Parametric Optimization of 3D Printing Process Using MCDM Method

S. Vinodh and Priyanka Shinde

Abstract Additive Manufacturing is identified as a key emerging technology and has received much attention during recent years. Three-Dimensional Printing (3D printing) is an Additive Manufacturing (AM) method and has tremendous applications in industries. Selection of appropriate AM process for an application requires consideration of various conflicting criteria. The right AM option ensures competitive performance of manufacturing which in turn affects the quality of the parts. For achieving the best results of any manufacturing process, parametric optimization is essential which has been attempted in the case of 3D printing process using Multi-Criteria Decision-Making (MCDM) techniques. This paper represents the application of an MCDM technique, viz. Multi-Objective Optimization using Ratio Analysis (MOORA) method, to optimize the parameters of 3D printing process, which takes into account any number of criteria, both quantitative as well as qualitative, and offers a simple computational procedure. Three process parameters of FDM based 3D printer, viz. layer thickness, build pattern and fill pattern are considered in this study. Surface roughness and building time of part are taken as response parameters. Effect of each process parameter on surface roughness and build time has been studied.

Keywords Additive manufacturing · 3D printing · Fused deposition modelling Multi-criteria decision-making · MOORA

Nomenclature

Y_i Normalized assessment value
R_a Surface roughness
I^+ Positive ideal solution

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I^- Negative ideal solution
S_i^+ Distance between PIS and normalized values
S_i^- Distance between NIS and normalized values
CC_i Closeness coefficient

1 Introduction

Additive Manufacturing (AM) is one of the revolutionary technologies that fabricates 3D objects from CAD data. Additive manufacturing has been visualized as an innovative path for future manufacturing due to its ability to create one-off custom products and capability to manufacture complex designs as a single unit. 3D printing is one of the potential AM technology in which 3D model of object is sliced in successive layers under computer control and these layers are laid down one over the other to create object. Most commonly used 3D printing technology is material extrusion process. This technology also named as Fused Deposition Modelling (FDM) uses extrusion nozzle to extrude material to create successive layers. Most commonly used materials for FDM process are thermoplastics such as Acrylonitrile Butadiene Styrene (ABS), Poly-Carbonate (PC) and Poly Lactic Acid (PLA). FDM printer is connected with a computer interface that processes STL file (Stereo lithography file format) according to which the extrusion nozzle moves both horizontally and vertically following the designed path. Build material is fed to the printer extrusion nozzle in the form of solid where it gets heated past their glass transition temperature and extruded from nozzle in the form of thin filament. These filament strings get deposited on one another to generate 3D model. By using 3D printing process, any complex geometry can be produced.

This chapter presents optimization of process parameters of a non-laser based 3D printing process working on FDM technology using MOORA method. Three process variables are considered, viz. layer thickness, build pattern and fill pattern. Layer thickness is a measure of height of each layer in additive manufacturing process measured along vertical axis (*Z*-axis). It is one of the important technical characteristics of printer which has impact on part quality. Build pattern is the way in which internal structure of the part is created. Fill pattern is associated with support structure style. Support structure is required to support if any overhang or cantilever is present in geometry. This affects build time and support material volume usage. Different settings of these parameters are taken and surface roughness and build time are calculated in each case. Process variables of 3D printing influence the quality of 3D printed parts (Abdullaha et al. 2015). Major quality indicator considered in this study is surface roughness of parts. Similarly, build time is also an influencing parameter that implies the time needed to build part. These two parameters have been optimized in this study to get the best setting of process variables.

1.1 Objectives of the Present Study

FDM process is the most commonly used AM technology. Parts manufactured using this process show different properties. In order to overcome certain shortcomings of this process, proper understanding of FDM process and its input parameters is essential. This study attempts to understand and analyse the FDM process thoroughly so as to make the components manufactured by this process more reliable and also to make this process more cost-efficient and environment-friendly than any other process. Taking into consideration above factors, objectives of this study are as follows:

1. One of the important objective is optimization of the printing process parameters of FDM based 3D printing. To get optimal settings of process parameters, a multi-objective optimization problem is formulated and solved using MOORA method (Multi-objective optimization using ratio analysis). Finally, the results obtained using MOORA method have been analysed using TOPSIS method and ranks obtained for each experimental run are compared.
2. A detailed study of various process parameters of FDM is carried out and their impact on part quality is investigated. Effect of each process parameter on response parameters has been studied.

2 Literature Review

Multiple studies have been conducted for optimization of process parameters for 3D printing. The studies identify how printing parameters affect various response parameters such as dimensional accuracy of 3D printed parts, surface finish and manufacturing time.

Thrimurthulu et al. (2004) determined optimal part orientation for FDM process in order to enhance surface finish and minimize build time. To obtain optimum results, genetic algorithm was used. Two case studies were carried out in this work with two parts namely axisymmetric part and a 3D part. Two contradictory objectives were achieved as minimum build time and maximum surface finish. Also, support structure minimization was implicitly done in this work. They developed a model for assessing the build time and average part surface roughness. Their contributed methodology can be used to recognize optimum part orientation for any complex part.

