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Research Article

OPTIMAL MATERIAL SELECTION FOR 3D PRINTING (PLA) USING MULTI-CRITERIA DECISION ANALYSIS

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Abstract: Material selection in additive manufacturing is a critical factor that directly affects the quality, cost, and performance of the final product. This paper addresses the problem of selecting the optimal PLA material for 3D printing using multi-criteria decision analysis. The methodology is based on the application of the Analytic Hierarchy Process, enabling a systematic evaluation of multiple criteria such as cost, mechanical properties, print quality, temperature resistance, and environmental impact. A case study is conducted to demonstrate the ranking process of alternative materials, resulting in an optimal solution based on quantitative analysis. The results confirm that multi-criteria methods are effective tools for supporting engineering decision-making.

Keywords: 3D printing, PLA, AHP, multi-criteria analysis, material selection

1. INTRODUCTION

Additive manufacturing (AM), commonly referred to as 3D printing, has emerged as a transformative technology in modern engineering and manufacturing systems (Gibson et al., 2015). Unlike conventional subtractive or formative processes, additive manufacturing builds components layer by layer directly from digital models, enabling unprecedented design flexibility, reduced material waste, and rapid prototyping capabilities. This paradigm shift has significantly impacted various industries, including aerospace, automotive, biomedical engineering, and consumer product design.

One of the most widely adopted techniques within additive manufacturing is Fused Deposition Modeling (FDM), which relies on thermoplastic materials extruded through a heated nozzle (Gibson et al., 2015). Among the available materials, Polylactic Acid (PLA) has gained substantial popularity due to its ease of processing, low melting temperature, minimal warping, and environmentally friendly origin (Chua & Leong, 2017). PLA is derived from

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renewable resources such as corn starch and sugarcane, making it an attractive alternative to petroleum-based polymers in the context of sustainable manufacturing (Chua & Leong, 2017).

Despite its advantages, PLA exhibits several limitations, including relatively low thermal resistance, brittleness, and limited mechanical performance under certain conditions (eSUN, 2023a). To address these drawbacks, various modified PLA materials have been developed, such as PLA+, Tough PLA, and recycled PLA blends. These materials offer improved mechanical strength, enhanced durability, or better environmental performance, but they also introduce trade-offs in terms of cost, printability, and overall performance.

As a result, the selection of the most appropriate PLA material becomes a complex decision-making problem involving multiple, often conflicting criteria (Triantaphyllou, 2000). For example, material with superior mechanical properties may have higher cost or lower environmental sustainability, while an eco-friendly option may not meet the required functional performance. Therefore, relying on a single criterion or intuitive judgment is insufficient for making optimal decisions in engineering practice.

In this context, multi-criteria decision-making (MCDM) methods provide a systematic and rational framework for evaluating and comparing alternative materials. Previous studies have demonstrated the applicability of AHP in engineering systems and production optimization (Srebrenkoska et al., 2023; Krstev et al., 2025). Among these methods, the Analytic Hierarchy Process is particularly suitable due to its ability to structure complex problems into hierarchical levels, incorporate both qualitative and quantitative criteria, and derive relative importance weights through pairwise comparisons (Saaty, 1980).

The primary objective of this study is to develop and demonstrate a structured approach for selecting the optimal PLA material for 3D printing applications using multi-criteria analysis. The research focuses on identifying relevant evaluation criteria, applying the AHP methodology, and ranking alternative materials based on their overall performance.

Furthermore, this study contributes to the broader field of sustainable and intelligent manufacturing by integrating decision-support tools into material selection processes. The proposed approach not only improves decision accuracy but also enhances transparency and reproducibility, which are essential for modern engineering design and optimization

2. THEORETICAL BACKGROUND

2.1. Additive Manufacturing and FDM Technology

Additive manufacturing (AM) represents a paradigm shift in production technologies, enabling the fabrication of complex geometries directly from digital models without the need for traditional tooling (Gibson et al., 2015). Among various AM technologies, Fused Deposition Modeling (FDM) is one of the most widely used due to its simplicity, cost-effectiveness, and accessibility.

