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Evaluation of FDM Process Parameter for PLA Material by Using MOORA-TOPSIS Method

[1]Priyank B Patel, [2]Jaksan D. Patel, [3]Kalpesh D. Maniya

[1]M.E. Student, Merchant Engineering College, Mehsana-384315, Gujarat, India.
[2]Assistant Professor,Department of Mechanical Engineering, Merchant Polytechnic College, Basna, Mehsana-384315 Gujarat, India.
[3]Assistant Professor,Department of Mechanical Engineering, C.K. Pithawalla College of Engg. And Tech., Surat-395007 Gujarat, India.

Abstract: **Fused Deposition Modelling (FDM) is one of the rapid prototype process that produce prototypes from plastic materials such as ABS, PLA, Naylon, etc. It is a process that creates parts in an additive layer by layer manner. In FDM process, the critical factors are selected for making component to measure different properties. The design investigates the effect of the process parameters layer thickness, orientation and infill on the tensile strength, tensile module, compressive strength, compressive module, and surface roughness. Experiments are conducted using Taguchi's design of experiments with three levels for each factor. Experiments were carried out on FDM replicator 2 machines coupled with Maker Ware™ software and PLA as main material. Tensile and compressive specimens were prepared as per the ASTM standard. Multi-objective optimization on the basis of ratio analysis (MOORA) and technique for order preferences by similarity to an ideal solution (TOPSIS) method are used to find the ranking of FDM process parameters and also compare the results of MOORA and TOPSIS Method.**

Keywords: **FDM, Layer Thickness, Orientation, Infill, MOORA, TOPSIS Method.**

1. INTRODUCTION

Reduce the product development cycle time is a major concern in industries to remain competitive in the market and hence, focus has shifted from traditional product development methodology to rapid fabrication techniques like rapid prototyping.[4] The Fused Deposition Modelling (FDM) is a typical example of a RP process, leading to the aforementioned characteristics. The FDM is able to produce prototypes from plastic materials, such as acrylonitrile butadiene styrene (ABS) or polylactic acid (PLA), and the process consists in the deposition of filaments of the material at the semi-molten state.[6] The filament is feed through a nozzle and located at the output of a heating device, and is deposited on to the partially constructed part. Since the material is extruded and laid in tracks at a semi-molten state, the newly deposited material fuses with adjacent material that has already been deposited. Afterwards, other material tracks are deposited, upon the completion of the current layer, and then the deposition of a new layer is started. Research community already benefits from the availability of low-cost 3D printers in that the machines such as the makerbot replicator allow experimentation with a variety of easily programmable technological parameters.[7] The study presented in this paper differs from the discussed investigations in two key points: (i) the material used in this study is polylactic acid (PLA), which, contrary to ABS, has not been extensively used in experiments of this kind, and (ii) the infill used to produce specimens ranges between 100 and 98%.

2. LITERATURE R EVIEW

Rayegani et al. (2014) found that both process parameters affect tensile strength. Negative air gap and smaller raster widths improve tensile strength. The zero part orientation maximum tensile strength is obtained. Increased raster angle also improves tensile strength. Marcincinova et al. (2012) presented different types of testing in the materials properties of selected methods of rapid prototyping technologies. Sood et al. (2011) have studied the effect of five important FDM machine process parameters and found that fibre-fibre bond strength must be strong which can be achieving by controlling the distortions arising during part build stage. Optimization of process parameters gives the maximum compressive stress of 17.4751 MPa and the optimum value of layer thickness, orientation, raster angle, raster width and air gap as 0.254 mm, 0.036 degree, 59.44 degree, 0.422 mm and 0.00026 mm respectively. Nancharaiah et al. (2010) they were found that the layer thickness and road width affect the surface quality and part accuracy greatly. Raster angle has little effect. But air gap has more effect on dimensional accuracy and little effect on surface quality. Sood et al. (2009) studied the influence of important process parameter and they conclude that maximization of grey relational grade shows that layer thickness of 0.178 mm, part orientation of 0 degree, raster angle of 0 degree, road width of 0.4564 mm and air gap of 0.008 mm will produced overall improvement in part dimensions. Galantucci et al. (2009) found that the slice height and raster width are important parameters while the tip diameter has a little important for surface running either parallel or perpendicular to the build direction. Panda et al. (2009) have used latest evolution any bacterial foraging algorithm to predict optimal parameters setting of FDM process. After the experimental work they have find out that the layer thickness and orientation angle is highly significant parameters for FDM fabricated parts whereas remaining parameter have little effect.