Wang et al. (2007) used Taguchi method with Grey Relational Analysis (GRA) to optimize FDM process parameters. Two specimens were prepared namely trapezoid test specimen and tensile test specimen. Six process parameters were taken namely layer thickness, support style, deposition style, deposition orientation in *Z*-direction, deposition orientation in *X*-direction and build location. Taguchi's L_{18} orthogonal array was applied to determine experimental runs.

Response parameters such as tensile strength, dimensional accuracy and surface roughness were taken. GRA was used to determine the optimum parameter setting. Results of GRA were verified using TOPSIS method. Results of this study showed that deposition in *Z*-direction was influencing parameter in case of tensile strength and dimensional accuracy whereas layer thickness was found to be the most influencing parameter in case of surface roughness. They proposed a methodology of integrating Taguchi method with GRA for optimizing RP processes. TOPSIS method was used to verify the resolutions of multiple quality characteristic problems.

Sood et al. (2009) investigated the influence of vital FDM parameters on dimensional accuracy of processed ABSP400 part. Process parameters studied were layer thickness, orientation angle, raster angle, air gap and raster width along with their interactions. Standard test specimens were taken and experiments were designed according to Taguchi's experimental design. Grey Taguchi method was adopted in this study in order to obtain optimum settings of process parameters. Minimization of percentage change in length, width and thickness simultaneously was achieved. It was observed from the study, that shrinkage is the dominating factor along with length and width direction of built part. They adopted grey Taguchi method for identifying common factor setting such that all the three dimensions of a fabricated part show lesser deviation from actual value. They found the optimal process parameters settings to reduce percentage change in length, width and thickness.

Anoop et al. (2011) carried out optimization study for FDM parameters using weighted principal component analysis. Process parameters taken in this study were layer thickness, orientation, air gap, raster angle and raster width. Taguchi method was used to determine experimental runs. L_{27} orthogonal array was taken in this study with five input parameters and three levels of each parameter. Tensile, flexural and impact specimen were prepared and data was collected in terms of three responses. Results of this study showed that all process parameters have significant effect on response parameters. To simultaneously optimize three responses, optimum parameter settings have been found. They concluded that factors such as layer thickness, raster angle, raster width and orientation have a great influence on the mechanical properties of FDM produced parts. They identified optimum parameter settings for optimizing three mechanical properties concurrently.

Zhang and Peng (2012) carried out Taguchi based optimization study to determine optimum parameters for FDM process. Four process parameters were selected in this study namely wire-width compensation, extrusion speed, layer thickness and filling speed. Dimensional error and warpage deformation were taken as response parameters. L_9 orthogonal array was used with four process parameters with three levels. For optimization, Taguchi method was used in combination with fuzzy comprehensive evaluation. Results showed that most significant parameter was wire-width compensation. They used Taguchi method in integration with fuzzy comprehensive evaluation for optimizing four process parameters. They found that performance index of FDM process is greatly influenced by 'wire-width compensation' followed by extrusion speed, layer thickness and filling speed.

Alhubail et al. (2013) worked on Taguchi method based optimization of FDM input parameters to get improved part quality. Process variables namely layer thickness, raster orientation, air gap, raster width and contour width were considered and impact of these parameters on quality characteristics such as tensile strength and surface roughness was studied. They concluded that setting layer thickness and raster width at lower values could minimize the surface roughness in addition to the air gap at −0.01 mm and also higher tensile strength can be obtained. They identified that tensile strength and surface roughness of a processed part is highly influenced by air gap parameter. Validation runs were done to confirm the predicted analysis.

Raol et al. (2014) studied the effect of FDM printing parameters on surface roughness. Printing parameters such as layer thickness, part built orientation and raster angle were considered. Experiments were conducted using response surface methodology and from the results of the experiments, mathematical model was developed. Experimental result analysis and surface plots concluded that part build orientation possesses most vital effect on surface roughness followed by layer thickness. Nevertheless, raster angle has the least vital influence on surface roughness.

Kumar et al. (2014) conducted study to optimize the process parameters of ABS-M30i parts built by FDM to get minimum surface roughness. Five parameters were considered in this study and Taguchi's design of experiments and ANOVA were used to analyse the effect of each parameter. It was found that in this study, not all FDM printer parameters have impact on surface roughness but vary in influence on each proposed response variables. Smooth surface construction and lower R_a were ensured with layer thickness value of 0.254 mm and negative air gap −0.01 mm or raster width of 0.508 mm. They analysed variable parameters of FDM process like laser thickness, air gap, raster width, counter width and raster orientation and their interactions. They determined that thinner layer and voids between deposited layers may minimize surface roughness.

