Optimization of PLA 3D Printing Parameters using a Combined SMART-MOORA Multi-Criteria Decision-Making Approach

Pham Ngoc Linh
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
linhpn@haui.edu.vn

Viet-Thanh Pham
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
thanhpv@haui.edu.vn

Ngo Quang Tu
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
tunq@haui.edu.vn

Van-Canh Nguyen
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
canhnv@haui.edu.vn (corresponding author)

Received: 24 September 2024 | Revised: 16 November 2024 | Accepted: 20 November 2024

 DOI: https://doi.org/10.48084/etasr.9085

ABSTRACT

This paper presents an optimization study of 3D printing parameters for Polylactic Acid (PLA) using a combined SMART-MOORA multi-criteria decision-making approach. The research focused on three key performance characteristics: tensile strength, strain, and modulus. By employing the Taguchi L_{27} orthogonal array, the authors conducted 27 experimental trials, varying the printing temperature, print speed, layer height, and bed temperature. The Simple Multi-Attribute Rating Technique (SMART) method was utilized to assign weights to the criteria, emphasizing tensile strength due to its significance in structural applications. Subsequently, the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method was applied to rank the experiments based on the weighted criteria. The findings demonstrated that experiments with high tensile strength and strain values were ranked the highest, underscoring the importance of balancing strength and flexibility in optimizing 3D-printed parts. The sensitivity analysis confirmed the robustness of the optimization results, as the rankings remained stable even when the importance of the criteria was adjusted. This study showcases the effectiveness of the SMART-MOORA approach in optimizing 3D printing parameters, providing a framework to enhance the mechanical performance of PLA parts.

Keywords-PLA 3d printing; smart-MOORA; optimization; sensitivity analysis

I. INTRODUCTION

Over the past several years, Additive Manufacturing (AM), commonly referred to as 3D printing, has undergone rapid advancements, enabling its integration into a diverse array of industries. This technology's ability to produce intricate geometries, minimize material waste, and facilitate customized production has driven its widespread adoption [1, 2]. Among the materials utilized in 3D printing, PLA has gained significant traction due to its biodegradable properties, ease of printing, and relatively low cost [3, 4]. PLA is derived from renewable sources, such as corn starch and sugarcane, positioning it as an environmentally friendly alternative to petroleum-based plastics, like ABS [5]. Dimensional accuracy is a critical factor in the 3D printing process, particularly for materials like PLA that are frequently employed in applications requiring precise measurements. Multiple studies have investigated the impact of various Fused Deposition Modeling (FDM) parameters on the dimensional accuracy of PLA-printed components. For instance, the dimensional accuracy of 3D-printed PLA dog-bone tensile samples was examined, revealing how specific printing parameters can significantly influence dimensional fidelity [6]. As a thermoplastic polymer, PLA offers good dimensional accuracy and a low tendency to warp, making it a highly suitable choice for both novice and experienced 3D printing practitioners [7].

Optimizing the printing process parameters for PLA is a significant challenge, as the performance of 3D-printed parts is highly sensitive to variations in factors, such as nozzle temperature, print speed, and layer height [8, 9]. These parameters significantly impact key properties, like tensile strength, surface roughness, and dimensional accuracy, all of which are critical for producing high-quality parts [10]. For instance, while a higher print speed can decrease production time, it may compromise surface quality and tensile strength. Addressing these trade-offs necessitates a systematic approach to optimization, as traditional trial-and-error methods are time-consuming and inefficient.

Researchers have increasingly turned to Multi-Criteria Decision-Making (MCDM) methods to address the challenges of evaluating and selecting optimal solutions when faced with multiple conflicting objectives [11]. These approaches provide a structured framework for decision-makers to assess the trade-offs between different performance criteria, ensuring that the selected process parameters lead to an overall improvement in the quality of the printed parts. One of the most widely utilized MCDM methods is MOORA, which ranks alternatives based on their performance across multiple criteria [12]. However, a notable limitation of MOORA is its assumption of equal importance across all criteria, which may not be appropriate when certain criteria, such as tensile strength, are more critical than others, like surface finish [13].

