernezhad et al., 2019). With the help of topology optimization to reduce the total weight (which reduces the fuel/energy consumption) of an aircraft, designers started using titanium instead of aluminium to make some components. As titanium is an expensive material, therefore, to reduce the cost of manufacturing, material wastage must be reduced, which can be implemented only by additive manufacturing technology as nearly zero material wastage is associated. It also reduces the lead time to marketing and gives design freedom (Orr, 2015).

This paper mainly considers an extrusion-based AM process known as material extrusion or fused deposition modeling (FDM) to make prototypes for product development purposes (Papazetis and Vosniakos, 2019). In this process, materials come in the form of wire through a heated chamber or nozzle and are deposited over a build platform (Fig. 1) according to the geometry of the model, which was previously prepared through CAD software. Generally, thermoplastic materials are used in this process which are deposited in semi-molten form. The products produced using the FDM process can be used as models for educational or research purposes. The experiments for this process have been conducted using simulation software named IdeaMaker, in which values of the parameters have been varied according to the full factorial design. After collecting the responses, the same have been analyzed using the MOORA method for optimization.

Among all the researchers, Hopkinson and Dickens first reported a cost analysis of AM comparing it with the traditional method of injection moulding (IM) (Hopkinson and Phill, 2020). Later, research has been conducted and the process has been used in a wide range of applications in aerospace and defense, automotive, biomedical, robotics and automation, architecture and construction, rapid prototyping, product design, education and research purposes and in many other industries (Sames et

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al., 2016). Several techniques of AM technology including the FDM process gained popularity due to their feature of mass customization. A lot of research has been carried out to identify critical factors and their levels that affect the performance of AM processes. Nancharaiah (2011) used three parameters layer thickness, air, gap and raster angle to conduct designed experiments and found that layer thickness and air gap affect the processing time greatly. Ali et al. (2014) chose Taguchi design of experiment (DoE) algorithms and used parameters like Slice height, road width, raster angle, number of contours, air gap, STL deviation & angle to determine the signal-to-noise ratio. In their research build time and material consumption was considered to lower the better type criteria. Baich et al. (2015) worked on infill patterns using cost sensitivity analysis and found that double-dense infill design is the most expensive. Also, they found that sparse build infill consumes the least time and low-density infill provided the largest cost savings. Liu et al. (2017) considered deposition orientation, layer thickness, deposition style, raster width, and raster gap as critical factors for analysis using the Taguchi method and ANOVA. In their research, the mechanical properties of FDM, products were optimized with the selection of best setting parameters. Rathee et al. (2017) worked on contour width, slice height, orientation, raster angle, raster width and air gap and used Response Surface Methodology (RSM) for analysis. They found that spatial orientation had a large impact on build time. Wu (2018) considered four parameters namely layer height, print time, printing supplies and print size accuracy for the study. In their research, the shortest print time was achieved at a print height of 0.14 mm fulfilling the print quality. Nandernezhad et al. (2019) chose three parameters as layer thickness, infill percentage, and infill pattern and used differential scanning calorimetry to study the effect of changing the mesostructure of 3D printed parts on the corresponding mechanical and thermal behavior. Papazetis et al. (2019) employed the Taguchi method, ANOVA and artificial neural network for analysis considering factors such as layer thickness, flow tweak, printing speed and orientation. In their research factor windows were identified in which material deposition stability was retained and defect-free parts were produced. Luca et al. (2020) used a single parameter, build orientation and found the driving factors for build time estimation and total build cost evaluation. Jaiswal et al. (2018) used a novel approach to identify optimal build orientation that minimizes both geometric and material composition errors. Fritz and Kim (2020) used two factors: surface area and support volume. In their research structural compliance was reduced along with the AM cost and time.

The objective of this paper is to determine the settings of process parameters for optimizing the responses. A multiple-criteria decision-making model consisting of a fuzzy analytic hierarchy process (FAHP) and multi-objective optimization based on ratio analysis (MOORA) has been chosen for this purpose. The FAHP method has been used to determine subjective weights of criteria whereas the MOORA method determines the performance score for each treatment combination of the experiment.