FDM operates by extruding thermoplastic filaments through a heated nozzle, depositing material layer by layer to form a three-dimensional object (ASTM, 2021). The quality and performance of the printed part are influenced by several process parameters, including layer height, extrusion temperature, printing speed, and infill density. However, one of the most critical factors affecting the final product is the material used.

The choice of material directly impacts mechanical strength, dimensional accuracy, surface finish, and durability. Therefore, material selection is not only a technological decision but also an economic and environmental consideration.

2.2. PLA Materials and Their Variants

Polylactic Acid (PLA) is a biodegradable thermoplastic polymer derived from renewable biological resources (Chua & Leong, 2017). Due to its favourable processing characteristics, PLA has become one of the most used materials in FDM-based 3D printing.

The key advantages of PLA include ease of printing, low shrinkage, good surface quality, and reduced emission of harmful fumes during processing. These characteristics make PLA particularly suitable for educational, prototyping, and low-load applications.

However, standard PLA exhibits certain limitations, such as low impact resistance, brittleness, and poor performance at elevated temperatures. To overcome these shortcomings, several modified PLA materials have been developed:

- PLA+: Enhanced formulation with improved mechanical strength and better layer adhesion
- Tough PLA: Designed to provide higher impact resistance and ductility
- Recycled PLA: Produced from reused material, offering improved environmental sustainability (eSUN, 2023b)

Each of these materials presents a different balance between performance, cost, and environmental impact. Consequently, selecting the most appropriate material requires a systematic evaluation of multiple attributes.

2.3. Material Selection in Engineering Design

Material selection is a fundamental aspect of engineering design and significantly influences product performance, manufacturing cost, and environmental impact (Triantaphyllou, 2000). Traditionally, material selection has been based on experience, empirical rules, or single-criterion optimization. However, modern engineering problems are characterized by increasing complexity and the need to consider multiple criteria simultaneously, particularly in the context of production system design and optimization (Srebrenkoska et al., 2023). In the context of additive manufacturing, material selection becomes even more critical due to the interaction between material properties and process parameters. Engineers must consider not only intrinsic material characteristics but also their behavior during the printing process and under service conditions.

Key criteria typically include:

- mechanical properties (strength, stiffness, toughness)
- thermal properties
- manufacturability (printability)
- economic factors (cost)
- environmental impact

The presence of multiple, often conflicting criteria necessitates the use of structured decision-making approaches.

2.4. Multi-Criteria Decision-Making (MCDM)

Multi-Criteria Decision-Making (MCDM) refers to a set of methods designed to evaluate and rank alternatives when multiple criteria must be considered simultaneously (Triantaphyllou, 2000). These methods are particularly useful in engineering applications where trade-offs between performance, cost, and sustainability are required.

MCDM methods enable (Triantaphyllou, 2000; Chau, 2007):

- systematic comparison of alternatives
- incorporation of both quantitative and qualitative data
- prioritization of criteria based on their importance
- transparent and reproducible decision-making

Common MCDM methods include AHP, TOPSIS, VIKOR, and ELECTRE. Among these, AHP is one of the most widely applied due to its simplicity and robustness (Chau, 2007).

2.5. Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process, developed by Thomas L. Saaty, is a structured technique for organising and analysing complex decisions (Saaty, 1980; Chau, 2007). It decomposes a decision problem into a hierarchical structure consisting of a goal, criteria, and alternatives.

The core principle of AHP is pairwise comparison, where elements are compared two at a time with respect to their importance relative to a higher-level criterion (Saaty, 1980). These comparisons are typically expressed using a numerical scale (1–9), representing equal importance to extreme importance.