Aim of this present study is selection of process parameter of FDM machine for polylactic acid material using MADM method. The responses considered in this study are mechanical property of FDM produced parts such as tensile strength (T_s), tensile module (T_m), compressive strength (C_s), compressive module (C_m) and surface roughness (SR). The specimens are prepared as per the ASTM standard at three different parameter and level such as layer thickness (100, 200, 300) (micron), orientations (0°, 45°, 90°) and infill (100%, 99%, 98%).

3. EXPERIMENTAL PROCEDURE

Specimens are fabricated using the FDM replicator 2 machine. The parts are modelled in modelling software and exported as STL file. STL file is imported to FDM software. The material used for specimen preparation is polylactic acid (PLA). For measuring tensile (ASTM D638) and compressive (ASTM D695) test respective standard specimens having respective dimensions 115mm X 19mm x 4mm for tensile and 12.7mm in diameter and 25.4mm length for Compressive are prepared. Experimental run are create in minitab16. Orthogonal array L9 are develop in the taguchi shows in table 1. After fabricating the specimens, these specimens were tested. Tensile and compressive test is conducted on INSTRON 5965 and 5982 machine. And surface roughness measure by using surface roughness tester SJ210. The specimens after testing are depicted in fig. 1 and 2. And testing results are shown in Table 1.

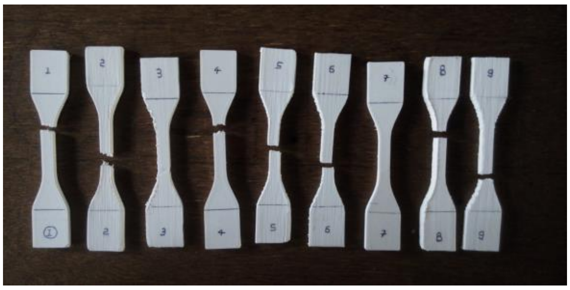

Fig.1 Tensile specimen after test

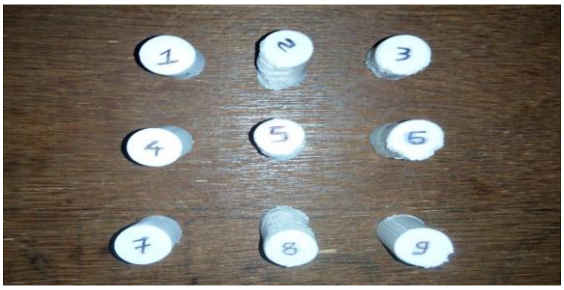

Fig.2 Compressive specimen after test

Table 1: Experimental data obtained from the L9 orthogonal array

Exp. No	Later thickness (micron)	Orientation (degree)	Infill (%)	(T_s) (N/mm²)	(T_m) (N/mm²)	(C_s) (N/mm²)	(C_m) (N/mm²)	(SR) (µm)
1	100	0	100	49.09	2246.51	57.68	1621.85	2.82
2	100	45	99	53.13	2849.02	30.53	570.82	3.03
3	100	90	98	55.71	3460.73	39.43	1413.65	2.13
4	200	0	99	39.79	2082.42	56.72	1701.20	4.30
5	200	45	98	54.27	2931.98	35.56	1087.45	2.68
6	200	90	100	51.49	2997.07	54.43	1892.66	2.01
7	300	0	98	36.50	1802.38	54.37	1353.65	2.44
8	300	45	100	47.60	2803.67	47.73	1015.89	2.55
9	300	90	99	49.09	2977.42	52.12	1800.29	2.47

4. MULTIPLE ATTRIBUTE DECISION MAKING METHODS

4.1 Analytic Hierarchy Process / Multi-Objective Optimization on the Basis of Ratio Analysis (AHP/MOORA Method)

This section describes the proposed integrated AHP/MOORA method for selection of appropriate FDM machine. The AHP method is a potential decision making tool developed by Saaty (1980) while the MOORA method, is introduced by Brauers (2004) In the past many decision making applications were reported using MOORA method. The main steps of the proposed model are described below.