The paper is organized as follows. Section 2 provides a selection of process parameters and experimental planning. Section 3 conducts the optimization method using the MOORA method. Section 4 provides the results and discussion. Finally, section 5 reports the conclusion.

2. Selection of process parameters and experimental planning

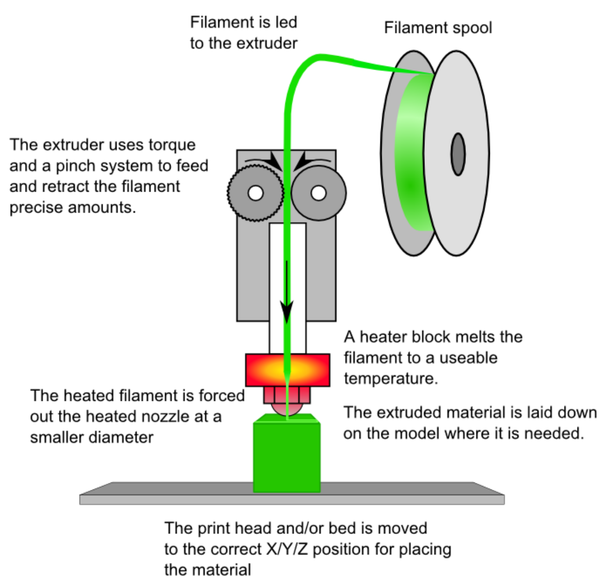

Fig. 1. FDM Process (Source: http://www/peparp.org

From the previous literature it has been found that the layer height and build orientation have much effect on the print time as well as print quality. Also, the previous research indicates that the properties like surface roughness are affected by the travel speed of the nozzle. Another factor namely build orientation influences the build time greatly. So, for the present research, we have selected three parameters (i) layer height, (ii) print speed and (iii) build orientation to run the experiment. Here, layer height represents the distance between the tip of the nozzle and the build platform, over which the material is extruded. It is also the thickness between two adjacent layers. Print speed, refers to the velocity of the nozzle during the fabrication of the part over the build platform in the X-Y plane and build orientation, refers to the rotation of the part concerning the Z-axis before the starting of printing.

Three factors each having three levels of values are shown in Table 1. The range and the values are selected from published literature and FDM machine specifications provided by the manufacturer and are tabulated in Table 2. The printing operation has been conducted as per the design of experiment (DoE) based on full factorial design. Using this technique, experiments having more than one input factor or parameter can be manipulated to determine their effects on the desired output or response. Full factorial design is a part of DoE, which consists of two or more inputs each having its discrete levels and all their possible combinations are considered for optimization.

For this present work, for each experiment, the following two variables have been chosen as response variables. A CAD model of the cam follower mechanism has been developed for experimenting using FDM technology (Di Angelo et al., 2020).

Table 1
Factors and their levels for the experiment

Parameter	Unit	Level		
		-1	0	1
Layer height	mm	0.15	0.25	0.35
Print speed	mm/s	30	65	100
Orientation	degree	0	45	90

(i) Total time consumed for each experiment: Here total time includes pre and post-processing time and actual building or printing time. The pre-processing time is nearly similar for all the experiments and is approximated as 10 minutes. The post-processing time mainly depends upon the size and complexity of the part. Post-processing time for the cam-follower mechanism (Dimension: 33.22×110×50.83 mm^3) is approximated as 20 minutes and actual printing time which varies for different parameter settings has been obtained from the experiment.

(ii) Cost of printing: It has been determined as a product of machine hour rate (expressed in Rupees per hour) and actual printing time (expressed in hours). Machine hour rate has been determined by taking the sum of financial cost, power cost, tooling cost and labor cost on an hourly basis. For Raise3D make FDM machine the calculated machine hour rate becomes Rs. 437.00 per hour.

The number of experiments can be calculated for full factorial design as m^n, where m is the number of levels of values and n is the number of factors used. Here we are using three factors each having three levels of values. So, twenty-seven numbers of experiments were conducted.