The application of MCDM techniques in 3D printing process optimization has been an area of growing research interest in recent years. Several studies have explored the use of methods, such as TOPSIS, AHP, VIKOR, and MOORA, to optimize the manufacturing process parameters, including machining and 3D printing, for various materials, involving PLA, ABS, and PETG [2, 13-16]. These studies have demonstrated the effectiveness of MCDM techniques in identifying optimal printing conditions by balancing multiple performance criteria.

The weakness of MOORA method regarding weighting can be overcome by combining it with a method for determining weights, such as Entropy or SMART, which can enhance the effectiveness of calculations and decision-making. For instance, authors in [17] applied the TOPSIS method to optimize process parameters for PLA, focusing on improving dimensional accuracy and mechanical properties. Similarly, authors in [18] used MOORA to optimize parameters for PETG 3D printing, emphasizing the importance of balancing mechanical strength with printing speed.

The SMART method has been widely employed in solving MCDM, exhibiting advantages due to its simplicity in calculations and flexibility in evaluating criteria. However, there has been limited research combining SMART with the MOORA method in optimizing 3D printing processes. The integration of SMART-MOORA promises to offer a robust approach, balancing the subjective importance of criteria with the objective performance, thereby enhancing the quality and efficiency of 3D printing processes, and potentially extending to other materials and applications in additive manufacturing.

To address this limitation, the present study proposes combining the SMART method with MOORA. SMART is a flexible weighting method that enables decision-makers to assign subjective importance to each criterion based on their specific preferences or expert judgment. By incorporating SMART into the MOORA framework, it is ensured that the criteria are appropriately weighted according to their importance, providing a more accurate and comprehensive ranking of the alternatives. This SMART-MOORA combination has been successfully applied in various fields, including material selection and manufacturing optimization, and is considered a robust approach to balancing conflicting objectives in 3D printing optimization.

The current paper aims to optimize 3D printing parameters for PLA deploying the combined SMART-MOORA method. Multiple conflicting criteria, such as tensile strength, surface roughness, and printing time, are evaluated to identify the most favorable set of process parameters that maximize overall performance. The study includes 27 experimental runs with varying process parameters to demonstrate the effectiveness of the SMART-MOORA approach in optimizing the 3D printing process for PLA. The findings from this research are expected to provide valuable insights into the optimal use of PLA in 3D printing and contribute to the broader field of additive manufacturing.

II. METHODOLOGY

A. Experimental Setup and Specimen

The present study utilized a Taguchi method-based L_{27} orthogonal array design to systematically optimize the experimental conditions. The Taguchi approach is extensively applied in manufacturing and engineering to minimize the number of experiments required for process optimization while maintaining the robustness of the results. It is particularly well-suited when there are multiple factors with varying levels, as is the case with PLA 3D printing. In the present experiment, four input factors were investigated, each set at three distinct levels, leading to an L_{27} orthogonal array experimental design. This experimental design allows for the efficient exploration of the multi-factorial parameter space to identify the optimal conditions for the PLA 3D printing process. The four process parameters considered in this experiment are: Nozzle Temperature ($T_{printing}$), Print Speed ($v_{printing}$), Layer Height (h_{layer}), and Bed Temperature (T_{bed}). The use of Taguchi's L_{27} orthogonal array allows studying the effects of these four parameters at three different levels with a manageable number of experimental runs.

TABLE I. INPUT PARAMETERS AND THEIR LEVELS FOR THE L_{27} TAGUCHI EXPERIMENTAL DESIGN

Variants	Symbol	Unit	Level		
			1	*2*	*3*
Nozzle Temperature	$T_{printing}$	°C	190	210	230
Print Speed	$v_{printing}$	m/min	40	60	80
Layer Height	h_{layer}	mm	0.1	0.2	0.3
Bed Temperature	T_{bed}	°C	30	45	60

The experiments were carried out utilizing a tensile test machine to evaluate the mechanical properties of the 3D-printed PLA specimens. The geometry of the specimen used for testing was designed according to standard dimensions, as shown in Figure 1. Figure 2 depicts the actual PLA specimen after being printed and prepared for tensile testing.