The main steps of AHP include:

- structuring the decision hierarchy
- constructing pairwise comparison matrices
- normalizing the matrices
- calculating priority vectors (weights)
- checking consistency through the consistency ratio (CR)

AHP provides several advantages, including the ability to handle subjective judgments, integrate qualitative and quantitative criteria, and ensure consistency in decision-making.

2.6. Relevance of AHP in Material Selection

The application of AHP in material selection is particularly valuable in situations where multiple criteria must be balanced. Similar approaches have already been successfully applied in engineering systems and production optimization problems, demonstrating the effectiveness of AHP-based decision models (Srebrenkoska et al., 2023; Krstev et al., 2023; Krstev et al., 2025). In the case of PLA materials for 3D printing, AHP allows engineers to:

- evaluate trade-offs between performance and cost
- incorporate expert knowledge
- rank materials based on overall suitability
- improve decision transparency and justification

By applying AHP, the decision-making process becomes more structured, reducing uncertainty and increasing the reliability of the selected solution.

3. METHODOLOGY

The proposed methodology is based on a structured multi-criteria decision-making framework for optimal material selection in additive manufacturing (Saaty, 1980). The framework integrates engineering knowledge with a quantitative decision-support model based on the Analytic Hierarchy Process.

The overall procedure consists of the following phases: (i) problem definition and hierarchy structuring, (ii) criteria identification and weighting, (iii) evaluation of alternatives, and (iv) aggregation and ranking of results. This systematic approach ensures transparency, consistency, and reproducibility of the decision-making process.

The decision problem is structured into a hierarchical model consisting of three levels:

- **Level 1 (Goal):** Selection of the optimal PLA material for 3D printing
- **Level 2 (Criteria):** Cost, mechanical strength, print quality, temperature resistance, environmental impact
- **Level 3 (Alternatives):** PLA, PLA+, Tough PLA, Recycled PLA

The hierarchical decomposition enables the transformation of a complex decision problem into a set of simpler pairwise comparisons.

In AHP, the relative importance of criteria is determined through pairwise comparisons. A comparison matrix A=[a_ij]is constructed, where each element a_ijrepresents the relative importance of criterion iover criterion j.

The matrix has the following properties:

- $a_{ij} > 0$
- $a_{ji} = \frac{1}{a_{ij}}$
- $a_{ii} = 1$

The pairwise comparisons are performed using Saaty's fundamental scale (1–9), where 1 indicates equal importance and 9 indicates extreme importance.

The priority vector (weights) is obtained by normalizing the comparison matrix and computing the principal eigenvector.

The normalized matrix is calculated as:

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (1)$$

The weight of each criterion is then determined as:

$$w_i = \frac{1}{n}\sum_{j=1}^{n} \bar{a}_{ij} \quad (2)$$

Alternatively, the weight vector wcan be derived from the eigenvalue problem:

$$Aw=\lambda\_max\ w \quad (3)$$

where λ_maxis the maximum eigenvalue of matrix A.

To ensure the reliability of the pairwise comparisons, the consistency of the decision matrix is evaluated using the Consistency Index (CI) and Consistency Ratio (CR).

The Consistency Index is defined as:

$$CI=(\lambda\_max-n)/(n-1) \quad (4)$$

The Consistency Ratio is calculated as:

$$CR=CI/RI \quad (5)$$

where RIis the Random Index, which depends on the size of the matrix.

A consistency ratio CR<0.1indicates acceptable consistency of the judgments. If this condition is not satisfied, the pairwise comparisons must be revised.

The overall score for each alternative is calculated using a weighted sum model:

$$S_i = \sum_{j=1}^{m} w_j \cdot x_{ij} \quad (6)$$

- S_i is the overall score of alternative i
- w_j is the weight of criterion j

- x_{ij} is the normalized performance value

The alternatives are then ranked in descending order based on their scores.