Table 2
The principal technical specifications of the 3D printing machine

Item	Specification
Company	Raise3D
Machine	Raise3D Pro2
Maximum dimension	305 × 305 × 300 mm^3
Positioning Resolution	0.78125 micron on the X/Y axis
Nozzle diameter	0.2, 0.4, 0.6, 0.8 and 1.0 mm
Filament diameter	1.75 mm
Supported Materials	PLA, ABS, HIPS, PC, TPU, NYLON, PETG, etc.
Print head Travel Speed	30-150 mm/sec

Another important aspect of the experiment is to select suitable printing material. Polymers are the most popular and widely used material for making parts using the FDM process. Due to better mechanical properties and availability, poly lactic acid (PLA) material has been used in the simulation of the experiment. For the biodegradable property of PLA, it is also called biodegradable plastic.

3. Research methodology

The domain of multiple criteria decision making (MCDM) has been enriched by the contribution of many researchers in respect of introducing many exotic methods such as AHP, DEMATEL, ISM, ANP, TOPSIS, MOORA, VIKOR, ELECTRE, etc. to facilitate decision making over the last fifty years (Roy, 1968; Wang et al., 2016; Dixit et al., 2020; Mohammadfam et al., 2022). Multi-objective optimization based on ratio analysis (MOORA) is selected as the research methodology for the optimization of the selected parameters. For optimization of response variables, the Fuzzy AHP method has been used to determine subjective weights for total time consumed and printing cost (Chang, 1996). The performance score of experiments with various parameter settings has been determined using the MOORA method (Brauers, 2004; Brauers & Zavadskas, 2006). This method has been chosen because of its simplicity and robustness of the result. The method works as follows.

3.1 *MOORA method*

The working of the MOORA method can be described in the following steps.

Step 1. Form decision matrix, D= $[X_{ij}]_{mxn}$, where X_{ij} becomes the outcome of the experiment for i^{th} alternative against the j^{th} criterion. Here, m= number of alternatives and n= number of criteria.

Step 2. Normalize the decision matrix using the following formula.

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \quad (\textit{for } j=1,,2....n) \tag{1}$$

Step 3. Determine the performance score (y_i) as algebraic sum weighted normalized elements of the decision matrix. Here the subjective weights (w_j) have been determined using the extent analysis method of fuzzy AHP as introduced by Chang (1996), Asadabadi et al. (2019) and Saaty (1990).

$$y_i = \sum_{j=1}^{g} w_j\, x_{ij}^{*} - \sum_{j=g+1}^{n} w_j\, x_{ij}^{*} \tag{2}$$

where, $j = 1, 2,\ldots g$ for the responses to be maximized (higher the better type) and $j = g + 1, g + 2,\ldots\ldots n$ for the responses to be minimized (lower the better type).
The alternatives are ranked in descending order of performance score (y_j).

3.2 *Model preparation for the experiment*

For experimenting a cam follower model (shown in Fig. 2) has been prepared using the Solidworks platform. The model is then converted into (.stl) file format, as 3D printing software only supports this file type. Thus, the converted model is transferred to ideaMaker software for the purpose of slicing followed by the execution of further steps for printing.

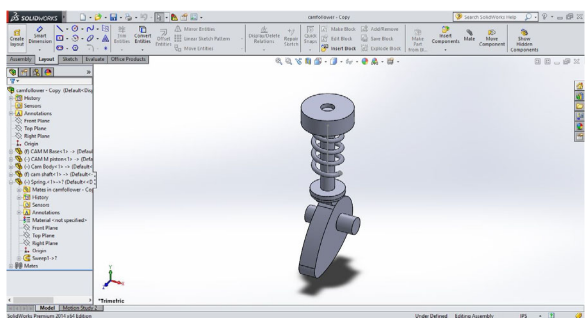

Fig. 2. Cam follower mechanism

3.3 *Application*

In this paper, three factors have been used along with three levels of values. So total of twenty-seven (3^3) experiments have been conducted according to full factorial design. Due to the Covid-19 pandemic situation access to the laboratory for doing actual experiments became a constraint. Therefore, the experiments were conducted through simulation using ideaMaker software. The machining parameters that have been kept fixed throughout the experiment are shown in Table 3.