Steps of the AHP method as follows: [13]

Step 1: Define the problem. This step is associated with to define the objective and identification of all the possible alternatives and its attributes. Let $A = \{A_i$ for $i = 1,2,3,\ldots m\}$ be a set of FDM machine alternative, $B = \{B_j$ for $j = 1,2,3,\ldots,n\ \}$ be a set of decision criteria or attributes of FDM machine alternative selection problem, and x_{ij} is the performance of alternative A_i when it examined with criteria B_j.

Step 2: Developing the hierarchical structure. A decision problem is structured as a hierarchy structure With the AHP, the goal, decision criteria and alternatives are arranged in a hierarchical structure similar to a family trees shown in fig. 3.

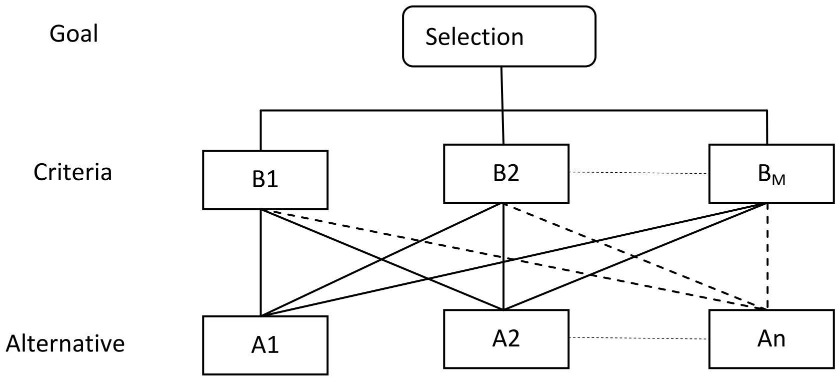

Fig.3 A hierarchy of the decision making problem [13]

Step 3: Generate pair wise matrices. A pair wise comparison matrix is constructed using a scale of relative importance as shown in Table 2. Let, there are M attributes are involved in the decision making, the pair wise comparison of attribute i with attribute j yields a square matrix $A1 = M \times M = [a_{ij}]_{M \times M}$. Where a_{ij} denotes the comparative importance of attribute i with respect to attribute j. In the matrix, $a_{ij} = 1$ when $i = j$ and $a_{ji} = 1/a_{ij}$.

$$A1_{MxM} = \begin{array}{c} B1 \\ B2 \\ B3 \\ - \\ - \\ BM \end{array} \begin{bmatrix} 1 & a_{12} & a_{13} & -- & -- & a_{1M} \\ a_{21} & 1 & a_{23} & -- & -- & a_{2M} \\ a_{31} & a_{32} & 1 & -- & -- & a_{3M} \\ -- & -- & -- & 1 & -- & -- \\ -- & -- & -- & -- & 1 & -- \\ a_{M1} & a_{M2} & a_{M3} & -- & -- & 1 \end{bmatrix}$$

Table 2: Scale of Relative importance [13]

Scale	Importance	Meaning of attributes
1	equal importance	Two attributes are equally important
3	moderate importance	One attribute is moderately important over the other
5	strong importance	One attribute is strongly important over the other
7	very importance	One attribute is very important over the other
9	Absolute importance	One attribute is absolutely important over the other
2,4,6,8, compromise importance between 1,3,5,7 and 9		

Step 4: Determination of relative normalized weight**.** A relative normalized weight at each level of hierarchy structure is calculated using Equation (1) and Equation (2).

$$GM_j = \left[\prod_{j=1}^{M} a_{ij}\right]^{\frac{1}{M}} \quad (1)$$

$$W_j = \frac{GM_j}{\sum_{j=1}^{M} GM_j} \quad (2)$$

If the judgment matrix or comparison matrix is inconsistent then judgment should be reviewed and improved it to obtain the consistent matrix. Hence, consistency test will be carried out using following steps.