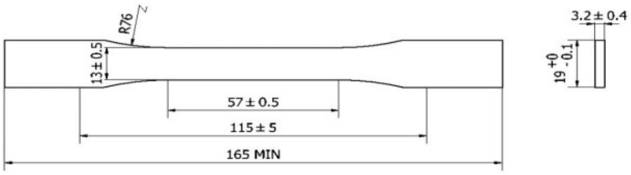

Fig. 1. Schematic diagram of the PLA specimen used in tensile testing.

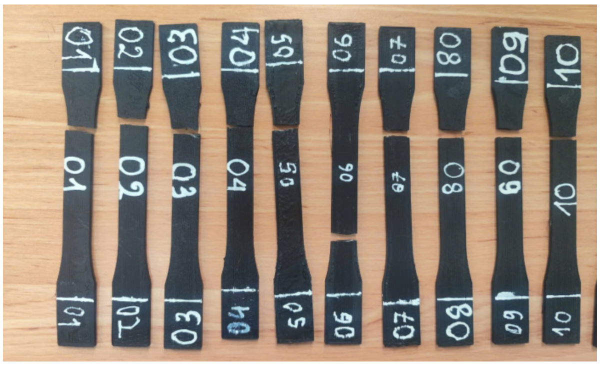

Fig. 2. Actual PLA specimen prepared for tensile testing.

Each experimental run was designed to investigate how these parameters affect the mechanical performance and dimensional accuracy of the PLA parts.

B. Data Collection and Performance Criteria

This study examines the key material properties of 3D-printed parts: tensile strength, strain, and modulus. Tensile strength indicates the maximum load the part can withstand, which is vital for structural integrity in high-load applications. Strain reflects the material's capacity for elongation before fracturing, which is crucial for applications requiring the part to withstand mechanical deformation. Modulus represents the material's stiffness and resistance to deformation under load, which is important for evaluating the part's rigidity and dimensional precision under stress. The experiments utilized the L_{27} orthogonal array, with each run being repeated three times to guarantee the reliability and consistency of the results. The response measurement for each condition was calculated as the mean of the three trials, which minimizes variability and ensures that the results accurately represent the performance of the 3D-printed parts under the given process parameters. The tensile test was performed using a mechanical apparatus capable of progressively loading the samples until failure. The tensile testing procedure has four primary phases: the linear domain, the yield point, the elongation region, and the fracture region, as illustrated in Figure 3. The consolidated findings of the L_{27} matrix and the measured response values are presented in Table II.

Fig. 3. Picture of the tensile testing process for the PLA specimen..

TABLE II. L_{27} ORTHOGONAL ARRAY

No	$T_{printing}$	$v_{printing}$	h_{layer}	T_{bed}	Max Load	Max Strain	Modulus
1	210	60	0.2	45	1.330	6.620	0.758
2	210	40	0.2	30	1.410	6.900	0.745
3	210	80	0.3	45	1.380	6.500	0.721
4	190	60	0.2	30	1.180	6.240	0.653
5	210	60	0.1	30	1.410	7.080	0.745
6	190	60	0.2	60	1.315	7.840	0.702
7	210	40	0.2	60	1.385	6.660	0.754
8	190	60	0.3	45	1.360	9.980	0.749
9	230	80	0.2	45	1.310	6.700	0.749
10	190	40	0.2	45	1.320	6.520	0.702
11	210	60	0.2	45	1.565	6.900	0.829
12	210	80	0.2	60	1.690	6.640	0.839
13	230	60	0.2	60	1.505	7.760	0.745
14	210	60	0.2	45	1.490	7.200	0.737
15	230	60	0.1	45	1.535	7.720	0.799
16	230	40	0.2	45	1.505	7.380	0.780
17	210	40	0.3	45	1.565	8.860	0.794
18	190	60	0.1	45	1.510	6.360	0.780
19	210	60	0.3	60	1.535	8.500	0.725
20	210	80	0.1	45	1.470	7.700	0.741
21	210	80	0.2	30	1.445	7.420	0.737
22	230	60	0.2	30	1.355	6.620	0.713
23	210	60	0.1	60	1.515	7.040	0.754
24	230	60	0.3	45	1.280	7.780	0.702
25	190	80	0.2	45	1.395	7.240	0.713
26	210	40	0.1	45	1.570	6.820	0.771
27	190	40	0.1	30	1.585	6.952	0.756

