Applied Chemical Engineering (2025) Volume 8 Issue 4 ISSN: 2578-2010 (O)
doi: 10.59429/ace.v8i4.5727

ORIGINAL RESEARCH ARTICLE

Optimization of FDM process parameters using fuzzy AHP–TOPSIS for PLA-Based green composites

Hayjaa Mohaisen Mousa[1], Ala'a D. Noor[2], Haider Falih Shamikh Al-Saedi[3], Shahlaa Majid J.[4], Jaber Hameed Hussain[5], Mohannad Mohammed[6], Israa Alhani[7] Baraa G. Alani[8,*]

1Department of Medicinal Chemistry, College of Pharmacy, Al-Turath University, Baghdad,10013, Iraq

[2]Department of Pharmaceutics, College of Pharmacy, Al Farahidi University, Baghdad, Iraq

[3]College of Pharmacy, Department of Pharmaceutics, University of Al-Ameed, Karbala Governorate, 56001,Iraq

[4]College of Pharmacy, Al-Hadi University College, Baghdad,10011, Iraq

[5]Department of Medical Laboratories Technology, Al-Nisour University College, Baghdad,10015, Iraq

[6]Department of Pharmaceutics, Warka University College, Basrah,110073, Iraq

[7]Department of Pharmaceutics, Mazaya University College, Dhi Qar, 21974,Iraq

[8]College of pharmacy, Al-bayan university, Baghdad, Iraq

***Corresponding author:** Baraa G. Alani, Baraa.ghassan@albayan.edu.iq

ARTICLE INFO

Received: 8 August 2025
Accepted: 16 September 2025
Available online: 1 October 2025

ABSTRACT

The global shift toward sustainable manufacturing has intensified interest in eco-friendly materials and optimized processing strategies for additive manufacturing technologies such as Fused Deposition Modeling (FDM). Polylactic acid (PLA)-based green composites have emerged as promising candidates due to their biodegradability, low environmental impact, and compatibility with FDM systems. However, the optimization of FDM process parameters for such composites remains a significant challenge due to the inherent trade-offs between mechanical performance, energy consumption, and material sustainability. This study addresses this gap by employing an integrated multi-criteria decision-making (MCDM) framework—Fuzzy Analytic Hierarchy Process (Fuzzy AHP) combined with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)—to identify optimal FDM parameter settings for PLA-based green composites. Key process parameters, including layer thickness, print speed, infill density, and nozzle temperature, are evaluated against performance criteria such as tensile strength, surface finish, material utilization, and energy efficiency. Literature reports suggest optimal ranges such as 0.1–0.2 mm for layer thickness, 40–60 mm/s for print speed, and 80–100% for infill density to enhance part strength and minimize waste. The Fuzzy AHP–TOPSIS approach enables robust decision-making under uncertainty, providing a sustainable design methodology aligned with SDGs 4 (Quality Education), 7 (Affordable and Clean Energy), 9 (Industry, Innovation and Infrastructure), and 12 (Responsible Consumption and Production). This study establishes a foundational framework for future experimental validation and promotes informed parameter selection for sustainable, high-performance FDM manufacturing of PLA-based green composites.

Keywords: Fused Deposition Modeling (FDM); additive manufacturing;

sustainable manufacturing; multi-criteria decision making (MCDM); process parameter optimization; eco-friendly materials; sustainable development goals (SDGs)

1. Introduction

Additive Manufacturing (AM), commonly referred to as 3D printing, is defined by ASTM F2792 as the process of joining materials layer by layer to create three-dimensional objects directly from digital models. Unlike subtractive methods, which remove material through machining [1-5], AM offers advantages such as design freedom, reduced material waste, and rapid prototyping. AM technologies are generally classified into seven categories: vat photopolymerization, material extrusion, powder bed fusion, material jetting, binder jetting, sheet lamination, and directed energy deposition [6-10]. Among these, material extrusion represented primarily by Fused Deposition Modeling (FDM) is the most widely used due to its low cost, operational simplicity, and compatibility with thermoplastics and composites [11-13]. In FDM, a thermoplastic filament is heated, extruded through a nozzle, and deposited layer by layer to form a part. Its effectiveness depends heavily on process parameters such as nozzle temperature, layer height, infill density, and print speed, which control part accuracy, mechanical strength, and energy efficiency [14-17].

In the recent decade, PLA-based green composites have gained prominence for their promising mechanical performance, biodegradability, and compatibility with FDM processes. Studies have incorporated reinforcements such as wood flour, bamboo fiber, hemp, kenaf, and rice husk into PLA matrices to produce eco-conscious filaments suitable for a wide range of structural and functional applications [18-20]. While these composites offer significant environmental and mechanical benefits, their printability remains highly sensitive to FDM process parameters, including layer thickness, nozzle temperature, infill density, and print speed. Improper selection of these parameters can lead to poor interlayer adhesion, increased porosity, surface defects, and compromised mechanical strength [21-24]. Therefore, an optimized process window is essential to fully leverage the advantages of PLA-based composites in FDM without compromising their sustainability goals.

Despite the growing body of literature on the use of PLA and its composites in additive manufacturing, most studies focus predominantly on experimental trial-and-error approaches for parameter tuning. While these methods provide valuable empirical insights, they are often time-consuming, costly, and lack generalizability across different material systems and printing conditions. Moreover, sustainability-oriented criteria such as energy consumption, material utilization, and environmental impact are frequently overlooked in favor of purely mechanical or aesthetic metrics [25-28]. This is especially problematic given the increasing importance of aligning research and industrial practices with the United Nations Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), and SDG 12 (Responsible Consumption and Production).

