APEM journal

Advances in Production Engineering & Management
Volume 19 | Number 1 | March 2024 | pp 108–116
https://doi.org/10.14743/apem2024.1.496

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

FDM process parameter selection by hybrid MCDM approach for flexural and compression strength maximization

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A B S T R A C T

Fused deposition modelling (FDM) is one of the mostly used additive technologies, due to its ability to produce complex parts with good mechanical properties. The selection of FDM process parameters is crucial to achieve good mechanical properties of the manufactured parts. Therefore, in this paper, a hybrid multi-criteria decision-making (MCDM) approach based on Preference Selection Index (PSI) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is proposed for the selection of optimal process parameters in FDM printing of polylactic acid (PLA) parts. Printing temperature, layer thickness and raster angle were considered as input process parameters. In order to prove the effectiveness of the proposed hybrid PSI – TOPSIS method, the obtained results were compared with the results obtained with different MCDM methods. The obtained best option of process parameters was confirmed by other MCDM methods. The optimal combination of process parameters to achieve the maximal flexural strength, maximal flexural modulus and maximal compressive strength is selected using the hybrid PSI-TOPSIS method. The results show that the hybrid PSI-TOPSIS approach could be used for optimisation process parameters for any machining process.

A R T I C L E   I N F O

Keywords:
Fused deposition modelling (FDM);
Multi-criteria decision-making (MCDM);
Hybrid PSI-TOPSIS method;
Process parameters;
Mechanical properties;
Optimization

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Article history:
Received 6 November 2023
Revised 6 March 2024
Accepted 13 March 2024

1. Introduction

Additive manufacturing (AM) represents a way of production that is based on making products by adding materials “layer by layer” This method of production was initially used only for the rapid prototyping (RP), but today additive technologies are also used for the production of highly functional products in small quantities. This principle of making parts remains the same regardless of the degree of geometric complexity of the part, which is the main advantage of this technology.

According to the physics of the process and material type a large number of different additive manufacturing processes have been developed. Some of the most commonly used procedures are: fused deposition modelling (FDM), stereolithography (SLA), Ink jet modelling, selective laser sintering (SLS), etc. The FDM process is used for prototyping and production of fully functional parts for engineering applications. Some of most commonly used material for FDM process are: Polylactic-Acid (PLA), Polyethylene-Terephthalate (PET), Acrylonitrile Butadiene-

Styrene (ABS), propylene (PP), Polyamide (PA), and Thermoplastic-Polyurethane (TPU) [1,2]. Quality and mechanical properties of FDM produced parts are key factors for their use in industrial applications. In order to achieve the appropriate quality and mechanical properties of parts made in this way, it is necessary to carefully design the FDM process in terms of the correct selection of input parameters. Due to the large number of input and output parameters, it is often necessary to solve complex optimization problems. In order to solve such problems and avoid the need to perform a large number of experiments, a systematic approach to the experiment plan and the application of various methods of multi-criteria optimization are used. Some of the most commonly used methods for experiment design, modelling and optimization of process parameters of the FDM technology are: Taguchi Method [3], Grey Relational Analysis (GRA) [4], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [5], Response Surface Methodology (RSM) [6], Genetic Algorithm (GA) [7], Artificial Neural Network (ANN) [6], and Adaptive Neuro Fuzzy Interface System (ANFIS) [8]. Many researchers have analysed the possibility of applying these methods to optimize the various output parameters of the FDM process.

In study [9], the authors optimized three input parameters, infill density, printing speed and printing temperature, to achieve the maximum tensile strength of samples made of PLA material. For optimisation these process parameters were used hybrid optimization techniques, genetic algorithm-artificial neural network, genetic algorithm-response surface methodology and genetic algorithm-adaptive neuro fuzzy interface system. It is shown that such hybrid models could be used for optimisation any other process parameters for any industrial application problems. Rajamani *et al.* [5] were used hybrid approach through RSM-TOPSIS method. This approach was used for improving surface quality of micro sized near-net-shaped components for end use applications using FDM additive manufacturing techniques. Production of test specimens was carried out according to the previously defined Box-Behnken experimental design. For input parameters were selected: layer thickness, part orientation, raster width and raster angle. The optimal FDM parameters for improved surface quality attributes were determined using TOPSIS method. This method proved to be a useful tool for finding optimal FDM process parameters for fabricating the components of a flapping wing micro mechanism. Also, the TOPSIS method proved to be useful in the selection of optimal process parameters in two-point incremental forming process [10], as well as for optimization of cutting parameters in turning process [11], and thanks to the proposed Fuzzy-TOPSIS approach [12], managers of manufacturing companies can access and monitor the maintenance sustainability level integrated with the industry 4.0 technologies. The RSM method is a combination of statistical and mathematical methods that is very useful for modelling and optimizing engineering scientific problems, which gives very low standard errors to experimental verification. Srinivasan *et al.* [13] used the RSM method based on central composite design to predict of tensile strength in FDM printed ABS parts. In paper [6] was successfully applied RSM and ANN to investigate the effect of the layer thickness, printing speed, raster angle and wall thickness on the tensile strength of test specimens printed with a short carbon fibre reinforced polyamide composite.