C. MCDM Approach

To optimize the printing parameters for PLA, the SMART and MOORA methods were combined. The SMART-MOORA method provides an effective framework for evaluating the experimental data and determining the optimal combination of the printing parameters for PLA.

1) Weight Assignment Using SMART

The SMART framework was employed to assign weights to each performance criterion, leveraging the expertise of domain specialists. Experts in the fields of 3D printing and materials science rated the significance of each criterion on a scale from 1 to 10, with tensile strength receiving the highest scores due to its pivotal influence on the mechanical characteristics of PLA components. The ratings were subsequently normalized to determine the relative importance weights for each evaluation criterion, ensuring that the total of the weights sums to 1 utilizing. This approach allowed for a comprehensive and quantitative assessment of the various performance factors, ensuring that the most critical criteria were given appropriate consideration in the evaluation process utilizing (1).

$$w_i = \frac{Rating_i}{\sum_{i=1}^{n} Rating_i} \quad (1)$$

where w_i is the weight of criterion i, $Rating_i$ is the importance rating of criterion i, and n is the total number of criteria.

2) Application of MOORA Method

The MOORA method was then applied to rank the 27 experimental runs based on their performance across the weighted criteria. The first step is the normalization of the performance values. Each performance value was normalized to make the criteria comparable. The normalization formula for each criterion is:

$$x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad (2)$$

where x_{ij} is the performance value of the experimental run i for criterion j, x'_{ij} is the normalized value of x_{ij}, and n is the total number of experimental runs.

The second step refers to the acquisition of the weighted normalized values using:

$$S_i = \sum\left(w_j . x'_{ij}\right) \quad (3)$$

where S_i is the weighted normalized score for the experimental run i, w_j is the weight of criterion j, and x'_{ij} is the normalized value for the experimental run i for criterion j.

The third step includes the ranking of the experiments. The final scores were computed by aggregating the weighted standardized values for each experimental trial. Higher scores indicated better performance across the multiple criteria that were evaluated. Benefit criteria, such as effectiveness and efficiency, were maximized, while cost criteria, including resource usage and time requirements, were minimized to identify the most favorable experimental conditions.

III. RESULTS AND DISCUSSION

Optimizing the 3D printing parameters for PLA material requires carefully weighing the evaluation criteria to determine the ranking of experiments. The three main criteria selected are max load, max strain, and elastic modulus, with their respective weights being based on their relative significance to the overall performance of the printed part. Max load is assigned the highest weight of 0.4, as it represents the load-bearing capacity of the printed part before failure, which is critical for applications demanding high structural integrity. Max strain, with a weight of 0.3, reflects the printed part's ability to withstand deformation before breaking, ensuring the flexibility of the product. Similarly, Elastic modulus, also weighted at 0.3, captures the material's stiffness and capacity to maintain shape under applied forces. These criteria are crucial in evaluating the performance and quality of the 3D printed parts made from PLA material. After the weights were selected, the MOORA method was applied to calculate and rank the experimental results. Equations (2) and (3) were used to normalize the values of each criterion and then multiply them by the corresponding weights. The aggregated MOORA scores were then utilized to determine the final ranking of the experiments, with the results, including the MOORA scores and rankings for each experiment, being presented in Table III.