Farzad and Godfrey (2014) optimized FDM parameters using group method for data handling and differential evolution. Relationship between FDM process parameters and tensile strength was determined. Initially, pretest was carried out considering two process parameters namely part orientation and raster angle. Results of pre-test showed that both parameters affect tensile strength. Further, parameters viz. air gap, part orientation, raster angle and raster width were taken and 16 runs were conducted. Optimal parameter settings were found using differential evolution.

Abdullah et al. (2015) investigated the impact of printing orientation and layer thickness on mechanical and topological properties of printed ABS samples. Two printing orientations (*XY* and *YZ*) with three different layer heights (0.1, 0.2 and 0.3 mm) were chosen and specimens were printed utilizing a 3D printer. ANOVA was carried out to investigate the relationship of layer height and printing orientation on tensile strength and surface roughness of the specimens. They concluded that layer height and orientation setting could be improved for better mechanical and topological properties for patient specific implant fabrication.

Manikandan et al. (2015) studied the effect of FDM parameters on flexural strength and surface roughness of PC-ABS mix using FDM 900mc machine. Parameters considered in the study were raster angle, contour style, raster width and air gap. Taguchi method was applied to design experiments and flexural strength and surface roughness were tested. They also found that contour style has the most vital effect on surface roughness of PC-ABS part made using FDM process in comparison with other parameters. They identified the best possible parameters of FDM process in order to ensure good flexural and surface roughness properties. They have shown that raster angle has great effect on flexural strength and counter style has great effect on surface roughness.

Nidagundi et al. (2015) used FDM process parameters for optimization. Process parameters considered for optimization were layer thickness, orientation angle and fill angle. Output parameters considered were ultimate tensile strength, surface roughness, dimensional accuracy and build time. Taguchi's L_9 array was used to conduct experimental runs. S/N ratio was applied to identify optimum parameter settings. They optimized the parameters of FDM process for enhancing properties namely; ultimate tensile strength; dimensional accuracy; surface roughness and manufacturing time. They validated the performance of optimum conditions of FDM by conducting verification experiment.

Rao and Rai (2016) carried out optimization study for FDM process using Teaching Learning-Based Optimization (TLBO) algorithm. FDM parameters such as air gap, layer thickness, orientation angle, raster angle and raster width were taken. Total five case studies were conducted to attain optimum combination of process parameters. Optimization algorithms used in this study were TLBO algorithm and Non-dominated Sorting TLBO (NSTLBO) algorithm. They considered three single-objective optimization problems and two multi-objective optimization problems of FDM process and solved using TLBO and NSTLBO algorithm. They concluded that TLBO algorithm shows better performance compared to GA and QPSO algorithm in terms of objective function value.

Srivastava et al. (2017) carried out optimization study for FDM process parameters using response surface methodology (RSM). Face-centred central composite design was used to conduct experiments using 86 experimental runs. In this study, contour width, orientation, raster angle, raster width, layer height and air gap were taken as process parameters. Response parameters such as build time, model material volume and support material volume for ABS were taken. Optimal parameter setting was obtained using RSM method. Developed mathematical models were tested using design expert software for accuracy.

FDM is a widely used AM technology and has tremendous role in 3D Printing. To achieve optimization of multiple input characteristics of FDM process, MOORA method is used in this study with effective experimental design, i.e. L_8 orthogonal array. Results have also been verified using TOPSIS method. Comparative analysis has been done to derive appropriate inferences. Details about process parameters, response parameters and experimental design are given in subsequent section.

Table 1 Parameter design

Process parameters	Level 1	Level 2
Layer thickness (mm)	0.2540	0.3302
Build pattern	Solid	Sparse-high density
Fill pattern	Basic	Smart

3 Experimental Setup

To determine the effect of process variables on printed parts, tensile specimens were built according to the standards ISO 527:1993 under different conditions of input parameters. Process parameters considered are (1) layer thickness, (2) build pattern and (3) fill pattern. Test specimens were manufactured using uPrint SE plus 3D printer machine and ABS plus plastic as build material. uPrint SE 3D Printer is used in this study which uses ABS plus as model material. Table 1 shows the selected values of process parameters. Two settings of layer thickness are used to build part, they are 0.254 and 0.3302 mm respectively. Build pattern is defined by 'Solid' and 'Sparse-High Density'. Two fill patterns namely 'Basic' and 'Smart' are used. Detailed description of process parameters used in this study is given in Sect. 3.1.

Two-level full factorial design is used to design the experiment runs using three process parameters and two levels providing 2^3 experiments (Hwang and Yoon 1981). Table 2 indicates experimental design according to 2^3 design. Figure 7 shows tensile specimens made by FDM 3D printing process.