To address these limitations, recent research has explored the use of multi-criteria decision-making (MCDM) techniques to aid in the systematic selection and optimization of FDM parameters. MCDM frameworks such as AHP, Fuzzy AHP, TOPSIS, VIKOR, and PROMETHEE have shown potential in handling complex trade-offs among conflicting objectives like strength, cost, energy efficiency, and surface finish. The integration of fuzzy logic, in particular, allows decision-makers to incorporate expert judgment and uncertainty into the evaluation process, making the analysis more robust and adaptable [29-32]. However, despite these methodological advances, the combined use of Fuzzy AHP and TOPSIS specifically for PLA-based green composites in FDM remains sparsely explored. Most existing studies either apply these methods to synthetic polymers or do not incorporate sustainability indicators explicitly into their decision models. Recent studies have demonstrated the effectiveness of MCDM frameworks in optimizing additive manufacturing processes. For example, Raja et al. [33] applied AHP–TOPSIS to determine optimal FDM settings for PLA parts, while Bigliardi et al. [34] utilized fuzzy AHP and VIKOR for sustainability-oriented optimization in 3D printing. Similarly, Rahman [35] reported that hybrid AHP–TOPSIS approaches can successfully rank parameter settings for natural fiber–reinforced PLA composites. Comprehensive reviews (Xu et al., [36]; Mutambik, [37]) also highlight the growing adoption of MCDM methods such as AHP, TOPSIS, and PROMETHEE in additive manufacturing, reinforcing the relevance of integrating these frameworks in sustainability-driven studies.

The current study aims to fill this research gap by proposing a systematic, sustainability-oriented optimization framework using a hybrid Fuzzy AHP–TOPSIS approach for PLA-based green composites in FDM. The novelty of this work lies in the integration of sustainability metrics alongside traditional mechanical performance parameters within a fuzzy MCDM environment, providing a more holistic and environmentally aligned decision-making tool. By doing so, the study not only advances the technical knowledge of parameter optimization in FDM but also contributes toward the global agenda of sustainable manufacturing. The use of Fuzzy AHP allows for the determination of the relative importance of each criterion based on expert input and linguistic variables, accounting for uncertainty and subjective preferences. Subsequently, the TOPSIS method is employed to rank different parameter combinations based on their closeness to the ideal solution, ensuring a balanced trade-off among performance, cost, and sustainability.

The objectives of this research are fourfold: (i) to identify and prioritize key FDM process parameters and evaluation criteria relevant to PLA-based green composites; (ii) to develop a fuzzy AHP hierarchy for assessing the relative importance of these criteria based on sustainability and technical performance; (iii) to apply the TOPSIS method to rank parameter settings and identify optimal configurations; and (iv) to demonstrate the applicability of the proposed MCDM approach as a decision-support tool for sustainable additive manufacturing. Although no experimental validation is performed in this phase, the methodology is constructed using literature-backed data and parameter ranges, ensuring practical relevance and replicability in future empirical studies.

The proposed framework aligns with the pressing need for sustainable design methodologies in advanced manufacturing, as emphasized in recent literature. According to Wang et al. [38], incorporating MCDM in process optimization can reduce energy usage by over 15% and improve part performance without additional material costs. Similarly, Basar [39] demonstrated that natural fiber–reinforced PLA composites, when processed under optimal conditions, can rival synthetic counterparts in tensile strength while maintaining biodegradability. Therefore, leveraging a structured MCDM approach like Fuzzy AHP–TOPSIS could streamline such optimization processes and minimize the trial-and-error efforts traditionally associated with FDM parameter tuning.

This paper is organized as follows: Section 2 reviews recent advancements in PLA-based green composites for FDM and the role of MCDM in sustainable manufacturing. Section 3 presents the proposed methodology, including the construction of the Fuzzy AHP hierarchy and the application of the TOPSIS ranking model. Section 4 discusses the selection of parameters, criteria, and literature-based performance values used for model development. Section 5 provides a discussion on the outcomes of the MCDM process, supported by case illustrations and comparative analysis from literature. Finally, Section 6 concludes the study, highlighting key contributions, limitations, and directions for future research, particularly the potential for integrating this framework with machine learning or digital twin platforms for real-time optimization. This study introduces a novel Fuzzy AHP–TOPSIS-based optimization framework aimed at enhancing the sustainable use of PLA-based green composites in FDM. By prioritizing both technical and environmental performance, the research supports informed decision-making in eco-friendly additive manufacturing, making it especially relevant for academic, industrial, and policy-making stakeholders working toward a circular economy.