TABLE III. MOORA RANKING RESULTS FOR 3D PRINTING EXPERIMENTS WITH WEIGHTED CRITERIA

No	T_{print}	v_{print}	h_{layer}	T_{bed}	Max Load	Max Strain	Modul.	Norm. Max. Load	Norm. Max. Strain	Norm. Modul.	Weighted Max. Load	Weighted Max. Strain	Weighted Modulus	S_i	Rank
1	210	60	0.2	45	1.33	6.62	0.76	0.177	0.174	0.195	0.071	0.052	0.058	0.182	22
2	210	40	0.2	30	1.41	6.90	0.75	0.188	0.182	0.191	0.075	0.055	0.057	0.187	17
3	210	80	0.3	45	1.38	6.50	0.72	0.184	0.171	0.185	0.073	0.051	0.056	0.180	24
4	190	60	0.2	30	1.18	6.24	0.65	0.157	0.164	0.168	0.063	0.049	0.050	0.162	27
5	210	60	0.1	30	1.41	7.08	0.75	0.188	0.187	0.191	0.075	0.056	0.057	0.188	16
6	190	60	0.2	60	1.32	7.84	0.70	0.175	0.207	0.180	0.070	0.062	0.054	0.186	19
7	210	40	0.2	60	1.39	6.66	0.75	0.184	0.175	0.194	0.074	0.053	0.058	0.185	20
8	190	60	0.3	45	1.36	9.98	0.75	0.181	0.263	0.192	0.072	0.079	0.058	0.209	2
9	230	80	0.2	45	1.31	6.70	0.75	0.174	0.177	0.192	0.070	0.053	0.058	0.180	23
10	190	40	0.2	45	1.32	6.52	0.70	0.176	0.172	0.180	0.070	0.052	0.054	0.176	26
11	210	60	0.2	45	1.57	6.90	0.83	0.208	0.182	0.213	0.083	0.055	0.064	0.202	6
12	210	80	0.2	60	1.69	6.64	0.84	0.225	0.175	0.216	0.090	0.052	0.065	0.207	3
13	230	60	0.2	60	1.51	7.76	0.75	0.200	0.204	0.191	0.080	0.061	0.057	0.199	7
14	210	60	0.2	45	1.49	7.20	0.74	0.198	0.190	0.189	0.079	0.057	0.057	0.193	13
15	230	60	0.1	45	1.54	7.72	0.80	0.204	0.203	0.205	0.082	0.061	0.062	0.204	5
16	230	40	0.2	45	1.51	7.38	0.78	0.200	0.194	0.200	0.080	0.058	0.060	0.199	8
17	210	40	0.3	45	1.57	8.86	0.79	0.208	0.233	0.204	0.083	0.070	0.061	0.215	1
18	190	60	0.1	45	1.51	6.36	0.78	0.201	0.168	0.200	0.080	0.050	0.060	0.191	15
19	210	60	0.3	60	1.54	8.50	0.73	0.204	0.224	0.186	0.082	0.067	0.056	0.205	4
20	210	80	0.1	45	1.47	7.70	0.74	0.196	0.203	0.190	0.078	0.061	0.057	0.196	11
21	210	80	0.2	30	1.45	7.42	0.74	0.192	0.196	0.189	0.077	0.059	0.057	0.192	14
22	230	60	0.2	30	1.36	6.62	0.71	0.180	0.174	0.183	0.072	0.052	0.055	0.179	25
23	210	60	0.1	60	1.52	7.04	0.75	0.202	0.186	0.194	0.081	0.056	0.058	0.194	12
24	230	60	0.3	45	1.28	7.78	0.70	0.170	0.205	0.180	0.068	0.062	0.054	0.184	21
25	190	80	0.2	45	1.40	7.24	0.71	0.186	0.191	0.183	0.074	0.057	0.055	0.186	18
26	210	40	0.1	45	1.57	6.82	0.77	0.209	0.180	0.198	0.084	0.054	0.059	0.197	10
27	190	40	0.1	30	1.58	6.95	0.76	0.210	0.183	0.194	0.084	0.055	0.058	0.197	9

A. MOORA Ranking Results

The SMART-MOORA method was applied to rank the experiments based on the three main criteria. As shown in Table III, the experiments that exhibited the best overall performance across the under study criteria were prioritized and ranked accordingly.