- Calculate matrices; $A_3 = A_1 \times A_2$ and $A_4 = A_3 / A_2$, Where; $A_1 = [r_{ij}]_{m\times m}$, $A_2 = [W_1, W_2, ., W_j]^T$
- Calculate Eigen value λ_{max} (average of matrix A_4)
- Calculate the consistency index: $CI = (\lambda_{max} - m) / (m - 1)$
- Calculate the consistency ratio: CR = CI/RI, select value of random index (RI) Table 3 according to number of attributes used in decision-making.
- **If CR < 0.1, considered as acceptable decision, otherwise judgment of the analyst about the problem under study.**

Table 3: Random Index (RI) for different matrix order [13]

Attributes	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49

Steps of the MOORA method as follows: [2], [3]

Step 5: Construct the decision matrix. Here 9 (alternatives A_1 to A_9) process parameters of FDM. Response process parameters of the FDM machine such as tensile strength, tensile module, compressive strength, compressive module and surface roughness.

Step 6: Find the dimensionless number or normalization value. Let R_{ij} is a dimensionless number which belongs to the interval zero to one representing the normalized performance of i^{th} alternative on j^{th} attribute. This R_{ij} value is calculated as suggested by Brauers. It can be expressed as below:

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (3)$$

Step 7: Determine the normalized performance of alternative. In this step, the normalized performance of alternatives is determined with considering weightage of selection criteria involved in the decision making process. For multi-objective optimization, these normalized performances are added in case of maximization (for beneficial attributes) and subtracted in case of minimization (for non beneficial attributes).

$$y_i = \sum_{j=1}^{g} W_j X_{ij} - \sum_{j=g+1}^{n} W_j X_{ij} \; (j = 1,2,3, \dots, n) \quad (4)$$

Where, g is the number of attributes to be maximized, (n-g) is the number of attributes to be minimized, w_j is the weight of j^{th} attribute, which can be determined applying analytic hierarchy process method as described in step3 and step 4, and y is the normalized performance value of i^{th} alternative with respect to all the attributes.

Step 8: Ranking and selection of alternative. The value of y value can be positive or negative depending of the totals of its maxima (beneficial attributes) and minima (non-beneficial attributes), A ranking of alternative will be carried out based on value of y and finally, the best alternative is considered who has the highest y value or ranked first while the worst alternative has the lowest y value or ranked last.

4.1.1 Illustration of Example Using AHP/MOORA Method

Step 1: Decide the all the possible alternative for a given application, its selection criteria, and its values. In present study, nine experiments is alternatives with five attributes, the attributes are tensile strength, tensile module, compressive strength, compressive module and surface roughness.

Step 2: A FDM process parameters selection problem can be decomposed procedure described in the hierarchy structure shown in fig. 4.

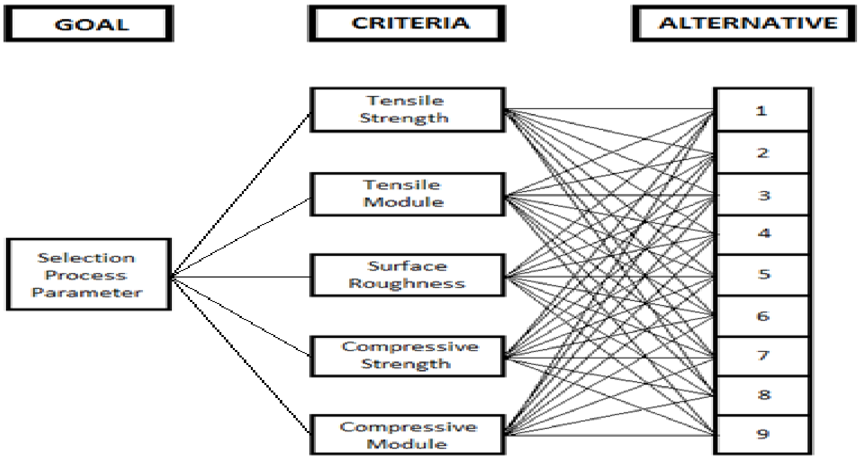

Fig.4 A hierarchy of FDM process parameters selection problem

Step 3: A relative importance of between attributes is assigned with respect to the goal. The judgments are entered using scale of relative importance of the AHP method as shown in Table 4.