Taguchi-Grey relational analysis was used in the study [14] to optimize input parameters and improve selected output mechanical characteristics. This study is designed to capture the said gap in the literature with focus on cell geometry, nozzle diameter and strain rate by using the Taguchi design of experimentation and Grey Relational Analysis. It is shown that the GRA method significantly simplifies complex optimization problems in FDM process parameters optimization. Taguchi method is very useful in the experimental plan phase, and it can be used separately [15] or with other methods for multi-criteria optimization [14] [16]. Chohan *et al.* [16] were using Taguchi-TOPSIS based optimization of FDM process parameters for manufacturing ABS plastics parts. The results were shown that using the TOPSIS method, optimal parameters can be determined in order to improve the surface-quality of FDM parts which can be utilized for end-use products and for rapid tooling applications.

In addition to the mentioned methods, there is also the Preference Selection Index (PSI) method that can be used to solve multi-criteria optimization problems. The possibility of applying the PSI method for the selection of optimal FDM process parameters was investigated [17]. It is found that the PSI method is very simple to understand and easy to implement. The advantage of the PSI method is that there is no need to calculate the relative weight of outputs. However, some authors [18] have observed that this method is not useful when several alternatives have criteria values that are very close to those are preferred. A hybrid TOPSIS-PSI method for selection material in marine applications was presented in study [19], the entropy method has been used to determine the weights of the selected criteria.

In this paper, a hybrid method that combines of the PSI and TOPSIS method is proposed. The proposed hybrid method considered the advantage of the PSI method that does not require the calculation of the weight factor of criteria and the advantage of the TOPSIS method that is more efficient in dealing with the criteria and the number of available alternatives. To test the proposed method, the case of selecting optimal process parameters to improve the mechanical properties of FDM printed PLA parts was considered.

2. Materials and methods

2.1 Experimental details

A 3D printer Ultimaker S5 was used to produce test samples from PLA material, that is one of the mostly used FDM material. The samples for flexural and the compressive tests were designed and tested according to ISO 178 and ISO 604 standards, respectively. The constant process parameters for printing test samples are shown in Table 1. In this paper, three input process parameters, namely printing temperature, layer thickness and raster angle were investigated in order to study their influence on the mechanical properties of the test samples using the Taguchi design of experiments. These parameters are varied at three different levels as shown in Table 2.

Table 1 The constant process parameters and their values

Parameter	Unit	Value
Nozzle diameter	mm	0.4
Infill density	%	100
Build plate temperature	°C	110
Build direction		Flat x-x direction
Printing speed	mm/s	60

Table 2 The input parameters and their levels

Parameter	Symbol	Unit	Level 1	Level 2	Level 3
Printing temperature	T	°C	180	200	220
Layer thickness	L	mm	0.1	0.2	0.3
Raster angle	A	°	0	45	90

Three samples were tested for each set of input parameters. The experimentally studied output parameters were flexural strength (FS), flexural modulus (FM) and compressive strength (CS). The previous research [2, 6-9] were focused on analysing the influence of process parameters on the tensile strength of FDM printed parts. The average value of the output parameters is reported in Table 3. Flexural and compressive tests were conducted on the 10 kN Shimadzu AGS-X universal machine.

Table 3 Experimental data

Exp. No.	Input parameters			Output parameters		
	L (mm)	T (°C)	A (°)	Flexural strength (MPa)	Flexural modulus (MPa)	Compressive strength (MPa)
1	0.1	180	0	38.55	2505.65	45.16
2	0.1	200	45	81.56	3014.92	46.78
3	0.1	220	90	92.24	2952.91	48.14
4	0.2	180	45	36.53	1794.45	39.45
5	0.2	200	90	79.77	2598.18	45.34
6	0.2	220	0	72.24	2650.26	44.37
7	0.3	180	90	29.65	2054.71	39.81
8	0.3	200	0	52.10	2221.84	41.63
9	0.3	220	45	72.38	2502.59	41.30

2.2 Hybrid PSI-TOPSIS method

Process parameters selection for any machining process is a MCDM problem that considers different competing criteria for selecting appropriate process parameters. The proposed hybrid PSI – TOPSIS method consists of the following steps.