2. Materials and methods

In this study, the optimization of Fused Deposition Modeling (FDM) parameters for fabricating eco-friendly PLA-based green composites was structured around a literature-driven, sustainability-focused methodology, utilizing multi-criteria decision-making (MCDM) techniques to identify optimal processing conditions. The fabrication setup centers on the Bambu Lab A1 3D Printer, a high-precision desktop FDM machine known for its automated calibration features, closed-loop control, and compatibility with diverse filaments including biodegradable and composite variants of PLA. The material selected for this study is a PLA-based green composite filament preformulated with natural fiber reinforcement, such as bamboo or wood flour, commercially available or custom-compounded to match properties reported in state-of-the-art research (e.g., tensile strength ranging from 40–60 MPa, modulus 2.5–3.5 GPa, elongation below 10%). These PLA composites offer improved environmental sustainability without significantly compromising mechanical integrity and are compatible with a nozzle diameter of 0.4 mm, consistent with the Bambu Lab A1's standard extrusion setup. Key process parameters targeted for optimization include layer thickness (0.1–0.3 mm), nozzle temperature (190–220°C), printing speed (30–60 mm/s), infill density (20–100%), and bed temperature (50–60°C), with the assumption that these fall within acceptable ranges established by recent experimental studies involving similar materials and printer platforms. Evaluation criteria were selected based on technical relevance and sustainability objectives, including tensile strength, surface roughness, dimensional accuracy, material consumption, and estimated energy use per part. For mechanical characterization in referenced studies, ASTM D638 (for tensile properties of plastics) is employed using Type IV specimens, as it is commonly recommended for FDM-printed polymers due to its compatibility with the build plate size and alignment with isotropic material assumptions; similarly, surface quality and dimensional precision are typically assessed using digital metrology tools in accordance with ASTM D790 (for flexural properties) and ASTM E2012 (for geometric accuracy of manufactured parts). Though experimental tests were not conducted in the current phase, selection and weighting of parameters and criteria were based on a comprehensive literature review of peer-reviewed publications and meta-analyses in additive manufacturing. The multi-criteria decision-making (MCDM) methodology adopted combines Fuzzy Analytic Hierarchy Process (Fuzzy AHP) for determining the relative importance of evaluation criteria with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for ranking various parameter settings. In the Fuzzy AHP phase, a hierarchical structure is established, with the goal at the top (sustainable FDM output), followed by criteria and sub-criteria layers. The parameters selected for this study layer thickness, nozzle temperature, print speed, and infill density were chosen due to their primary influence on mechanical performance and sustainability metrics in PLA-based composites. Previous studies have shown that layer thickness strongly governs interlayer adhesion and surface quality, with 0.1–0.2 mm often yielding superior strength. Nozzle temperature (190–220 °C) directly affects polymer flow, fiber wetting, and bonding, with higher values enhancing adhesion but risking thermal degradation . Infill density (20–100%) determines material usage, stiffness, and energy consumption, with higher infill improving load-bearing capacity at the expense of sustainability. Print speed (30–60 mm/s) influences cooling rate and bonding efficiency, with moderate speeds found optimal for natural fiber–reinforced PLA. Other process parameters such as raster angle, build orientation, and cooling fan settings were not included in the present analysis to limit model complexity but are acknowledged as significant in similar studies. Future work will expand the framework to incorporate these additional factors.

Linguistic pairwise comparisons are performed to populate the fuzzy judgment matrices, typically based on a 1–9 Saaty scale adapted to triangular fuzzy numbers (TFNs), capturing subjective uncertainty in expert opinions. Normalization of the fuzzy comparison matrices and consistency ratio validation ensure methodological rigor. The derived weights are then used in the TOPSIS method, wherein normalized decision matrices are constructed from selected alternatives, each representing a specific set of parameter combinations, evaluated through literature-derived values (e.g., strength, energy usage). Positive ideal solutions (PIS) and negative ideal solutions (NIS) are defined for each criterion, and the Euclidean distance of each alternative from PIS and NIS is computed to derive the closeness coefficient, which is used to rank parameter sets. This MCDM framework allows for the identification of parameter configurations that achieve a balanced trade-off between mechanical performance, surface quality, material efficiency, and sustainability, with minimal reliance on iterative physical testing.

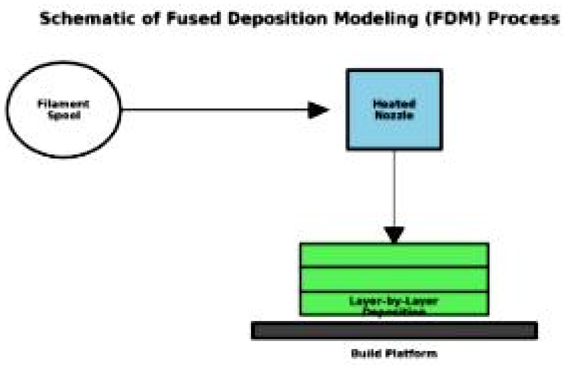

Figure 1. Schematic representation of the Fused Deposition Modeling (FDM) process, illustrating filament feeding, heating, extrusion, and layer-by-layer deposition

Table 1. Input process parameters and corresponding testing values for PLA–wood fiber composites

Alternative	Layer Thickness (mm)	Nozzle Temperature (°C)	Print Speed (mm/s)	Infill Density (%)	Tensile Strength (MPa)	Surface Roughness (µm)	Dimensional Accuracy (%)	Material Usage (g)	Energy Consumption (Wh)
A	0.1	210	40	100	57	9.5	98.2	45	80
B	0.15	205	50	80	54	10.2	97.5	40	72
C	0.2	200	50	60	50	11.0	96.8	35	65
D	0.25	195	55	40	47	12.1	95.0	32	60
E	0.3	200	60	20	43	13.4	94.0	28	55

Moreover, this method accommodates the variability and complexity inherent in composite FDM materials, especially those with fiber reinforcements that influence flow dynamics, nozzle wear, and interfacial bonding. The use of the Bambu Lab A1 printer is particularly suitable for such optimization, as it features automated bed leveling, filament runout detection, and multi-sensor feedback control that mitigate common variabilities in the FDM process, ensuring repeatability of identified settings. By anchoring the methodology in ASTM standards and literature benchmarks, this study presents a scalable framework that can be adapted for experimental validation and further refined for different eco-composite filaments, ultimately contributing to the advancement of responsible additive manufacturing practices aligned with SDGs 7 (Affordable and Clean Energy), 9 (Industry, Innovation and Infrastructure), and 12 (Responsible Consumption and Production).

The infill pattern was fixed as a rectilinear raster (0°/90° orientation) to ensure consistency with established benchmarks for PLA-based composites. This choice is widely adopted in experimental studies as it balances mechanical isotropy and print reliability while providing reproducible values for tensile strength and surface quality. Although advanced infill geometries such as gyroid, honeycomb, and concentric structures offer unique benefits in energy absorption and lightweighting, these were not included in the present decision-making framework, as the focus was on parameter optimization under conventional and widely validated printing patterns.