3.1 Details About Process Parameters

Process parameters involved in this study are layer thickness, build pattern and fill pattern. For this study, uPrint SE Plus FDM printer is used. This printer has two settings of layer thickness, three settings of build patterns or model interior style and three settings of fill pattern or support style. The software accompanied with

Table 2 L_8 experimental design

Experiment No.	Process parameters		
	Layer thickness (mm)	Build pattern	Fill pattern
1	0.2540	Solid	Basic
2	0.2540	Solid	Smart
3	0.2540	Sparse-high density	Basic
4	0.2540	Sparse-high density	Smart
5	0.3302	Solid	Basic
6	0.3302	Solid	Smart
7	0.3302	Sparse-high density	Basic
8	0.3302	Sparse-high density	Smart

this machine is Catalyst EX 4.4. With reference to this software, detailed description about printer parameters with appropriate figures is given below (Catalyst EX 4.4 software manual):

1. *Layer thickness*: Layer thickness is a measure of the height of each successive layer of material in AM or 3D printing process. The number of layers required to create a part determines the build time required. The thinner the layers, the longer it takes to produce a part of a given height. It is the thickness of layers of material deposited by nozzle and depends on nozzle type. For this study, FDM SE plus 3D printer is used which has two settings of layer thickness, viz. 0.254 and 0.3302 mm.
2. *Build pattern*: Build pattern sometimes called as part interior style is an important parameter. Build pattern influences some important characteristics of prototypes like strength, weight, material consumption build time, etc. 3D printer has three build patterns namely solid, sparse-high density and sparse-low density. Some important features of each pattern are given below:

   a. *Solid*: This pattern has dense fill. There is no gap between adjacent rasters and rasters run perpendicular to those on the preceding layer. For this pattern, model material consumption is higher. Also, it takes longer time to build the part than other patterns. Figure 1 shows solid build pattern.
   b. *Sparse-Low density*: This pattern gives hollow interior with internal lattice for structural rigidity. Large air gaps will be there between rasters and there will be unidirectional rasters on each layer. The interior will be 'honeycombed/hatched'. This pattern results in lowest model material consumption and shortest build time. Figure 2 illustrates sparse-low density build style.
   c. *Sparse-High density*: This interior style is default and is widely applied because of lesser build times, reduced material usage and reduction of the probability of part curl for geometries with higher mass. This pattern also gives hollow interior with internal lattice for structural rigidity. It consumes slightly more model material and takes slightly longer time for building as compared to sparse-low density. Figure 3 illustrates sparse-high density build style.

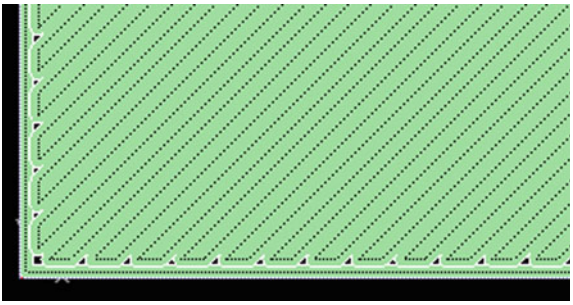

Fig. 1 Solid build pattern

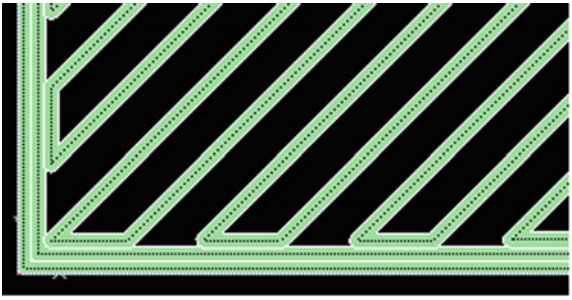

Fig. 2 Sparse-low density build pattern

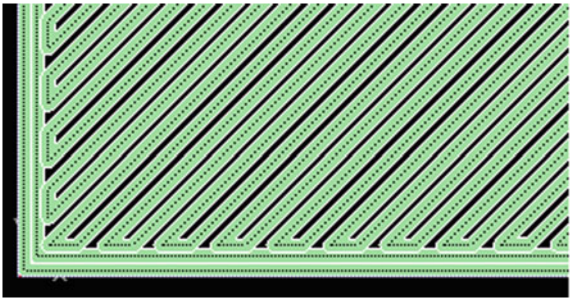

Fig. 3 Sparse-high density build pattern

3. *Fill pattern*: Fill pattern also can be taken as support style. Selection of fill pattern is important as it determines the build time required for the model. Part supports are temporary structures generated during modelling or production phase in order to enable overhang type features. Three important fill patterns are basic, smart and surround and their features are as follows:
   a. *Basic pattern*: Basic support style is the standard raster pattern support structure. It uses a consistent, narrow spacing between support raster toolpaths. This is suitable for all parts and is the default for builds using breakaway support materials. Figure 4 illustrates the basic fill pattern.
   b. *Surround pattern*: This support style encloses the entire model with support material. This style of supports is useful for tall parts with thin features that require extra support and stability during build process. Surround supports require higher build times and to be used only with soluble support material. Figure 5 shows surround support style.
   c. *Smart pattern*: This support style reduces the usage of support material, minimizes build time and enhances support removability for many parts. This style is the default style for builds using soluble supports. SMART supports can be effectively used as it reduces build time up to 14% and also reduces material consumption up to 40%. SMART supports are compatible for almost all parts, and those with large support regions. Figure 6 shows smart support style.