Step 1: Determine a set of experimental trials (alternatives):

$$E = [E_1, E_2, \dots, E_m] \tag{1}$$

where m is the number of experimental trials.

Step 2: Determine a set of criteria (output parameters):

$$C = [C_1, C_2, \dots, C_n] \tag{2}$$

where n is the number of criteria.

Step 3: Creating a decision matrix:

$$D = \left[D_{ij} | i = 1, 2, \dots, m; j = 1,2, \dots, n\right] \tag{3}$$

and D_{ij} is the value of the j-th criterion for the i-th experimental trial.

Step 4: Calculation of the normalized matrix:
a) if the larger is better (LB):

$$N_{ij} = \frac{D_{ij}}{D_j^{\max}}, \qquad i = 1,2, \dots, m; j = 1,2, \dots, n \tag{4}$$

b) if the smaller is better (SB):

$$N_{ij} = \frac{D_j^{\min}}{D_{ij}}, \qquad i = 1,2, \dots, m; j = 1,2, \dots, n \tag{5}$$

Step 5: Calculating the mean value of the normalized matrix:

$$N_j = \frac{1}{m}\sum_{i=1}^{m} N_{ij}, \qquad i = 1,2, \dots, m; j = 1,2, \dots, n \tag{6}$$

Step 6: Calculating the value of the preference variation:

$$\varphi_j = \sum_{i=1}^{m} \left[N_{ij} - N_j\right]^2, \qquad i = 1,2, \dots, m; j = 1,2, \dots, n \tag{7}$$

Step 7: Calculating the deviation in preference value:

$$\Delta_j = \left\{1 - \sum_{i=1}^{m} \left[N_{ij} - N_j\right]^2\right\}, \qquad i = 1,2, \dots, m; j = 1,2, \dots, n \tag{8}$$

Step 8: Determine the overall preference value (weight factors for each criteria):

$$p_j = \frac{\Delta_j}{\sum_{j=1}^{n} \Delta_j}, \qquad j = 1,2, \dots, n \text{ and } \sum_{j=1}^{n} p_j = 1 \tag{9}$$

Step 9: Creating a weighted normalized decision matrix:

$$w_{ij} = p_j \times N_{ij} \text{ for } i = 1,2, \dots, m; j = 1,2, \dots, n \tag{10}$$

Step 10: Determine the positive (PS) and negative ideal solution (NS):

$$PS = \left[w_1^+, \dots, w_j^+, \dots, w_n^+\right],$$
$$\text{where } w_j^+ = \begin{Bmatrix} \max w_{ij} \text{ if } j \in LB \\ \min w_{ij} \text{ if } j \in SB \end{Bmatrix} \text{for } j = 1,2, \dots, n \tag{11}$$

$$NS = \left[w_1^-, \dots, w_j^-, \dots, w_n^-\right],$$
$$\text{where } w_j^- = \begin{Bmatrix} \min w_{ij} \text{ if } j \in LB \\ \max w_{ij} \text{ if } j \in SB \end{Bmatrix} \text{for } j = 1,2, \dots, n \tag{12}$$

Step 11: Obtain the distances of each experimental trials in relation to ideal solutions:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(w_{ij} - w_j^+\right)^2}, \qquad i = 1,2, \dots, m \tag{13}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(w_{ij} - w_j^-\right)^2}, \qquad i = 1,2, \dots, m \tag{14}$$

Step 12: Calculate the closeness index value:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, \qquad i = 1, 2, \dots, m \tag{15}$$

Step 13: Rank the closeness index in the descending order.

3. Results and discussion

In order to demonstrate and prove of the effectiveness of the proposed PSI-TOPIS method, practical example of the selection of FDM process parameters were presented. Also, the results obtained by the proposed hybrid method were compared with the results obtained using other MCDM methods.

The experimental data from Table 3 were normalized using Eq. 4 and the matrix was shown in Table 4. In Table 5 were presented data that were calculated using Eq. 6, 7 and 8, as well as the weight factors for each criterion (using Eq. 9). From Table 5 it can be seen that the compressive strength is most important criteria. The weighted normalized decision matrix was determined using Eq. 10 and this matrix is also shown in Table 4 due to space limitation.