4. RESULTS AND DISCUSSION

The decision model was populated with real technical and market data for four commercially available materials: eSUN PLA, eSUN PLA+, UltiMaker Tough PLA, and Prusament PLA Recycled. The cost criterion was expressed as price per kilogram. For Prusament PLA Recycled, the official price is listed for a 2 kg spool, therefore the unit price was recalculated on a per-kilogram basis. The properties used were tensile strength, flexural strength, heat deflection temperature, and impact strength, as reported in the manufacturers' technical documentation (eSUN, 2023c; Ultimaker, 2022; Prusament, 2023).

Table 1. Input data used in the analysis

Material	Cost (USD/kg)	Tensile strength (MPa)	Flexural strength (MPa)	HDT (°C)	Impact strength (kJ/m²)
PLA (eSUN)	11.99	72.00	90.00	53.0	5.4
PLA+ (eSUN)	16.99	53.34	81.16	53.0	5.5
Tough PLA (UltiMaker)	66.60	45.30	91.60	58.3	8.9
PLA Recycled (Prusament)	24.995	49.00	82.00	55.0	14.0

Source note: eSUN PLA price and PLA+ price were taken from the official eSUN EU store; UltiMaker Tough PLA price from the official UltiMaker store; Prusament PLA and Prusament PLA Recycled prices from official Prusa/Prusament listings. Standard PLA tensile/flexural/impact/HDT values come from the eSUN PLA TDS; PLA+ values from the eSUN PLA+ TDS; Tough PLA values from the UltiMaker TDS; recycled PLA values from the Prusament PLA Recycled TDS.

The criteria were weighted using an AHP-based preference structure in which tensile strength was considered the most important criterion, followed by cost, heat resistance, flexural strength, and impact strength. The adopted weight vector was:

$$w = [0.25,\ 0.30,\ 0.15,\ 0.20,\ 0.10]$$

where:

- $w_1 = 0.25$ for cost
- $w_2 = 0.30$ for tensile strength
- $w_3 = 0.15$ for flexural strength
- $w_4 = 0.20$ for HDT
- $w_5 = 0.10$ for impact strength

The corresponding reciprocal AHP matrix was formed as:

$$A = \begin{bmatrix} 1 & 0.833 & 1.667 & 1.25 & 2.50 \\ 1.20 & 1 & 2.00 & 1.50 & 3.00 \\ 0.60 & 0.50 & 1 & 0.75 & 1.50 \\ 0.80 & 0.667 & 1.333 & 1 & 2.00 \\ 0.40 & 0.333 & 0.667 & 0.50 & 1 \end{bmatrix}$$

Because this matrix was generated directly from the weight ratios, the maximum eigenvalue is $\lambda_{\max} = 5$, which gives:

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{5-5}{4} = 0$$

$$CR = \frac{CI}{RI} = 0 \qquad (7)$$

Thus, the consistency requirement is fully satisfied. This means that the criteria-priority structure used in the analysis is mathematically consistent.

Since the criteria are measured in different units, normalization was required before aggregation. For the cost criterion, which is non-beneficial, the following transformation was used:

$$r_{ij} = \frac{\min(x_j)}{x_{ij}} \tag{8}$$

For the beneficial criteria (tensile strength, flexural strength, HDT, impact strength), normalization was performed as:

$$r_{ij} = \frac{x_{ij}}{\max(x_j)} \tag{9}$$

The resulting normalized matrix is given below.

Table 2. Normalized decision matrix

Material	Cost	Tensile	Flexural	HDT	Impact
PLA (eSUN)	1.0000	1.0000	0.9825	0.9091	0.3857
PLA+ (eSUN)	0.7057	0.7408	0.8860	0.9091	0.3929
Tough PLA (UltiMaker)	0.1800	0.6292	1.0000	1.0000	0.6357
PLA Recycled (Prusament)	0.4797	0.6806	0.8952	0.9434	1.0000

The normalized results show that standard PLA dominates in cost and tensile strength, Tough PLA leads in flexural strength and HDT, while recycled PLA has the highest impact strength. This already indicates that no single material is best in every category, which justifies the use of a multi-criteria framework.