Table 4: Pair Wise Comparison Matrix for Different Criteria

Attribute	B_1	B_2	B_3	B_4	B_5
B_1	1	1	3	3	4
B_2	1	1	2	3	3
B_3	1/3	1/2	1	1	4
B_4	1/3	1/3	1	1	2
B_5	1/4	1/3	1/4	1/2	1

Step 4: A relative normalized weight of attributes is calculated using Eq. (1) and Eq. (2). Here determined the criteria weights as: $W_{Ts} = 0.3475$, $W_{Tm} = 0.3025$, $W_{Cs} = 0.1566$, $W_{Cm} = 0.1253$, $W_{SR} = 0.0681$. Further, the value of CR is 0.0374. Therefore CR value less than 0.1, the judgments are acceptable. These criteria weights were used for the MOORA method-based analysis.

Step 5: Present study total 9 experiments (Alternatives A1 Up to A9) are considered using Taguchi concept and the response process parameters of the FDM such as tensile strength, tensile module, compressive strength, compressive module, and surface roughness are as shown in Table 5 as decision matrix.

Table 5: Decision matrix table

Alternative	(T_s) (N/mm²)	(T_m) (N/mm²)	(C_s) (N/mm²)	(C_m) (N/mm²)	(SR) (µm)
A_1	49.09	2246.51	57.68	1621.85	2.82
A_2	53.14	2849.02	30.53	570.82	3.03
A_3	55.71	3460.73	39.43	1413.65	2.13
A_4	39.79	2082.43	56.72	1701.20	4.30
A_5	54.27	2931.98	35.56	1087.45	2.68
A_6	51.49	2997.07	54.43	1892.67	2.01
A_7	36.50	1802.38	54.37	1353.65	2.44
A_8	47.60	2803.67	47.73	1015.90	2.55
A_9	49.10	2977.42	52.12	1800.29	2.47

Step 6: Using Eq. (3) determine the x_i is a dimensionless number which belongs to the interval [0, 1] representing the normalized performance of response process parameters of FDM as show in Table 6.

Table 6: Dimensionless number (xi) for each alternative

Alternative	(T_s) (N/mm²)	(T_m) (N/mm²)	(C_s) (N/mm²)	(C_m) (N/mm²)	(SR) (µm)
A_1	0.1163	0.0830	0.0620	0.0470	0.0230
A_2	0.1259	0.1053	0.0328	0.0165	0.0247
A_3	0.1319	0.1279	0.0424	0.0409	0.0174
A_4	0.0942	0.0769	0.0610	0.0493	0.0350
A_5	0.1285	0.1083	0.0382	0.0315	0.0218
A_6	0.1220	0.1107	0.0585	0.0548	0.0163
A_7	0.0865	0.0666	0.0585	0.0392	0.0199
A_8	0.1127	0.1036	0.0513	0.0294	0.0208
A_9	0.1163	0.1100	0.0560	0.0521	0.0201

Step 7 and 8: For multi objective optimization, these normalized performances are added in case of maximization (for beneficial attributes) and subtracted in case of minimization (for non-beneficial attributes). tensile strength, tensile module, compressive strength and compressive module are considered as beneficial attribute (i.e. higher values are desirable), surface roughness is considered as non-beneficial attribute (i.e. lower values are desirable).Using Eq. (4) calculate the weighted assessment value. The best alternative has the highest y_i value, while the worst alternative has the lowest y_i value as shown in Table 7.

Table 7: Weighted assessment values (yi) and ranking for selection of the process parameters of FDM

Alternative	(T_s) (N/mm²)	(T_m) (N/mm²)	(C_s) (N/mm²)	(C_m) (N/mm²)	(SR) (µm)	y_i	Rank
Weight	0.3475	0.3025	0.1566	0.1253	0.0681	-	-
A_1	0.1163	0.0830	0.0620	0.0470	0.0230	0.2853	4
A_2	0.1259	0.1053	0.0328	0.0165	0.0247	0.2558	7
A_3	0.1319	0.1279	0.0424	0.0409	0.0174	0.3258	2
A_4	0.0942	0.0769	0.0610	0.0493	0.0350	0.2465	8
A_5	0.1285	0.1083	0.0382	0.0315	0.0218	0.2848	5
A_6	0.1220	0.1107	0.0585	0.0548	0.0163	0.3297	1
A_7	0.0865	0.0666	0.0585	0.0392	0.0199	0.2308	9
A_8	0.1127	0.1036	0.0513	0.0294	0.0208	0.2763	6
A_9	0.1163	0.1100	0.0560	0.0521	0.0201	0.3144	3