The top-ranking experiments demonstrated a well-balanced combination of tensile strength and strain, which are pivotal factors in assessing the load-bearing capacity and flexibility of the 3D-printed components. In particular, experiments with high max load and favorable max strain scores tended to predominate the top ranks. This aligns with the optimization goal, as tensile strength is essential for applications demanding robust structural integrity, while strain ensures that the part can withstand mechanical deformation without failure.

Conversely, studies featuring a high modulus but lower max load and max strain were ranked lower in the overall assessment. Although stiffness is a crucial factor, the ranking suggests that flexibility and load-bearing capacity were prioritized in this study. This implies that experiments with higher tensile strength and strain capabilities were preferred and given higher priority in the overall evaluation and assessment process.

B. Sensitivity Analysis

The sensitivity analysis was performed by adjusting the weights assigned to the criteria, and the results remained relatively stable even with changes being made in the importance of each individual criterion. This demonstrates that the SMART-MOORA method is a flexible and robust approach, effectively balancing multiple performance factors without being overly reliant on any single criterion.

IV. CONCLUSIONS

This investigation employed the Simple Multi-Attribute Rating Technique (SMART) combined with Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) approach to optimize the 3D printing parameters for the Polylactic Acid (PLA) material, concentrating on three crucial performance metrics: tensile strength, strain, and modulus. The relative importance of these criteria was chosen to find the balance between the mechanical performance and flexibility of the printed components.

The findings demonstrated that the experiments exhibiting high tensile strength and strain levels achieved the top rankings, indicating that the material's capacity to withstand loads and deform without failure is crucial for optimizing 3D-printed PLA components. Conversely, while modulus was considered, it played a secondary role in the ranking, underscoring that stiffness alone is inadequate for performance optimization when flexibility and load-bearing capacity are also essential. The sensitivity analysis confirmed the robustness of the ranking, revealing that the overall results remained stable even when adjusting the relative importance of the criteria. This highlights the effectiveness of the SMART-MOORA method in addressing multi-criteria optimization for the 3D printing processes.

This study proposes, as far as is known, a novel application of the SMART-MOORA method to optimize the 3D printing parameters for the PLA material. This integrates the weighting flexibility of SMART and the objective ranking of MOORA, providing a more comprehensive solution to the multi-objective nature of 3D printing. The combined framework enhances optimization accuracy by appropriately weighting practical criteria, and increases robustness in selecting optimal parameters. This contribution advances additive manufacturing knowledge by offering a validated methodology adaptable to other materials and processes, expanding MCDM applications in 3D printing optimization.

In conclusion, the combination of SMART and MOORA provided a systematic and reliable approach for optimizing the 3D printing parameters of PLA. This methodology can be further applied to other materials and printing conditions, contributing to the development of high-performance 3D-printed components in various industrial applications.

ACKNOWLEDGMENT

This research was funded by the Hanoi University of Industry under the project code: 02-2024-RD/HĐ-ĐHCN.

REFERENCES

[1] A. Jandyal, I. Chaturvedi, I. Wazir, A. Raina, and M. I. Ul Haq, "3D printing – A review of processes, materials and applications in industry 4.0," *Sustainable Operations and Computers*, vol. 3, pp. 33–42, Oct. 2022, https://doi.org/10.1016/j.susoc.2021.09.004.

[2] G.-H. Tzeng and J.-J. Huang, *Multiple Attribute Decision Making: Methods and Applications*, 1st ed. New York, NY, USA: Chapman and Hall/CRC, 2011.

[3] T. M. Joseph *et al.*, "3D printing of polylactic acid: recent advances and opportunities," *The International Journal of Advanced Manufacturing Technology*, vol. 125, no. 3, pp. 1015–1035, Mar. 2023, https://doi.org/10.1007/s00170-022-10795-y.

[4] L. Ranakoti *et al.*, "Critical Review on Polylactic Acid: Properties, Structure, Processing, Biocomposites, and Nanocomposites," *Materials*, vol. 15, no. 12, Jun. 2022, Art. no. 4312, https://doi.org/10.3390/ma15124312.

[5] J. P. Davim, *Introduction to Mechanical Engineering*. New York, NY, USA: Springer International Publishing, 2018.