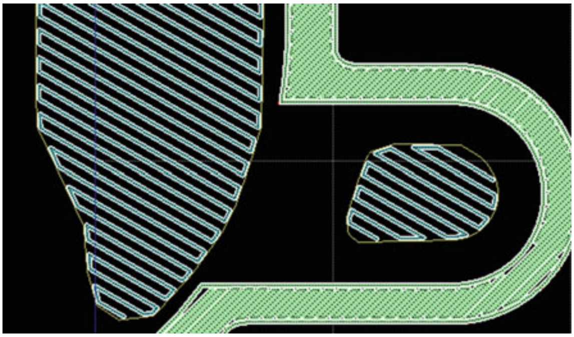

Fig. 4 Basic support style

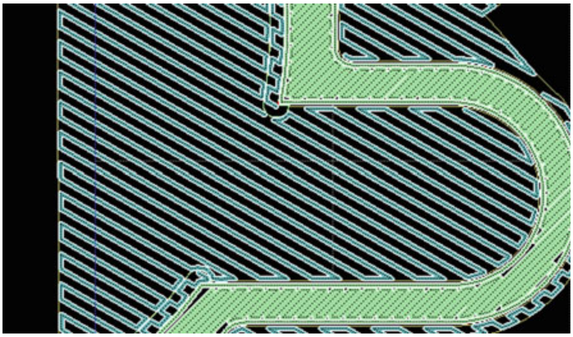

Fig. 5 Surround support style

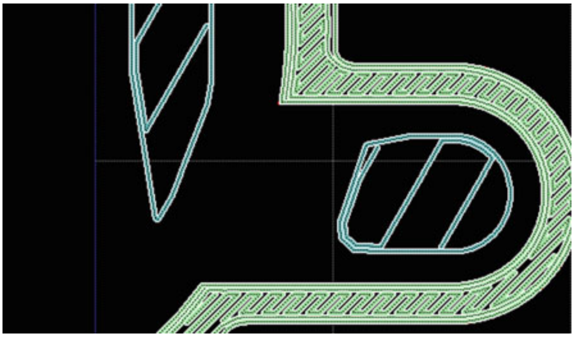

Fig. 6 Smart support style

3.2 Selection of Response Parameters

Nowadays, FDM is considered as a potential solution for manufacturing of plastic components in batch size. This process is not only considered for making prototypes or models for visualization and testing but also to make final products. Apart from commercial and customized products, implants manufactured by this process are being used in many of the biological and biomedical applications. To make this

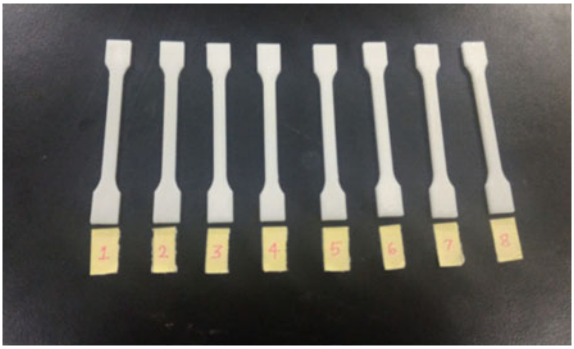

Fig. 7 Tensile specimens built using FDM 3D printer

process more environment-friendly and cost-efficient, it is essential to consider some critical parameters of FDM printers. Following response parameters are taken in this study:

a. Build time: One of the most important applications of FDM process is making prototypes for either design visualization or testing. FDM can be taken as most effective process for making prototypes rather than any other conventional process. Therefore, attention must be given to reduce the cost of prototyping. FDM process mainly influences with its build time. In order to make this process cost efficient, build time needs to be reduced.
b. Surface roughness: FDM parts in some cases are considered as final products and are being used directly. Therefore, parameters like surface finish and part interior properties are important factors to consider.

FDM printer mostly comes with different parameter settings. These printers consist of some critical parameters which directly influence the parts manufactured by this process. Input parameters like layer thickness and part orientation directly affect part surface finish and part strength. In order to take full advantage of FDM process, these input parameters need to be optimized in order to get good part quality. In this study, MOORA method is used to solve optimization problem as discussed in Sect. 4.

4 MOORA Method

MOORA method considers all attributes with their relative importance, and provides an effective assessment of the alternatives. This procedure is computationally simple, logical and robust which can concurrently include any number of quantitative and qualitative selection attributes. As it is based on simple ratio analysis, it has the least amount of mathematical calculations and is useful for practitioners also. Also, computation procedure is not influenced by the addition of any parameter.