4.2 TOPSIS METHOD

Technique for order preferences by similarity to an ideal solution (TOPSIS), known as a classical multiple attribute decision-making (MADM) method, has been developed in 1981. In TOPSIS method, the optimal alternative selected should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The procedure can be categorized in six steps: [17]

Step 1: Creating the decision matrix. The method starts with a decision matrix of responses of different alternatives to evaluation criteria.

Step 2: Construct normalized decision matrix. This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across criteria. Normalize scores or data as follows:

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (5)$$

Step 3: Construct the weighted normalized decision matrix by multiplying the normalized decision matrix by its associated weights. Here weightage of each output parameters are calculated using Analytical hierarchy process .The weighted normalized value v_{ij} is calculated as:

$$V_{ij} = W_j * R_{ij} \tag{6}$$

Step 4: Determine the positive ideal solution and negative ideal so

$$V_j^* = \left\{ \sum_{i=1}^{max} V_{ij} \;/\; j\epsilon J, \; \sum_{i=1}^{min} V_{ij} \;/\; j\epsilon J' \right\} \tag{7}$$

$$V_j = \left\{ \sum_{i=1}^{min} V_{ij} \;/\; j\epsilon J, \; \sum_{i=1}^{max} V_{ij} \;/\; j\epsilon J' \right\} \tag{8}$$

Where J is associated with the benefit criteria, J = 1, 2, 3… n

Where J’ is associated with the cost criteria, J’ = 1, 2, 3… n

Determine Ideal Solution Vj*. Vj* = {V1*, V2* …Vn*}

Determine Negative Ideal Solution Vj. Vj = {V1, V2 …Vn}

Step 5: Calculate the separation measures for each alternative. The separation of each alternative from the positive ideal one is given by:

$$S_i^* = \sqrt{\Sigma_{j=1}^{n} (V_{ij} - V_j^*)^2} \tag{9}$$

Where i = 1, 2… m

Similarly, the separation of each alternative from the negative ideal one is given by:

$$S_i = \sqrt{\Sigma_{j=1}^{n} (V_{ij} - V_j)^2} \tag{10}$$

Where i = 1, 2… m

Step 6: Calculate the relative closeness to the ideal solution Ci* and rank the preference order.

$$C_i^* = S_i \,/ (S_i^* + S_i) \tag{11}$$

Where i = 1, 2… m

4.2.1 Illustration of Example Using TOPSIS Method

Step 1: Construct the decision matrix as shown in Table 5.

Step 2 Normalize the decision matrix D by using the Eq. (5) and shown in Table 6.

Step 3: Construct the weighted normalized decision matrix using Eq. (6) by multiplying the normalized decision matrix by its associated weights. Here weightage of each output parameters are calculated using Analytical hierarchy process. The weighted normalized value v_{ij} is as shown in Table 8.

Table 8: Weighted normalized decision matrix

Alternative	(T_s) (N/mm²)	(T_m) (N/mm²)	(C_s) (N/mm²)	(C_m) (N/mm²)	(SR) (µm)
A_1	0.1163	0.0830	0.0620	0.0470	0.0230
A_2	0.1259	0.1053	0.0328	0.0165	0.0247
A_3	0.1319	0.1279	0.0424	0.0409	0.0174
A_4	0.0942	0.0769	0.0610	0.0493	0.0350
A_5	0.1285	0.1083	0.0382	0.0315	0.0218
A_6	0.1220	0.1107	0.0585	0.0548	0.0163
A_7	0.0865	0.0666	0.0585	0.0392	0.0199
A_8	0.1127	0.1036	0.0513	0.0294	0.0208
A_9	0.1163	0.1100	0.0560	0.0521	0.0201

Step 4: Determine the positive ideal solution and negative ideal.

Determine Ideal Solution V_j* using Eq. (7).