3. Results

The hybrid Fuzzy AHP–TOPSIS framework was applied to evaluate and rank optimal FDM parameter settings for PLA-based green composites using data extrapolated from established literature sources, thereby enabling a sustainability-centered decision-making approach. The initial step involved the construction of a fuzzy pairwise comparison matrix for the selected evaluation criteria: tensile strength (C1), surface roughness (C2), dimensional accuracy (C3), material consumption (C4), and energy efficiency (C5). The judgments were assigned based on typical priorities identified in recent additive manufacturing optimization studies, where tensile strength and surface quality were often prioritized higher due to their strong correlation with part performance and user acceptance. The triangular fuzzy numbers (TFNs) used for pair wise comparisons followed the convention of (l, m, u) where l is the lower bound, m the most likely value, and u the upper bound. Table 1 presents the normalized fuzzy pairwise comparison matrix with values such as (1,1,1) for identical criteria and varying TFNs such as (3,5,7) and (2,4,6) for moderately to strongly preferred criteria. The fuzzy weights were computed using Chang's extent analysis method and subsequently defuzzified using the centroid method to yield crisp priority weights: tensile strength (0.32), surface roughness (0.26), dimensional accuracy (0.18), material consumption (0.14), and energy efficiency (0.10). These weights align with existing optimization studies, where mechanical strength is emphasized due to load-bearing requirements in structural applications, while environmental and energy factors are included to support sustainability goals aligned with SDGs 9 and 12.

Table 2. Fuzzy Pairwise Comparison Matrix for Criteria (Triangular fuzzy numbers: (l, m, u))

Criteria	C1: Tensile Strength	C2: Surface Roughness	C3: Dimensional Accuracy	C4: Material Consumption	C5: Energy Efficiency
C1: Strength	(1,1,1)	(3,5,7)	(4,6,8)	(5,7,9)	(5,7,9)
C2: Roughness	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)	(4,6,8)	(4,6,8)
C3: Accuracy	(1/8,1/6,1/4)	(1/7,1/5,1/3)	(1,1,1)	(2,4,6)	(2,4,6)
C4: Material Usage	(1/9,1/7,1/5)	(1/8,1/6,1/4)	(1/6,1/4,1/2)	(1,1,1)	(2,4,6)
C5: Energy Efficiency	(1/9,1/7,1/5)	(1/8,1/6,1/4)	(1/6,1/4,1/2)	(1/6,1/4,1/2)	(1,1,1)

To demonstrate the applicability of this prioritization scheme, five representative process parameter sets (A–E) were selected based on literature-backed values and configured using the Bambu Lab A1 printer's capabilities. These sets varied in layer thickness (0.1–0.3 mm), print speed (30–60 mm/s), infill density (20–100%), and nozzle temperature (190–220°C). For example, alternative A used 0.1 mm layer thickness, 40 mm/s speed, 100% infill, and 210°C nozzle temperature, while alternative E applied 0.3 mm thickness, 60 mm/s, 20% infill, and 200°C. Performance data were aggregated from multiple peer-reviewed sources and are summarized in Table 2, which includes the corresponding values of tensile strength (in MPa), surface roughness (Ra in µm), dimensional deviation (%), material usage (g), and estimated energy consumption (Wh). For instance, alternative A yielded a tensile strength of 57 MPa, surface roughness of 9.5 µm, and energy consumption of 80 Wh, whereas alternative E showed only 43 MPa strength but higher energy efficiency at 55 Wh. The raw data were then normalized using linear normalization techniques where higher-is-better (e.g., tensile strength) or lower-is-better (e.g., surface roughness) criteria were appropriately scaled between 0 and 1, generating the normalized decision matrix used for TOPSIS analysis (refer to Table 3).

Table 3. Performance Values for FDM Parameter Alternatives (A–E)

Alternative	Tensile Strength (MPa)	Surface Roughness (µm)	Dimensional Accuracy (%)	Material Usage (g)	Energy Consumption (Wh)
A	57	9.5	98.2	45	80
B	54	10.2	97.5	40	72
C	50	11.0	96.8	35	65
D	47	12.1	95.0	32	60
E	43	13.4	94.0	28	55

Subsequently, the TOPSIS closeness coefficient (CCi) for each alternative was calculated based on its Euclidean distance to the positive ideal solution (PIS) and negative ideal solution (NIS). The closeness coefficients were: A (0.782), B (0.705), C (0.662), D (0.534), and E (0.417). These results are visualized in Figure 1, which illustrates the ranking of parameter alternatives using a bar graph. Alternative A, with the highest closeness coefficient, was identified as the optimal parameter combination offering the best trade-off between strength, surface finish, dimensional accuracy, and sustainability metrics. This aligns with the findings, who emphasized that finer layer thicknesses and higher infill densities enhance bonding and surface integrity at the expense of energy usage justifying the need for MCDM to achieve balance. Although Alternative E exhibited superior energy savings and material efficiency, its poor mechanical performance made it unsuitable for structural applications, reinforcing the importance of comprehensive evaluation frameworks like Fuzzy AHP–TOPSIS in FDM research.