Steps in MOORA method includes the following:

Step 1 The first step is to recognize the relevant evaluation attributes.

Step 2 A decision matrix is formulated which depicts the performance of different alternatives with reference to different criteria. The data can be represented as matrix X.

$$X = \begin{vmatrix} x_{11} & x_{12} & \cdots & \cdots & \cdots & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & \cdots & \cdots & \cdots & x_{2n} \\ \vdots & \vdots & & & & & \vdots \\ x_{m1} & x_{m2} & \cdots & \cdots & \cdots & \cdots & x_{mn} \end{vmatrix} \quad (1)$$

where x_{ij} in above equation is measure of ith alternative on jth attribute, m and n denote the number of alternatives attributes respectively.

Step 3 The next step is to develop a ratio system. In this step, each performance on an attribute is compared to denominator which is representative for all alternatives pertaining to that attribute. Brauers et al. (2008) mentioned different ratio systems (Mandal and Sarkar 2012) and mentioned that for this denominator, the best alternative is square root of sum of squares of each alternative per attribute. Ratio is given by:

$$X_{ij}^{a} = X_{ij} / \sqrt{\sum\nolimits_{i=0}^{n} X_{ij}^{2}} \quad (j = 1, 2, \ldots n) \quad (2)$$

where x_{ij} denote dimensionless number which pertains to the interval [0, 1] indicating the normalized values of ith alternative on jth attribute.

Step 4 These normalizes performances are summed for maximization (for beneficial attributes) and subtracted for minimization (for non-beneficial attributes). Then optimization problem is:

$$Y_i = \sum_{j=1}^{g} X_{ij}^{a} - \sum_{j=g+1}^{n} X_{ij}^{a} \quad (3)$$

where g denotes number of attributes to be maximized, $(n - g)$ denote number of attributes to be minimized, and Y_i denotes normalized assessment value of ith alternative with reference to all the attributes.

Step 5 Y_i values can be positive or negative depending on totals of its maxima (beneficial attributes) and minima (non-beneficial attributes) in decision matrix (Manikandan et al. 2015). Final preferences are indicted by ordinal ranking of Y_i values. Thus, best choice possesses highest value of Y_i while worst choice possesses lowest value of Y_i. In this study, MOORA method is used for optimization. To get more accurate results, fuzzy evaluation methods can be used which deals with subjectivity and vagueness associated with data.

Application of MOORA method for optimization problem is shown in Sect. 5.

5 Optimization of Process Parameters

MOORA method is used for selecting optimized process parameters of FDM 3D printer. Parameters associated with quality of part were build time and surface roughness as depicted in Table 3. The input parameters considered are layer thickness, build pattern and fill pattern. In this study, major quality characteristics examined are surface roughness of parts. Quality of parts is good with lower surface roughness values. Also, parts which require lower build time are considered as cost-effective parts. Therefore, both surface roughness and build time correspond to lower-the-better (LB) criterion. The selected response parameters were widely applied in prior research studies (Thrimurthulu et al. 2004; Choi and Samavedam 2002). The surface roughness was measured using Mitutoyo SURF TEST SJ-301 tester. The measurement was taken in the middle of gauge length of the tensile specimen. Table 3 shows objective data obtained from experimental trials. Table 4 shows normalized assessment values of alternatives with reference to attributes, as calculated using Eq. (2).

Further, Eq. (3) has been applied to each reading and the normalized assessment scores (Y_i) of all alternatives with reference to considered attributes have been calculated. To calculate Y_i values, both build time and surface roughness are taken as non-beneficial attribute (lower values are desirable in both cases). Ranks are given according to descending assessment values and specimen having rank 1 is considered to be built with best setting of process parameters. Table 4 shows rankings of MOORA method based computations which suggest that optimum values of process parameters are layer thickness as 0.3302 mm, build pattern as Solid and fill pattern as Smart.

Table 3 Objective data

Experiment No.	Process parameters			Build time (min)	Surface roughness (R_a) (μm)
	Layer thickness (mm)	Build pattern	Fill pattern		
1	0.2540	Solid	Basic	7	10.48
2	0.2540	Solid	Smart	6	9.70
3	0.2540	Sparse-high density	Basic	6	12.09
4	0.2540	Sparse-high density	Smart	6	9.76
5	0.3302	Solid	Basic	6	8.73
6	0.3302	Solid	Smart	5	4.29
7	0.3302	Sparse-high density	Basic	5	6.43
8	0.3302	Sparse-high density	Smart	5	5.07

Table 4 Results of multi-objective analysis (normalized assessment)

Experiment No.	Squared values		Ratio		Normalized assessment value (Y_i)	Rank
	Build time	Surface roughness	Build time	Surface roughness		
1	49	109.83	0.4276	0.4254	−0.8530	7
2	36	94.09	0.3665	0.3938	−0.7603	5
3	36	146.16	0.3665	0.4908	−0.8573	8
4	36	95.25	0.3665	0.3962	−0.7627	6
5	36	76.21	0.3665	0.3544	−0.7209	4
6	25	18.40	0.3054	0.1741	−0.4795	1
7	25	41.34	0.3054	0.2610	−0.5664	3
8	25	25.70	0.3054	0.2058	−0.5112	2
	$\sqrt{268} = 16.37$	$\sqrt{606.98} = 24.63$				

6 Comparative Analysis of MOORA Results Using TOPSIS

In order to verify the ranks obtained using MOORA method, TOPSIS method is used. Ranks obtained using both the methods were compared in order to derive appropriate inferences with multiple input characteristics.