Table 3
Slicing parameters set for ideamaker software

Fixed Parameters	Values
Infill density	30%
Extrusion width	0.40 mm
Infill pattern type	Grid
Support printing speed	100 mm/sec
Platform addition	Raft only
Support infill type	Honeycomb
Heated bed temperature	60°C
Primary bed temperature	205°C

In the present work on the basis of experimental results, a decision matrix with 27 sets of experiments (m=27) with 2 response variables (No. of performance evaluation criteria, n=2) has been formed and shown in Table 4. The performance of each set of experiments considered as an alternative has been determined using the Fuzzy AHP-MOORA method. For this purpose, subjective weights of evaluation criteria have been determined following the steps of the extent analysis method of fuzzy AHP as introduced by Chang (1996). Thus, the weights for the criteria of printing time and printing cost become (0.637, 0.363).

Table 4
Decision matrix showing coded parameter values with performance evaluation criteria

Experimental run order	Coded parameter values			Performance evaluation criteria	
	Layer height	Print speed	Orientation	Printing time (Hr.)	Printing cost (Rs.)
1	-1	-1	-1	6.873	3004
2	-1	-1	0	8.029	3509
3	-1	-1	1	7.677	3355
4	-1	0	-1	4.813	2103
5	-1	0	0	6.028	2634
6	-1	0	1	5.624	2458
7	-1	1	-1	4.274	1868
8	-1	1	0	5.64	2465
9	-1	1	1	5.269	2303
10	0	-1	-1	4.234	1850
11	0	-1	0	4.928	2154
12	0	-1	1	4.715	2060
13	0	0	-1	2.928	1280
14	0	0	0	3.727	1629
15	0	0	1	3.486	1523
16	0	1	-1	2.678	1170
17	0	1	0	3.494	1527
18	0	1	1	3.269	1429
19	1	-1	-1	3.582	1565
20	1	-1	0	4.15	1814
21	1	-1	1	3.301	1443
22	1	0	-1	2.489	1088
23	1	0	0	3.151	1377
24	1	0	1	2.952	1290
25	1	1	-1	2.281	997
26	1	1	0	2.954	1291
27	1	1	1	2.769	1210

In the next step, the criteria for all the alternatives are normalized using Eq. (1) and subsequently, the corresponding performance score has been determined as a weighted algebraic sum of normalized elements using Eq. (2). As both of the performance evaluation criteria are lower the better type, the computed performance scores become negative for all alternatives. The same has been presented in Table 5.

Table 5
Performance score for each parametric combination of the experiment

Experimental run order	Coded parameter values			Performance score (y_i)
	Layer height	Print speed	Orientation	
1	-1	-1	-1	-0.29145
2	-1	-1	0	-0.34047
3	-1	-1	1	-0.32554
4	-1	0	-1	-0.20409
5	-1	0	0	-0.25562
6	-1	0	1	-0.23849
7	-1	1	-1	-0.18124
8	-1	1	0	-0.23916
9	-1	1	1	-0.22343
10	0	-1	-1	-0.17954
11	0	-1	0	-0.20897
12	0	-1	1	-0.19994
13	0	0	-1	-0.12416
14	0	0	0	-0.15804
15	0	0	1	-0.14782
16	0	1	-1	-0.11356
17	0	1	0	-0.14816
18	0	1	1	-0.13862
19	1	-1	-1	-0.15189
20	1	-1	0	-0.17598
21	1	-1	1	-0.13998
22	1	0	-1	-0.10555
23	1	0	0	-0.13362
24	1	0	1	-0.12518
25	1	1	-1	-0.09673
26	1	1	0	-0.12526
27	1	1	1	-0.11742

4. Results

The Performance score of every parametric combination based on the MOORA method has been determined and presented in Table 6. The Table shows that the largest performance score is associated with experiment number 25 at parameters of layer height of 0.35mm (level 1), print speed of 100mm/s (level 1) and orientation of 0° (level -1).