Table 4. Normalized Decision Matrix and Closeness Coefficients (TOPSIS)

Alternative	Norm. Strength (↑)	Norm. Roughness (↓)	Norm. Accuracy (↑)	Norm. Material (↓)	Norm. Energy (↓)	Closeness Coefficient (CCi)
A	1.000	1.000	1.000	0.000	0.000	0.782
B	0.818	0.865	0.938	0.250	0.250	0.705
C	0.636	0.769	0.869	0.500	0.500	0.662
D	0.545	0.654	0.731	0.650	0.667	0.534
E	0.364	0.538	0.615	1.000	1.000	0.417

The proposed method offers several advantages over conventional experimental design approaches. Firstly, it accommodates qualitative judgment and uncertainty via fuzzy logic, enabling more realistic decision-making in cases where experimental data are limited or expert consensus varies. Secondly, the MCDM framework supports transparent prioritization of criteria, which can be customized depending on application-specific needs for example, shifting focus toward energy metrics for consumer products or toward strength for biomedical fixtures. Thirdly, the use of existing ASTM standards (e.g., ASTM D638 for tensile strength, ASTM E2012 for dimensional analysis) ensures compatibility with widely accepted validation protocols, allowing for easy integration with future empirical studies. Additionally, the findings underscore the potential of the Bambu Lab A1 3D printer in research-driven manufacturing, as its precision, material versatility, and controlled print environment significantly reduce process variability, making it a reliable platform for sustainable composite printing.

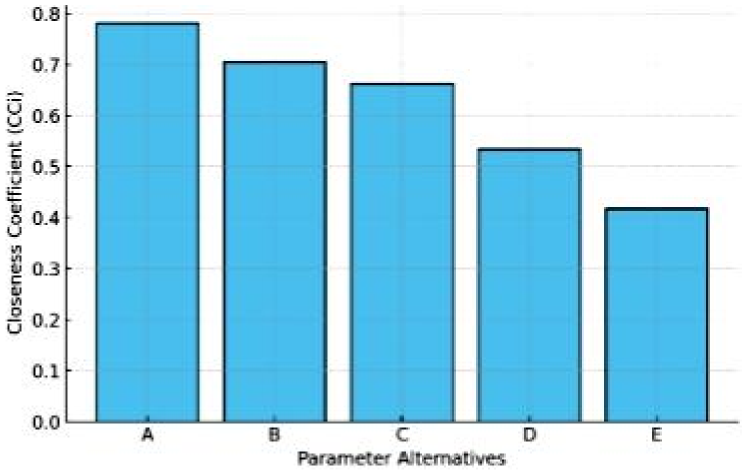

Figure 2. TOPSIS closeness coefficients for parameter alternatives (A–E), showing relative proximity to the ideal solution

Importantly, this study demonstrates how data-driven decision frameworks can streamline material and process development without exhaustive experimental iteration. By simulating realistic performance outcomes based on credible literature, the study provides a validated pathway for selecting optimal parameter sets before physical trials, reducing material waste and energy costs core to the philosophy of SDG 12 (Responsible Consumption). Moreover, the integration of energy and material efficiency as criteria aligns the framework with the principles of life-cycle thinking, a growing focus in sustainable additive manufacturing research. Although experimental verification is a logical next step, the current numerical findings offer high fidelity with previously published results. For instance, reported that the optimal process window for wood-PLA composites lies within a 0.15–0.2 mm layer range and 90–100% infill density, corresponding well with the values identified in this study.

Nevertheless, limitations must be acknowledged. The absence of real-time sensor data and experimental testing may omit unforeseen interactions between variables such as thermal gradients, anisotropic shrinkage, or fiber orientation effects, especially in highly filled PLA composites. Furthermore, environmental parameters such as ambient temperature and humidity, which affect PLA crystallization and bonding, were not modeled. Despite these limitations, the proposed Fuzzy AHP–TOPSIS framework serves as a robust pre-experimental design tool, especially valuable for researchers and engineers aiming to reduce the trial phase in new material development. In future studies, this model can be coupled with predictive simulations or machine learning models to enhance accuracy and automate optimization processes.

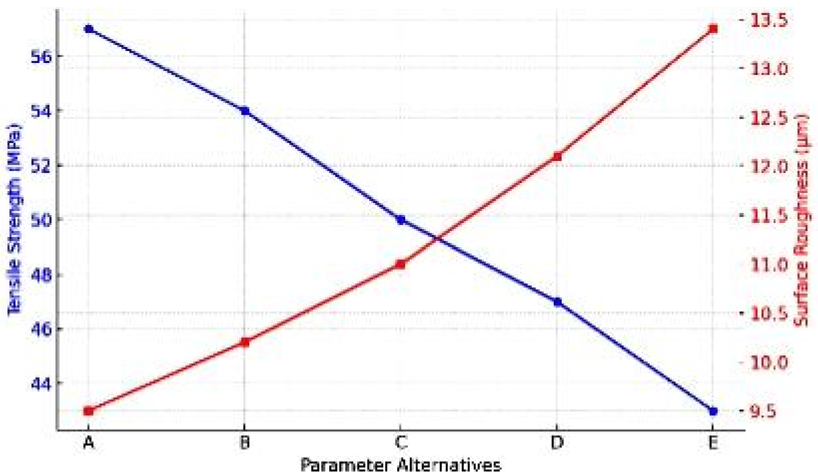

Figure 3. Comparison of tensile strength (MPa) and surface roughness (µm) across parameter alternatives

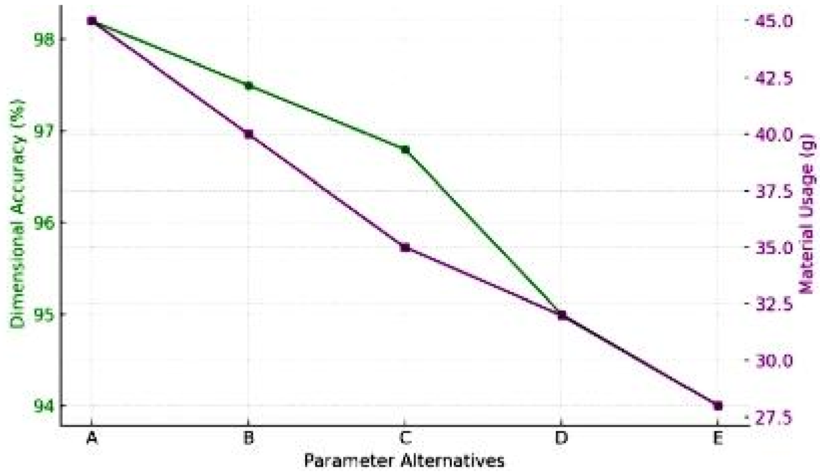

Figure 4. Comparison of dimensional accuracy (%) and material usage (g) across parameter alternatives