TOPSIS method

TOPSIS is a Multi-Criteria Decision-Making (MCDM) technique used to decide preference order. This method is called 'Technique for order preference by similarity to ideal solution' which was developed by Yoon and Hwang in 1981 (Hwang and Yoon 1981). Preference order is decided based on the closest alternative to the ideal solution. In this method, alternatives are graded based on the closeness to the ideal solution. The alternative which is nearer to the ideal solution is assigned the highest grade. This method follows certain steps described as below:

Step 1 *Normalization of data*

In this step, experimental data is being normalized in order to compare the parameters. Normalized values of each parameter are obtained using the following equation:

$$N_{ij} = \frac{p_{ij}}{\sqrt{\sum_{i=1}^{m} p_{ij}^2}} \tag{4}$$

where $i = 1\ldots m$ and $j = 1\ldots n$. p_{ij} represents the actual value of the ith value of jth experiment number and N_{ij} represents the corresponding normalized value.

Step 2 *Computation of weighted normalized matrix*

After normalizing the data, weights associated with each parameter are determined. Weighted normalized matrix is obtained by multiplying normalized value with corresponding weight. It is given by;

$$R_{ij} = W_i \times N_{ij} \tag{5}$$

where W_i represents the weights of respective parameters.

Step 3 *Computation of positive ideal solution (PIS) and negative ideal solution (NIS)*

Based on the objective, values of PIS and NIS are decided. If objective is maximization of parameters, then maximum value among each parameter obtained from weighted normalized matrix is taken as PIS (I^+) and minimum value among each parameter obtained from weighted normalized matrix is taken as NIS (I^-). If the objective is minimization, then minimum value among each parameter obtained from weighted normalized matrix is taken as PIS (I^+) and maximum value among each parameter obtained from weighted normalized matrix is taken as NIS (I^-).

PIS and NIS is calculated using the following equations:

$$I^+ = \left(P_1^+, P_2^+, P_3^+, P_4^+ \ldots\right) \text{ maximum values} \tag{6}$$

$$I^- = \left(P_1^-, P_2^-, P_3^-, P_4^- \ldots\right) \text{ minimum values} \tag{7}$$

Step 4 *Computation of distance between PIS and NIS*

$$S_i^+ = \sqrt{\sum_{i=1}^{m} \left(r_{ij} - P_i^+\right)^2} \tag{8}$$

$$S_i^- = \sqrt{\sum_{i=1}^{m} \left(r_{ij} - P_i^-\right)^2} \tag{9}$$

where S_i^+ is distance between PIS and normalized values and S_i^- is distance between NIS and normalized values.

Step 5 *Computation of closeness coefficient*

Closeness Coefficient (CC_i) is calculated using following equation:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{10}$$

Based on closeness coefficient value, ranking of each alternative is obtained. Highest value of closeness coefficient gives the best choice of alternative. Hence, preference order is decided based on CC_i values.

Application of TOPSIS method and results

TOPSIS method is applied in this study to compare results obtained using MOORA method. Ranks obtained by MOORA method are compared with TOPSIS ranks and results are validated. In this study, two response parameters are taken such as build time and surface roughness. Objective of this study is to minimize both response parameters and obtain optimal settings. According to TOPSIS method, these two parameters are normalized using Eq. (4). After normalization of data, weighted normalized matrix is obtained by multiplying weights of corresponding parameters with normalized value. In this study, weight for both build time and surface roughness are being taken equal to 0.5. Weighted normalized matrix is obtained using Eq. (5). Now PIS and NIS are obtained using Eqs. (8) and (9). In this study, $P^{+}_{\text{Roughness}} = 0.08706$; $P^{+}_{\text{Buildtime}} = 0.1527$; $P^{-}_{\text{Roughness}} = 0.2454$; $P^{-}_{\text{Buildtime}} = 0.2138$. Finally, closeness coefficient is calculated using Eq. (10). All results are summarized in Table 5. Table 5 shows closeness coefficient values. Based on this value, preference order is decided and the best alternative is obtained.