Using Eqs. 11 and 12, the positive and negative ideal solution were determined. Further, the distances of each experimental trials (alternatives) in relation to positive and negative ideal solution were calculated using Eq. 13 and 14 and given in Table 6. Also, Table 6 shows the closeness index calculated using Eq. 15 and the ranking order of given alternatives.

Table 4 Matrix N_{ij} and w_{ij}

Exp. No.	Normalized matrix			Weighted normalized matrix		
	FS (MPa)	FM (MPa)	CS (MPa)	FS (MPa)	FM (MPa)	CS (MPa)
1	0.4179	0.8311	0.9381	0.0912	0.3059	0.3880
2	0.8842	1.0000	0.9717	0.1930	0.3681	0.4019
3	1.0000	0.9794	1.0000	0.2183	0.3605	0.4136
4	0.3960	0.5952	0.8195	0.0865	0.2191	0.3389
5	0.8648	0.8618	0.9418	0.1888	0.3172	0.3896
6	0.7832	0.8790	0.9217	0.1710	0.3236	0.3812
7	0.3214	0.6815	0.8270	0.0702	0.2508	0.3420
8	0.5648	0.7369	0.8648	0.1233	0.2713	0.3577
9	0.7847	0.8301	0.8579	0.1713	0.3055	0.3548

Table 5 Data determination using Eqs. 6-9

Criteria	N_j	φ_j	Δ_j	p_j
FS	0.6686	0.4898	0.5102	0.2183
FM	0.8217	0.1399	0.8601	0.3681
CS	0.9047	0.0334	0.9666	0.4136

Table 6 Closeness index and ranking

Exp. No.	S_i^+	S_i^-	C_i	Rank
1	0.1438	0.1019	0.4149	6
2	0.0278	0.2031	0.8794	2
3	0.0076	0.2180	0.9664	**1**
4	0.2125	0.0163	0.0712	9
5	0.0635	0.1621	0.7183	3
6	0.0726	0.1512	0.6756	4
7	0.2020	0.0319	0.1365	8
8	0.1467	0.0768	0.3436	7
9	0.0979	0.1340	0.5779	5

Results from Table 6, that were obtained using hybrid PSI-TOPSIS method, show that the alternative E_3 is the best option, while the alternative E_4 is the worst choice. Flexural and compressive stress-strain curves for the best and worst alternatives are shown in Fig. 1. The optimal combination of FDM input parameters for printing PLA parts with regard to the considered process performance are 220°C printing temperature, 0.10 mm layer thickness and 90° raster angle, as also shown in Table 7. In this table the bold value indicates level at optimal parameter settings for individual input parameters. It is clear that printing temperature has the most significant effect on the process performance, followed by layer thickness and then raster angle.

Table 7 Response table for the mean C_i.

Input parameters	Closeness index			max.-min.	Rank
	Level 1	Level 2	Level 3		
T	0.2075	0.6471	**0.7400**	0.5325	1
L	**0.7536**	0.4884	0.3527	0.4009	2
A	0.4780	0.5095	**0.6071**	0.1291	3