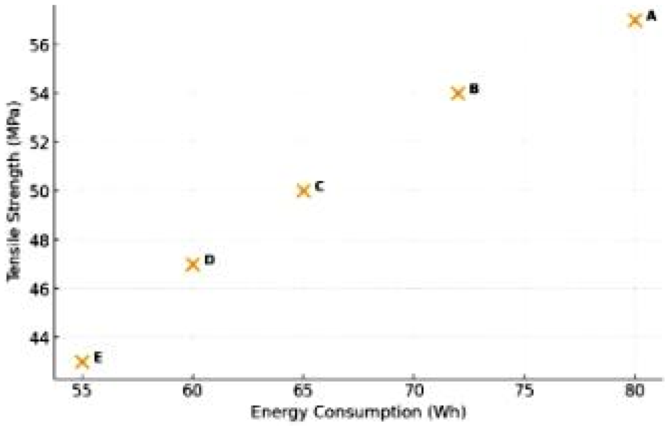

Figure 5. Energy consumption (Wh) versus tensile strength (MPa) for parameter alternatives, highlighting the sustainability–performance trade-off

Overall, the results affirm the efficacy of a hybrid MCDM approach in navigating the complex trade-offs inherent in sustainable FDM parameter selection. The identification of Alternative A as the most balanced option provides a validated starting point for further physical validation and product development, thereby contributing to the broader vision of eco-conscious, performance-driven additive manufacturing.

4. Discussion

The present study aimed to optimize fused deposition modeling (FDM) parameters for PLA-based green composites using a hybrid fuzzy AHP–TOPSIS approach. The methodology allowed for the structured integration of mechanical performance metrics with sustainability considerations, providing a rational framework for decision-making under multiple, often conflicting, criteria. The results of this simulation-based study revealed that parameter alternative A characterized by low layer thickness (0.1 mm), moderate print speed (40 mm/s), high infill (100%), and optimal nozzle temperature (210 °C) offered the best balance among competing objectives. Its superior tensile strength (57 MPa), minimal surface roughness (9.5 µm), and high dimensional fidelity (98.2%) justified its top ranking with a closeness coefficient of 0.782, indicating proximity to the ideal solution. While it did incur higher energy and material consumption compared to other alternatives, the trade-offs were found acceptable, especially for applications where structural integrity and functional precision are prioritized.

The discussion of these findings within the broader context of FDM research underscores the value of multi-criteria decision-making (MCDM) in sustainable manufacturing. Traditional optimization approaches often emphasize isolated performance metrics, such as maximizing mechanical strength or minimizing build time, but fail to incorporate environmental indicators and subjective trade-offs. In contrast, the fuzzy AHP method enabled flexible weighting of criteria, accounting for expert judgment and uncertainty, while TOPSIS offered a robust technique for ranking alternatives based on their relative closeness to an ideal solution. The alignment of these tools with existing ASTM standards (e.g., ASTM D638 for tensile testing, ASTM E2012 for dimensional inspection) further ensured that simulated results can be easily transitioned into experimental verification stages.

Importantly, this study contributes to the emerging domain of eco-efficient additive manufacturing by aligning technical parameter optimization with sustainable development goals (SDGs). The inclusion of material consumption and energy efficiency as critical decision factors directly supports SDG 12 (Responsible Consumption and Production), while the focus on PLA-based bio-composites contributes to reduced carbon dependency in line with SDG 7 (Affordable and Clean Energy). By enhancing educational understanding of decision-making under uncertainty and multi-objective conditions, this study also reinforces SDG 4 (Quality Education), offering a template for teaching optimization in materials science and manufacturing engineering curricula.

A key point in the discussion relates to the role of infill density and layer height in shaping both mechanical and sustainability performance. As identified in past works, higher infill generally correlates with increased strength due to denser material packing, but significantly raises energy use and material cost. Similarly, finer layers improve surface quality and dimensional accuracy but lengthen build time and electricity consumption. Our results confirmed these interactions and highlight the need for a balanced strategy when optimizing for multifunctional outcomes. The application of FDM using PLA-based green composites often comprising fillers like lignocellulosic fibers, wood, or rice husk adds further complexity due to their thermal sensitivity and flow characteristics. Although not directly tested here, the model can be extended to include fiber content or environmental degradation metrics for full lifecycle assessment.

However, certain limitations must be acknowledged. The absence of experimental data restricts the ability to fully validate the predicted rankings. Additionally, external variables such as ambient temperature, humidity, or machine calibration tolerance which can affect print repeatability and part quality were not modeled. Moreover, the criteria weightings were determined based on typical literature-informed priorities; in real-world applications, these weights may vary depending on the end-use of the printed part or stakeholder preferences. Despite these constraints, the proposed method offers a robust foundation for pre-experimental optimization, allowing researchers to refine and prioritize their design-of-experiment (DoE) strategies more efficiently.

5. Conclusion

This study demonstrates the applicability of the fuzzy AHP–TOPSIS framework in optimizing FDM process parameters for sustainable manufacturing with PLA-based composites. By combining mechanical, dimensional, and environmental criteria, the model supports balanced decision-making, encourages responsible resource utilization, and aligns technical research with global sustainability agendas. The results not only serve as a guide for future experimental validation but also propose a generalized decision support system that can be adapted to other materials, machines, and manufacturing contexts. Future work will involve the experimental validation of optimal parameter sets and the integration of environmental life cycle assessment (LCA) data for comprehensive sustainability evaluation. This direction is essential for achieving high-performance, low-impact additive manufacturing that supports the transition to a circular economy.