[6] D. G. Zisopol, A. I. Portoaca, and M. Tanase, "Dimensional Accuracy of 3D Printed Dog-bone Tensile Samples: A Case Study," *Engineering, Technology & Applied Science Research*, vol. 13, no. 4, pp. 11400–11405, Aug. 2023, https://doi.org/10.48084/etasr.6060.

[7] K. D. Agashe, A. Sachdeva, and S. Chavan, "3D Printing And Advance Material Technology," *International Journal of Grid and Distributed Computing*, vol. 13, no. 2, pp. 1899–1936.

[8] X. Wang *et al.*, "Research progress in polylactic acid processing for 3D printing," *Journal of Manufacturing Processes*, vol. 112, pp. 161–178, Jan. 2024, https://doi.org/10.1016/j.jmapro.2024.01.038.

[9] S. A. Raj, E. Muthukumaran, and K. Jayakrishna, "A Case Study of 3D Printed PLA and Its Mechanical Properties," *Materials Today: Proceedings*, vol. 5, no. 5, Part 2, pp. 11219–11226, Jun. 2018, https://doi.org/10.1016/j.matpr.2018.01.146.

[10] D. Frunzaverde *et al.*, "The Influence of the Printing Temperature and the Filament Color on the Dimensional Accuracy, Tensile Strength, and Friction Performance of FFF-Printed PLA Specimens," *Polymers*, vol. 14, no. 10, May 2022, Art. no. 1978, https://doi.org/10.3390/polym14101978.

[11] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making*. Berlin, Germany: Springer, 1981, http://dx.doi.org/10.1007/978-3-642-48318-9.

[12] V. C. Nguyen, T. D. Nguyen, and D. H. Tien, "Cutting Parameter Optimization in Finishing Milling of Ti-6Al-4V Titanium Alloy under

MQL Condition using TOPSIS and ANOVA Analysis," *Engineering, Technology & Applied Science Research*, vol. 11, no. 1, pp. 6775–6780, Feb. 2021, https://doi.org/10.48084/etasr.4015.

[13] V. Q. Nguyen, H. T. Dung, V. T. Nguyen, V. D. Pham, and V. C. Nguyen, "Multiple Response Prediction and Optimization in Thin-Walled Milling of 6061 Aluminum Alloy," *Engineering, Technology & Applied Science Research*, vol. 13, no. 2, pp. 10447–10452, Apr. 2023, https://doi.org/10.48084/etasr.5667.

[14] J. John, D. Devjani, S. Ali, S. Abdallah, and S. Pervaiz, "Optimization of 3D printed polylactic acid structures with different infill patterns using Taguchi-grey relational analysis," *Advanced Industrial and Engineering Polymer Research*, vol. 6, no. 1, pp. 62–78, Jul. 2023, https://doi.org/10.1016/j.aiepr.2022.06.002.

[15] B. Singaravel, T. Niranjan, M. Vasu Babu, and K. Nagarjuna, "Optimization of Fused Deposition Modeling Control Parameters Using Hybrid Taguchi and TOPSIS Method," in *Sustainable Machining and Green Manufacturing*, Hoboken, NJ, USA: John Wiley & Sons, Ltd, 2024, pp. 289–304, https://doi.org/10.1002/9781394197866.ch14.

[16] I. M. Alarifi, "Mechanical properties and numerical simulation of FDM 3D printed PETG/carbon composite unit structures," *Journal of Materials Research and Technology*, vol. 23, pp. 656–669, Jan. 2023, https://doi.org/10.1016/j.jmrt.2023.01.043.

[17] O. Tunçel, K. Tüfekci, and Ç. Kahya, "Multi-objective optimization of 3D printing process parameters using gray-based Taguchi for composite PLA parts," *Polymer Composites*, vol. 45, no. 14, pp. 12870–12884, 2024, https://doi.org/10.1002/pc.28674.

[18] A. Paul and M. Das, "A decision support system for the selection of FDM process parameters using MOORA," *Management Science Letters*, vol. 14, no. 3, pp. 181–188, 2024, https://doi.org/10.5267/j.msl. 2023.11.003.