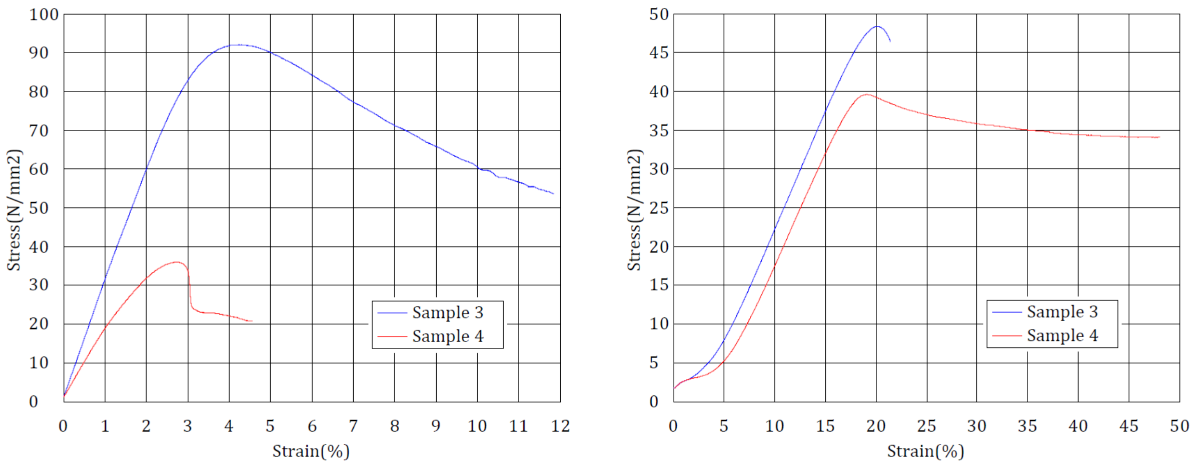


Fig. 1 The flexural (left) and compressive (right) stress-strain curves for the best (sample 3) and worst (sample 4) options

The effect of input parameters on the flexural strength and compressive strength are illustrated in Fig. 2 and Fig. 3, respectively. Results showed that flexural strength and compressive strength increased by increasing the printing temperature. This can be explained by the fact that by increasing the printing temperature, the stronger cohesive forces were realized between individual raster and layers, that resulted in higher flexural and compressive strength.

By increasing of layer thickness, flexural strength and compressive strength decrease, because the porosity between individual layers increases. Also, it can be observed that the highest values of flexural and compressive strength were achieved at a raster angle of 90°, because in this case, the direction of material deposition coincides with the direction of the load. The lowest value of the flexural strength was obtained at a raster angle of 0°, because in this case the strength of the test samples primarily depends on the cohesive force between individual raster. While the lowest value of the compressive strength was achieved at a raster angle of 45° due to the shear stresses between individual raster.