Vj* = {0.1319, 0.1279, 0.0620, 0.0548, 0.0163}

Determine Negative Ideal Solution V_j' using Eq. (8).

Vj' = {0.0865, 0.0666, 0.0328, 0.0165, 0.0350}

Step 5: Calculate the separation measure using Eq. (9) the separation of each alternative from the positive ideal one is given by:

Table 9: Positive ideal solution

Vj*	0.1319	0.1279	0.0620	0.0548	0.0163	
A^*	Ideal Solution					S_i^*
A_1	0.00024439	0.00201564	0.00000000	0.00006131	0.00004459	0.0486
A_2	0.00003657	0.00051232	0.00085100	0.00146448	0.00007048	0.0542
A_3	0.00000000	0.00000000	0.00038418	0.00019209	0.00000116	0.0240
A_4	0.00141777	0.00259677	0.00000101	0.00003060	0.00034921	0.0663
A_5	0.00001128	0.00038296	0.00056484	0.00054320	0.00003013	0.0391
A_6	0.00009869	0.00029462	0.00001205	0.00000000	0.00000000	0.0201
A_7	0.00206467	0.00375839	0.00001249	0.00024327	0.00001290	0.0780
A_8	0.00036736	0.00059097	0.00011392	0.00064409	0.00002006	0.0417
A_9	0.00024357	0.00032006	0.00003546	0.00000709	0.00001459	0.0249

Similarly, the separation of each alternative from the negative ideal one is given by: using Eq. (10) and shown in Table 10.

Table 10: Negative ideal solution

Vj'	0.0865	0.0666	0.0328	0.0165	0.035	
A^*	Ideal Solution					S_i
A_1	0.00088608	0.00026910	0.00085404	0.00092842	0.00014454	0.0555
A_2	0.00154863	0.00149502	0.00000000	0.00000000	0.00010618	0.0561
A_3	0.00206542	0.00375366	0.00009215	0.00059733	0.00031062	0.0826
A_4	0.00006001	0.00010695	0.00079483	0.00107375	0.00000000	0.0451
A_5	0.00176744	0.00174145	0.00002953	0.00022480	0.00017454	0.0628
A_6	0.00125783	0.00194795	0.00066193	0.00146790	0.00034844	0.0754
A_7	0.00000000	0.00000000	0.00065873	0.00051542	0.00022827	0.0374
A_8	0.00068818	0.00136827	0.00034324	0.00016696	0.00020224	0.0526
A_9	0.00088763	0.00188440	0.00054034	0.00127006	0.00022143	0.0693

Step 6: Calculate the relative closeness to the ideal solution by using Eq. (11) and rank the preference order as shown in Table 11.

Table 11: Relative closeness to the ideal solution

Alternative	C_i^*	Rank
A_1	0.5330	6
A_2	0.5088	7
A_3	0.7746	2
A_4	0.4049	8
A_5	0.6158	4
A_6	0.7892	1
A_7	0.3242	9
A_8	0.5581	5
A_9	0.7356	3

5. RESULT & DISCUSSION

Here, based on evaluation criteria weights obtained by AHP, the ranking for selection of the process parameters of FDM using MOORA and TOPSIS method, as present in Table No 12. MOORA and TOPSIS ranking results show that alternative 6-3-9 is the best three choices among the 9 alternatives. Results we found that 100micron layer thickness, 90° orientation and 98% infill get optimum result of all response.

Table 12: A result comparison of MOORA and TOPSIS

Alternative	Ranking result	
	MOORA method	TOPSIS method
A_1	4	6
A_2	7	7
A_3	2	2
A_4	8	8
A_5	5	4
A_6	1	1
A_7	9	9
A_8	6	5
A_9	3	3

6. CONCLUDING REMARKS

The present work concluded that in order to get effective selections of a FDM machine using PLA material; it is necessary to consider possible alternatives and attributes. The MADM method, the AHP provides opportunity to select the best alternative of FDM machine considering with multi attributes having different measures. The priority or ranking of alternatives depends on attributes weight or relative importance assigned between attributes and on the values of the selected attributes. The AHP can handle tangible (objective) as well as non-tangible (subjective) attribute measures. It has been observed that MOORA method is very simple, stable and robust. It requires minimum Mathematical calculations and computational time.

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