The final composite score for each material was calculated using the weighted sum model:

$$S_i = \sum_{j=1}^{5} w_j r_{ij}$$

For the first alternative, standard PLA, the score is:

$$S_{\mathrm{PLA}} = 0.25(1.0000) + 0.30(1.0000) + 0.15(0.9825) + 0.20(0.9091) + 0.10(0.3857)$$

$$S_{\mathrm{PLA}} = 0.2500 + 0.3000 + 0.1474 + 0.1818 + 0.0386 = 0.9178$$

For PLA+:

$$S_{\mathrm{PLA+}} = 0.25(0.7057) + 0.30(0.7408) + 0.15(0.8860) + 0.20(0.9091) + 0.10(0.3929)$$

$$S_{\mathrm{PLA+}} = 0.1764 + 0.2222 + 0.1329 + 0.1818 + 0.0393 = 0.7527$$

For Tough PLA:

$$S_{\mathrm{Tough}} = 0.25(0.1800) + 0.30(0.6292) + 0.15(1.0000) + 0.20(1.0000) + 0.10(0.6357)$$

$$S_{\mathrm{Tough}} = 0.0450 + 0.1888 + 0.1500 + 0.2000 + 0.0636 = 0.6473$$

For PLA Recycled:

$$S_{\mathrm{Recycled}} = 0.25(0.4797) + 0.30(0.6806) + 0.15(0.8952) + 0.20(0.9434) + 0.10(1.0000)$$

$$S_{\mathrm{Recycled}} = 0.1199 + 0.2042 + 0.1343 + 0.1887 + 0.1000 = 0.7471$$

Table 3. Final scores and ranking

Rank	Material	Final score
1	PLA (eSUN)	0.9178
2	PLA+ (eSUN)	0.7527
3	PLA Recycled (Prusament)	0.7471
4	Tough PLA (UltiMaker)	0.6473

The final ranking identifies standard PLA as the best overall alternative under the selected weighting scheme. Its dominance is primarily explained by its extremely favorable cost and the highest tensile strength among the analyzed options, while still maintaining competitive flexural performance. PLA+ occupies the second position because it remains balanced but does not outperform standard PLA in the two most heavily weighted criteria. Recycled PLA ranks third; despite its strong impact performance and acceptable heat resistance, it is penalized by lower tensile performance and higher cost than standard PLA. Tough PLA ranks fourth because its superior flexural and thermal behavior is outweighed by its significantly higher price per kilogram.

4.1. Statistical analysis of the obtained scores

To evaluate the dispersion of the final scores, descriptive statistics were calculated for the score vector:

$$S = \{0.9178,\ 0.7527,\ 0.7471,\ 0.6473\}$$

The arithmetic mean is:

$$\bar{S} = \frac{0.9178 + 0.7527 + 0.7471 + 0.6473}{4} = 0.7662$$

The sample standard deviation is:

$$s = \sqrt{\frac{\sum_{i=1}^{4}(S_i - \bar{S})^2}{4-1}} = 0.1120$$

The coefficient of variation is:

$$CV = \frac{s}{\bar{S}} = \frac{0.1120}{0.7662} = 0.1462$$

A coefficient of variation of 14.62% indicates a moderate spread of results. This means that the alternatives are not identical, but neither are they radically separated. In practical terms, the first-ranked alternative is clearly preferable, while the middle-ranked options remain relatively close and may switch order if managerial priorities change.

The score gap between the first and second alternatives is:

$$\Delta_{1,2} = 0.9178 - 0.7527 = 0.1651$$

The gap between the second and third alternatives is:

$$\Delta_{2,3} = 0.7527 - 0.7471 = 0.0056$$

This is a very important result: **PLA+ and PLA Recycled are almost tied**, while standard PLA is clearly separated from both. Therefore, the decision is robust for the first place, but much less robust for the second and third places.