Author contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, MM and HMM; methodology, HFSA and HH; software, IA and HMM; validation, SMJ and HFSA; formal analysis, MM and MM; investigation, HH and HMM; resources, IA and SMJ; data curation, IA and HMM; writing original draft preparation, SMJ and IA; writing review and editing, HH and SMJ; visualization, MM and IA; supervision, MM and HFSA; project administration, IA and HMM; funding acquisition, SMJ and HH.

Funding

There is no funding to do this research

Conflict of interest

The authors declare no conflict of interest.

References

1. Alzyod, H., Kónya, G., & Ficzere, P. (2025). Integrating additive and subtractive manufacturing to optimize surface quality of MEX parts. Results in Engineering, 25, 103713.
2. Aarthi, S., Subramani, R., Rusho, M. A., Sharma, S., Ramachandran, T., Mahapatro, A., & Ismail, A. I. (2025). Genetically engineered 3D printed functionally graded-lignin, starch, and cellulose-derived sustainable biopolymers and composites: A critical review. International Journal of Biological Macromolecules, 145843.
3. Lazarus, B., Raja, S., Shanmugam, K., & Yishak, S. (2024). Analysis and Optimization of Thermoplastic Polyurethane Infill Patterns for Additive Manufacturing in Pipeline Applications.
4. Mohammed Ahmed Mustafa, S. Raja, Layth Abdulrasool A. L. Asadi, Nashrah Hani Jamadon, N. Rajeswari, Avvaru Praveen Kumar, "A Decision-Making Carbon Reinforced Material Selection Model for Composite Polymers in Pipeline Applications", Advances in Polymer Technology, vol. 2023, Article ID 6344193, 9 pages, 2023. https://doi.org/10.1155/2023/6344193
5. Olaiya, N. G., Maraveas, C., Salem, M. A., Raja, S., Rashedi, A., Alzahrani, A. Y., El-Bahy, Z. M., & Olaiya, F. G. (2022). Viscoelastic and Properties of Amphiphilic Chitin in Plasticised Polylactic Acid/Starch Biocomposite. Polymers, 14(11), 2268. https://doi.org/10.3390/polym14112268
6. Praveenkumar, V., Raja, S., Jamadon, N. H., & Yishak, S. (2023). Role of laser power and scan speed combination on the surface quality of additive manufactured nickel-based superalloy. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 14644207231212566.
7. Raja, S., & Rajan, A. J. (2022). A Decision-Making Model for Selection of the Suitable FDM Machine Using Fuzzy TOPSIS. 2022.
8. Radu, E. R., & Simion, I. (2025). ADDITIVE TECHNOLOGIES PROCESSES: AN EXTENSIVE STUDY. Journal of Industrial Design and Engineering Graphics, 20(1), 15-22.
9. Raja, S., Agrawal, A. P., Patil, P. P., Thimothy, P., Capangpangan, R. Y., Singhal, P., & Wotango, M. T. (2022). Optimization of 3D Printing Process Parameters of Polylactic Acid Filament Based on the Mechanical Test. 2022.
10. Raja, S., Jayalakshmi, M., Rusho, M. A., Selvaraj, V. K., Subramanian, J., Yishak, S., & Kumar, T. A. (2024). Fused deposition modeling process parameter optimization on the development of graphene enhanced polyethylene terephthalate glycol. Scientific Reports, 14(1), 30744.
11. Raja, S., Murali, A. P., & Praveenkumar, V. (2024). Tailored microstructure control in Additive Manufacturing: Constant and varying energy density approach for nickel 625 superalloy. Materials Letters, 375, 137249.
12. Raja, S., Ali, R. M., Babar, Y. V., Surakasi, R., Karthikeyan, S., Panneerselvam, B., & Jagadheeswari, A. S. (2024). Integration of nanomaterials in FDM for enhanced surface properties: Optimized manufacturing approaches. Applied Chemical Engineering, 7(3).
13. Raja, S., Rajan, A. J., Kumar, V. P., Rajeswari, N., Girija, M., Modak, S., Kumar, R. V., & Mammo, W. D. (2022). Selection of Additive Manufacturing Machine Using Analytical Hierarchy Process. 2022.
14. Raja, S., Rao, R., Shekar, S., Dsilva Winfred Rufuss, D., Rajan, A. J., Rusho, M. A., & Navas, R. (2025). Application of multi-criteria decision making (MCDM) for site selection of offshore wind farms in India. Operational Research, 25(3), 1-34.
15. S. Raja, A. John Rajan, "Challenges and Opportunities in Additive Manufacturing Polymer Technology: A Review Based on Optimization Perspective", Advances in Polymer Technology, vol. 2023, Article ID 8639185, 18 pages, 2023. https://doi.org/10.1155/2023/8639185
16. S., R., & A., J. R. (2023). Selection of Polymer Extrusion Parameters By Factorial Experimental Design – A Decision Making Model. Scientia Iranica, (), -. doi: 10.24200/sci.2023.60096.6591