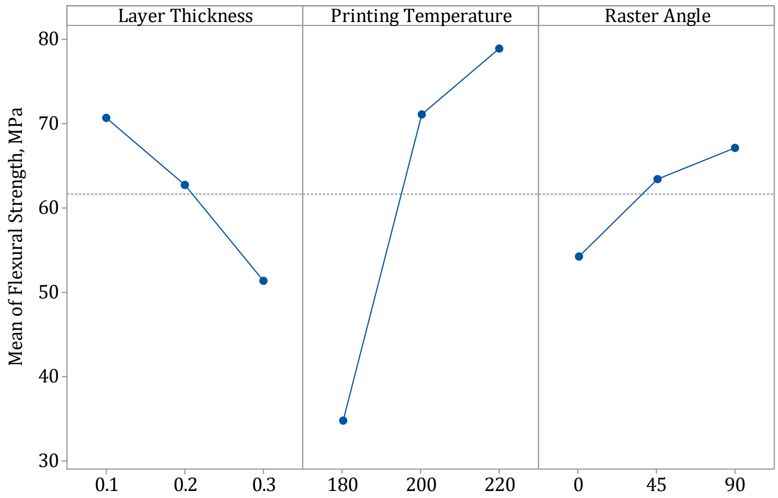


Fig. 2 Mean of the flexural strength for different levels of input parameters

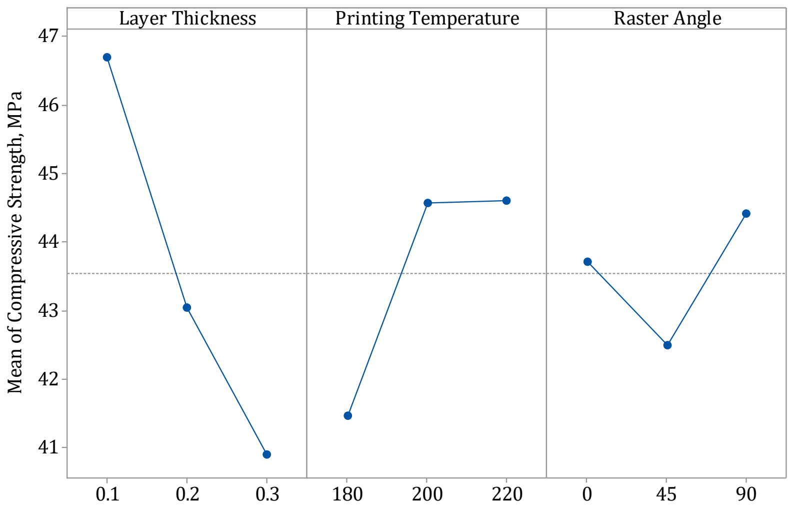


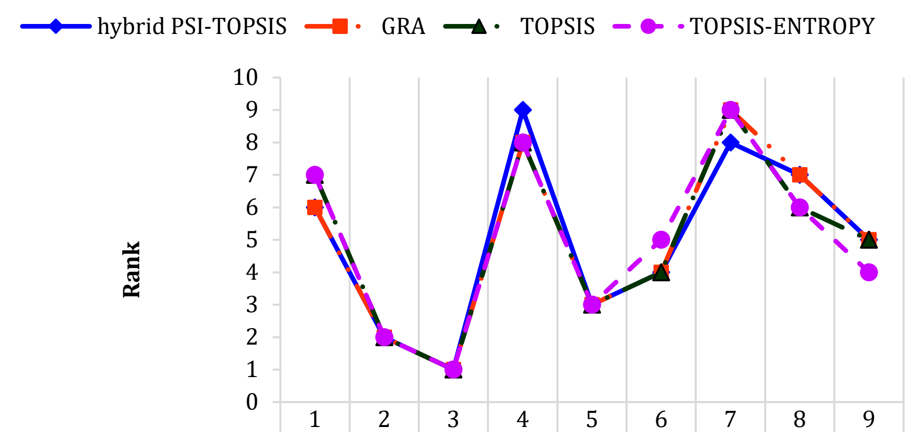
Fig. 3 Mean of the compressive strength for different levels of input parameters

Therefore, based on everything stated above, it can be concluded that the proposed hybrid PSI-TOPSIS method provides effectively very good results.

According to the proposed method, the best option (alternative no. 3) was achieved at the highest varied printing temperature, the smallest varied layer thickness and the raster angle of 90°. The best choice (alternative 3) was confirmed by all other MCDM methods (GRA, TOPSIS and TOPSIS-ENTROPY), as can be seen in Fig. 4.

The worst option, as predicted by the hybrid PSI-TOPSIS method, is alternative no. 4. This was not predicted by the other MCDM methods, as clearly shown in Fig. 4. Thus, the worst choice, as predicted by the others considered methods, is alternative no.7. The worst option, predicted by the proposed PSI-TOPSIS method, was achieved at the lowest varied printing temperature, the mean value of the layer thickness and the raster angle of 45° (it is most unfavourable angle for the compressive strength, as seen in Fig. 3). Alternative 7, as the worst choice predicted by the other methods, was also achieved at the lowest value of the printing temperature. Given that the results (as seen in Table 7) showed that the printing temperature has a most important effect on the process performance and that by decreasing the printing temperature the flexural and compressive strength decrease (as shown in Fig. 2 and Fig. 3), this proves the effectiveness of the proposed method. The effectiveness of the proposed method is also proven by the fact that the worst option (alternative 4) was achieved at the most unfavourable raster angle for the compressive strength (compressive strength is the most important criteria, as shown in Table 5). This was not predicted by the other MCDM methods. The worst option predicted by the other MCDM methods was achieved at the raster angle of 90°. This raster angle is the most favourable angle for both considered criteria (flexural strength and compressive strength), as seen in Figs. 2 and 3.

Thus, in this paper, the determination of the best option does not depend on the MCDM methods used, it was also shown in [20]. However, the worst alternative predicted by the proposed hybrid method, unlike the other methods used, shows a good ranking order of the alternatives by the proposed method, that is an advantage proposed method in compared to the other methods used. Certainly, this advantage offered by the proposed method should be proven in other cases, that is a suggestion for future research.



	1	2	3	4	5	6	7	8	9
hybrid PSI-TOPSIS	6	2	1	9	3	4	8	7	5
GRA	6	2	1	8	3	4	9	7	5
TOPSIS	7	2	1	8	3	4	9	6	5
TOPSIS-ENTROPY	7	2	1	8	3	5	9	6	4

Fig. 4 Comparison of ranking with different MCDM methods

4. Conclusion

In this paper, a novel hybrid PSI-TOPSIS methodology was presented. The proposed method was tested on the example of selecting optimal process parameters during FDM printing of PLA samples. Also, the results obtained by the PSI-TOPSIS method were compared with the results that obtained by other MCDM methods. The results show that a printing temperature of 220°C, a layer thickness of 0.10 mm and a raster angle of 90° would be the best choice of process parameters according to PSI-TOPSIS analysis which has the best combination of mechanical properties of the tested samples.

In future research, a hybrid PSI-TOPSIS method will be proposed for the selection of process parameters in other non-conventional machining processes, such as laser cutting or abrasive water jet cutting.

Acknowledgement

The authors acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0157) and the Ministry of Science, Higher Education and Youth of the Sarajevo Canton.

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