4.2. Engineering interpretation of the results

From an engineering point of view, the ranking suggests that when cost efficiency and tensile strength are dominant decision priorities, standard PLA is the most rational choice. This is especially relevant for rapid prototyping, educational use, concept parts, and non-demanding functional components. The result also shows that PLA+ does not automatically outperform standard PLA; instead, its value depends on whether the user prioritizes toughness-related practical behavior over raw tensile performance.

Recycled PLA emerges as a highly competitive solution. Although it was not ranked first, its final score is very close to PLA+, and it achieves the best impact performance in the evaluated set. This makes it a strong option in scenarios where circularity, sustainability positioning, and improved impact response are important. The very small difference between

PLA+ and recycled PLA implies that either material could be selected depending on the specific industrial context.

Tough PLA exhibits the best flexural strength and the highest HDT in this dataset, which confirms its technical suitability for more demanding parts. However, its market price is substantially higher than the other alternatives, and under the current weighting structure this cost penalty dominates the final result. Therefore, Tough PLA would likely move upward in the ranking only if thermal resistance and structural rigidity were assigned much larger weights.

It should be noted that this case study combines vendor-specific materials from different manufacturers and uses datasheet values that are not fully generated under identical test protocols. eSUN standard PLA explicitly states that the listed physical and mechanical properties are based on injection-molded spline tests, while UltiMaker Tough PLA and Prusament PLA Recycled report mechanical performance from 3D-printed samples; eSUN PLA+ reports printed-sample values. Accordingly, the presented ranking should be interpreted as a real-market decision model rather than as a strict interlaboratory comparison.

5. CONCLUSION

This study presented a structured and quantitative approach for optimal material selection in additive manufacturing, focusing on PLA-based materials for FDM 3D printing. By integrating engineering performance data with a multi-criteria decision-making framework based on the Analytic Hierarchy Process, the research demonstrated how complex material selection problems can be systematically analyzed and resolved (Saaty, 1980; Triantaphyllou, 2000).

The results indicate that standard PLA achieves the highest overall score under the selected weighting scheme, primarily due to its superior cost efficiency and high tensile strength. These finding highlights that, despite the availability of advanced PLA variants, conventional PLA remains a highly competitive solution when economic and basic mechanical considerations dominate.

PLA+ and recycled PLA exhibit comparable performance, with a minimal difference in final scores. This suggests that both materials represent viable alternatives depending on specific application priorities. PLA+ offers a balanced improvement in printability and mechanical behavior, while recycled PLA provides enhanced impact performance and environmental benefits, making it particularly relevant in the context of sustainable manufacturing.

Tough PLA, although technically superior in terms of flexural strength and thermal resistance, was ranked lower due to its significantly higher cost. This result confirms that high-performance materials do not necessarily lead to optimal solutions unless their advantages align with the dominant decision criteria.

The statistical analysis further demonstrated that the obtained ranking is stable for the top-ranked alternative, while moderate sensitivity exists among the mid-ranked options. This emphasizes the importance of criteria weighting and decision-maker preferences in multi-criteria models.

From a methodological perspective, the study confirms that the application of AHP enables transparent, consistent, and reproducible decision-making. The integration of real-world data with mathematical modeling enhances both the practical relevance and scientific rigor of the approach.

However, certain limitations must be acknowledged. The analysis relies on manufacturer-provided data, which may differ in testing conditions, and therefore introduces a degree of uncertainty. Future research should incorporate experimentally validated data under standardized conditions, as well as extend the model to include additional criteria such as print time, surface roughness, and lifecycle environmental impact (LCA).

In conclusion, the proposed framework represents a robust and scalable decision-support tool for material selection in additive manufacturing. It can be readily extended to other materials, processes, and industrial applications, contributing to more informed, data-driven, and sustainable engineering decisions.

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