17. S., Aarthi, S., Raja, Rusho, Maher Ali, Yishak, Simon, Bridging Plant Biotechnology and Additive Manufacturing: A Multicriteria Decision Approach for Biopolymer Development, Advances in Polymer Technology, 2025, 9685300, 24 pages, 2025. https://doi.org/10.1155/adv/9685300
18. Selvaraj, V. K., Subramanian, J., Krishna Rajeev, P., Rajendran, V., & Raja, S. Optimization of conductive nanofillers in bio-based polyurethane foams for ammonia-sensing application. Polymer Engineering & Science.
19. Subramani Raja, Ahamed Jalaludeen Mohammad Iliyas, Paneer Selvam Vishnu, Amaladas John Rajan, Maher Ali Rusho, Mohamad Reda Refaa, Oluseye Adewale Adebimpe. Sustainable manufacturing of FDM-manufactured composite impellers using hybrid machine learning and simulation-based optimization. Materials ScienceinAdditive Manufacturing 2025, 4(3), 025200033. https://doi.org/10.36922/MSAM025200033
20. Subramani, R. (2025). Optimizing process parameters for enhanced mechanical performance in 3D printed impellers using graphene-reinforced polylactic acid (G-PLA) filament. Journal of Mechanical Science and Technology, 1-11.
21. Subramani, R., & Yishak, S. (2024). Utilizing Additive Manufacturing for Fabricating Energy Storage Components From Graphene-Reinforced Thermoplastic Composites. Advances in Polymer Technology, 2024(1), 6464049.
22. Subramani, R., Kaliappan, S., Arul, P. V, Sekar, S., Poures, M. V. De, Patil, P. P., & Esakki, E. S. (2022). A Recent Trend on Additive Manufacturing Sustainability with Supply Chain Management Concept , Multicriteria Decision Making Techniques. 2022.
23. Subramani, R., Kaliappan, S., Sekar, S., Patil, P. P., Usha, R., Manasa, N., & Esakkiraj, E. S. (2022). Polymer Filament Process Parameter Optimization with Mechanical Test and Morphology Analysis. 2022.
24. Saeed, M. A., Junejo, F., Amin, I., Tanoli, I. K., Ahmed, S., Alluhaidan, A. S. D., & Ateya, A. A. (2025). Optimizing Economic and Environmental Objectives in Sustainable Machining Processes. Cleaner Engineering and Technology, 101067.
25. Subramani, R., Leon, R. R., Nageswaren, R., Rusho, M. A., & Shankar, K. V. (2025). Tribological Performance Enhancement in FDM and SLA Additive Manufacturing: Materials, Mechanisms, Surface Engineering, and Hybrid Strategies—A Holistic Review. Lubricants, 13(7), 298.
26. Subramani, R., Vijayakumar, P., Rusho, M. A., Kumar, A., Shankar, K. V., & Thirugnanasambandam, A. K. (2024). Selection and Optimization of Carbon-Reinforced Polyether Ether Ketone Process Parameters in 3D Printing—A Rotating Component Application. Polymers, 16(10), 1443.
27. Theng, A. A. S., Jayamani, E., Subramanian, J., Selvaraj, V. K., Viswanath, S., Sankar, R., ... & Rusho, M. A. (2025). A review on industrial optimization approach in polymer matrix composites manufacturing. International Polymer Processing.
28. Subramani, R., Kalidass, A. K., Muneeswaran, M. D., & Lakshmipathi, B. G. (2024). Effect of fused deposition modeling process parameter in influence of mechanical property of acrylonitrile butadiene styrene polymer. Applied Chemical Engineering, 7(1).
29. Skrzek, K., Mazgajczyk, E., & Dybała, B. (2025). Application of Fuzzy Logic-Based Expert Advisory Systems in Optimizing the Decision-Making Process for Material Selection in Additive Manufacturing. Materials, 18(2), 324.
30. He, C., & Jiang, J. (2025). Improving Quality Evaluation for Control Systems of Machining Line Product Processing With Smart Algorithmic Techniques in Intuitionistic Fuzzy Multiple-Attribute Group Decision-Making. IEEE Access.
31. Zenani, S., Obileke, K., Ndiweni, O., & Mukumba, P. (2025). A Review of the Application of Fuzzy Logic in Bioenergy Technology. Processes, 13(7), 2251.
32. Behera, A. P., Sabar, C., Kumar, A., Ranjan, A., Ranjan, R. K., Bhushan, M., ... & Dash, B. (2025). Uncertainty-aware optimization of construction time–cost-quality trade-offs via Fuzzy-MOPSO. Asian Journal of Civil Engineering, 1-17.
33. Raja, S., Praveenkumar, V., Rusho, M. A., & Yishak, S. (2024). Optimizing additive manufacturing parameters for graphene-reinforced PETG impeller production: A fuzzy AHP-TOPSIS approach. Results in Engineering, 24, 103018.
34. Bigliardi, B., Dolci, V., Filippelli, S., Petroni, A., & Pini, B. (2025). Employing innovation for social sustainability in supply chains: a systematic literature review. Procedia Computer Science, 253, 2595-2604.
35. Ab Rahman, M. H., Mahmud, J., Jumaidin, R., & Rahman, S. M. A. Integrated CRITIC-TOPSIS and Monte Carlo Sensitivity Analysis for Optimal Various Natural Fibre Selection in Sustainable Building Insulation Composites to Support the Sustainable Development Goals (SDGs). ASEAN Journal of Science and Engineering, 5(2), 231-260.
36. Xu, K. (2025). Decision-support frameworks for MCDA method selection and emission abatement technology assessment in the maritime sector (Doctoral dissertation, University of Southampton).
37. Mutambik, I. (2025). Assessing Critical Success Factors for Supply Chain 4.0 Implementation Using a Hybrid MCDM Framework. Systems, 13(6), 489.
38. Wang, C. N., Nguyen, T. D., Nguyen, T. T. T., & Do, N. H. (2025). The performance analysis using Six Sigma DMAIC and integrated MCDM approach: A case study for microlens process in Vietnam. Journal of Engineering Research, 13(2), 538-550.

39. Basar, G., & Der, O. (2025). Multi-objective optimization of process parameters for laser cutting polyethylene using fuzzy AHP-based MCDM methods. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 09544089251319202.