Table 6
Ranking of parametric combinations based on performance score

Experimental run order	Layer height	Print speed	Orientation	Score	Rank
25	1	1	-1	-0.09673	1
22	1	0	-1	-0.10555	2
16	0	1	-1	-0.11356	3
27	1	1	1	-0.11742	4
13	0	0	-1	-0.12416	5
24	1	0	1	-0.12518	6
26	1	1	0	-0.12526	7
23	1	0	0	-0.13362	8
18	0	1	1	-0.13862	9
21	1	-1	1	-0.13998	10
15	0	0	1	-0.14782	11
17	0	1	0	-0.14816	12
19	1	-1	-1	-0.15189	13
14	0	0	0	-0.15804	14
20	1	-1	0	-0.17598	15
10	0	-1	-1	-0.17954	16
7	-1	1	-1	-0.18124	17
12	0	-1	1	-0.19994	18
4	-1	0	-1	-0.20409	19
11	0	-1	0	-0.20897	20
9	-1	1	1	-0.22343	21
6	-1	0	1	-0.23849	22
8	-1	1	0	-0.23916	23
5	-1	0	0	-0.25562	24
1	-1	-1	-1	-0.29145	25
3	-1	-1	1	-0.32554	26
2	-1	-1	0	-0.34047	27

5. Discussion

From the result, it is observed that, for making a cam follower arrangement using the FDM process with PLA material, parametric combinations used in experiment No. 25 are the optimum as it produces the best performance score. The average performance score (y_i) corresponding to each level of process parameter has been calculated by taking the arithmetic mean of all performance scores of that particular level and the same is presented in Table 7. Irrespective of the responses at the individual level, a higher performance score indicates better performance at the corresponding parameter setting. It has been observed from the values of average y_i (Table 7) that the optimal responses obtained are the same as the values obtained through the y_i values shown in Table 6. The range of average y_i of the FDM parameters at different levels has been computed and obtained as 0.12532 for layer height, 0.07002 for print speed and 0.03746 for orientation. As it is observed that the highest score, i.e., 0.12532 corresponds to layer height, it can be concluded that layer height becomes the most significant controllable parameter for this FDM process. The order of significance of controllable parameters based on the difference between the maximum and the minimum performance scores is layer height, print speed and orientation. The ranking of the parameter combinations based on y_i in descending order has been shown in Table 6. It is understood that the optimal setting of process parameters yielding optimal responses confirms the parametric combination with the highest performance score.

Table 7
Response table for performance score at each level

Process parameter	Average performance score (y_i)			Max-Min
	Level -1	Level 0	Level 1	
Layer height	-0.2555	-0.15765	-0.13018	0.12532
Print speed	-0.22375	-0.16584	-0.15373	0.07002
Orientation	-0.16091	-0.19837	-0.19238	0.03746

5. Conclusion

Additive manufacturing has the potential to redefine manufacturing in certain areas. This paper uses a methodology based on the design of experiments and MOORA to optimize the printing time and cost of the FDM process for making a cam follower model. From the result, it is clear that if the layer thickness is increased the print time decreases and with an increase in print speed. The build orientation has a significant effect on print time. Keeping all the parameters constant, with the changing of orientation, print time also changes. The outcomes of the present work are:

(i) A decision-making framework has been developed to optimize FDM process parameters using MOORA.
(ii) Based on the performance score, the optimum setting of parameters is a layer height of 0.35mm (level 1), print speed of 100mm/s (level 1) and orientation of 0° (level -1). The analysis also shows that layer height becomes the most significant parameter for the FDM process.
(iii) The analysis also reveals that the order of significance of controllable parameters based on the difference between the maximum and minimum performance score is layer height, print speed and orientation.

Therefore, the industry and academia in the domain of additive manufacturing can explore and exploit this parametric optimization model in general and the outcomes of this research in particular to enhance the quality of the manufacturing process.

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Conflict of interest

The author declares no potential conflict of interest concerning the research, authorship, and/or publication of this article.

Submission declaration

The submitted work has not been published previously anywhere in any language.

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