As shown in Table 5, first rank is obtained for experimental run 6 according to TOPSIS method. As shown in Table 4, first rank was obtained for experimental run 6 using MOORA method. Results of MOORA and TOPSIS methods are summarized in Table 6. In MOORA method, ranks are given according to descending order of ratios, i.e. first rank is given for the highest ratio. Similarly, in TOPSIS method, ranks are given based on descending order of CC_i values, i.e. highest CC_i value possesses first rank. Table 6 shows comparative ranking of MOORA and TOPSIS methods. It is clear from the table that all rankings for experimental runs using both the methods are found to be similar.

Table 5 Results obtained using TOPSIS method

Experiment No.	Normalized		Weighted normalized		S_i^{+}	S_i^{-}	CC_i	Rank
	Build time	Surface roughness	Build time	Surface roughness				
1	0.4276	0.4254	0.2138	0.2127	0.1397	0.0327	0.1897	7
2	0.3665	0.3937	0.1833	0.1969	0.114	0.0573	0.3345	5
3	0.3665	0.4907	0.1833	0.2454	0.1612	0.0305	0.1591	8
4	0.3665	0.3961	0.1833	0.1981	0.1151	0.0563	0.3285	6
5	0.3665	0.3543	0.1833	0.1772	0.0951	0.0747	0.4393	4
6	0.3054	0.1741	0.1527	0.0871	0	0.1697	1	1
7	0.3054	0.261	0.1527	0.1305	0.0434	0.1301	0.7499	3
8	0.3054	0.2058	0.1527	0.1029	0.0158	0.155	0.9075	2

Table 6 Comparison of ranks obtained using MOORA and TOPSIS methods

Experiment No.	MOORA ratio	Rank	TOPSIS CC_i	Rank
1	−0.8530	7	0.1897	7
2	−0.7603	5	0.3345	5
3	−0.8573	8	0.1591	8
4	−0.7627	6	0.3285	6
5	−0.7209	4	0.4393	4
6	−0.4795	1	1	1
7	−0.5664	3	0.7499	3
8	−0.5112	2	0.9075	2

7 Results and Discussions

In order to evaluate surface roughness and build time, each specimen is manufactured according to ISO standards. For each experiment, surface roughness and build time were measured. Build time was recorded at the time of each experimental run while surface roughness was measured with Mitutoyo SURF TEST SJ-301 tester. Table 3 shows the results of surface roughness test and build time readings under various settings of process parameters. MOORA method is applied to get the optimum setting of process parameters. In this study, MOORA method will be used for parametric optimization as this method has easy intermediate steps for calculation (Gadakh 2011). TOPSIS method is best suitable method to get preference order for alternatives (Wang et al. 2007). TOPSIS method is used to validate the results obtained using MOORA method. Table 4 shows the result of multi-objective analysis after MOORA method based computations. Also, these results are compared using TOPSIS method. As observed from Table 6, it is clear that ranks obtained by both the methods are similar for all experimental runs. The effect of printing parameters on surface roughness and build time has been studied. Results of analysis are as follows:

(a) Surface roughness: As observed from Table 3, R_a value which is the most widely used parameter to indicate the mean surface roughness is measured for each specimen. For the same layer thickness and build pattern, R_a value is lower for SMART fill pattern. However, for same values of layer thickness and fill pattern, R_a value is higher in case of SPARSE build style. Generally, as layer thickness increases surface roughness value decreases (Anitha et al. 2001).
(b) Build time: As inferred from Table 3, as layer thickness values increases, build time decreases. Also it is clear from the table that there is no significant effect of build pattern on build time. Although for SMART fill pattern, build time readings are lower. As compared to 'BASIC' fill pattern, SMART pattern will minimize the consumption of support material, reducing the build time of part and improving support removability for many parts.

8 Conclusions

The aim of this study was to carry out process parameters optimization for FDM based 3D printing process. MOORA method was applied as optimization method in this study. According to results, the following conclusions are drawn:

- Layer thickness and fill pattern are proved to be vital factors influencing part quality. It was found that build pattern and fill pattern are significant in influencing R_a value. Surface finish obtained at sparse-high density was obtained poor. There is a significant decrease in R_a value for smart fill pattern.
- Also, layer thickness was found to be an influencing parameter affecting build time. Build time was lower for higher values of layer thickness. Build time for SPARSE build style was obtained lower because it has large air gap between rasters and requires shortest build time.
- Under same layer thickness and build pattern, build time got decreased for smart fill pattern. Using MCDM method, optimum parameter setting for FDM printer was found as layer thickness 0.3302 mm, build pattern solid and fill pattern smart which gives lowest build time of 5 min and lower surface roughness value as 4.29 μm.
- Also, after comparison of MOORA method with TOPSIS method, it was observed that same ranks are obtained for all experimental runs. Hence optimal parameter settings obtained using both the methods is same i.e. experimental run 6 (Layer thickness—0.3302 mm; Build pattern—Solid; Fill pattern—Smart).
- In the present work, strength of the built parts was not measured. In future, strength could be measured. Also, tensile specimen is being used in the present work and in future, other types of specimen also could be considered. Also, in future, more comprehensive data with varying conditions could be studied.

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