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# Application of Fuzzy Analytic Network Process in Selection of Bio-composite Filament for Fused Deposition Modeling Process

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## ABSTRACT

The concurrent engineering approach necessitates integrating material selection into the product design to effectively align with client specifications. Premature product failure, leading to substantial losses, frequently arises as a consequence of inadequate material selection due to conflicting demands. The Multi-Criteria Decision Making (MCDM) procedures are essential for making wise decisions since choosing materials is complicated. This study employs fuzzy analytic network process (FANP) techniques to determine which bio-composite filaments will be the most effective for Fused Deposition Modeling (FDM). The requirements and available factors of egg carton packaging material determine the selection criteria for bio-composite filaments. These factors serve as the foundation for identifying ten essential features. The acquired data showed that the sugar palm fiber/polylactic acid composite (SPF/PLA) 7.5 wt.% fiber loading exhibited the highest priority score, 19.80%. The

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kenaf/acrylonitrile butadiene styrene (Kenaf/ABS) composite, with a fiber loading of 7.5%, exhibited the lowest ranking, scoring 4.4%. Subsequently, a sensitivity analysis was conducted to further corroborate the findings. It was observed that the SPF/PLA 7.5 wt.% fiber loading consistently ranked highest throughout all four examined scenarios. The study determined that a bio-composite filament material with a weight ratio of 7.5% SPF/PLA fiber loading is the optimal choice for utilizing FDM technology in the design of egg carton packaging.

*Keywords:* Bio-composites filaments, fused deposition modeling (FDM), fuzzy analytic network process, material selection process

## INTRODUCTION

The Fused Deposition Modeling (FDM) technique is extensively used in Three-dimensional (3D) printing because it can generate a wide variety of complicated pieces at a lower production cost and with various customizable materials. FDM typically employs a thermally controlled technique in which a melted thermoplastic filament is placed onto a build platform. Most FDM filament comprises thermoplastics like polylactic acid (PLA) or acrylonitrile-butadiene-styrene (ABS). Their favorable thermal and rheological qualities facilitate the production phase (Mohan et al., 2017). FDM material feedstock typically consists of rolled filaments between 1.75 and 3 mm diameter (Mohd Pu'ad et al., 2019). When the filament melts, the substance comes out of a nozzle. The liquidizer head moves along the X and Y axes, while the building platform moves along the Z axis. Figure 1 shows how an FDM printer creates an object by fusing filament spools to make layers.

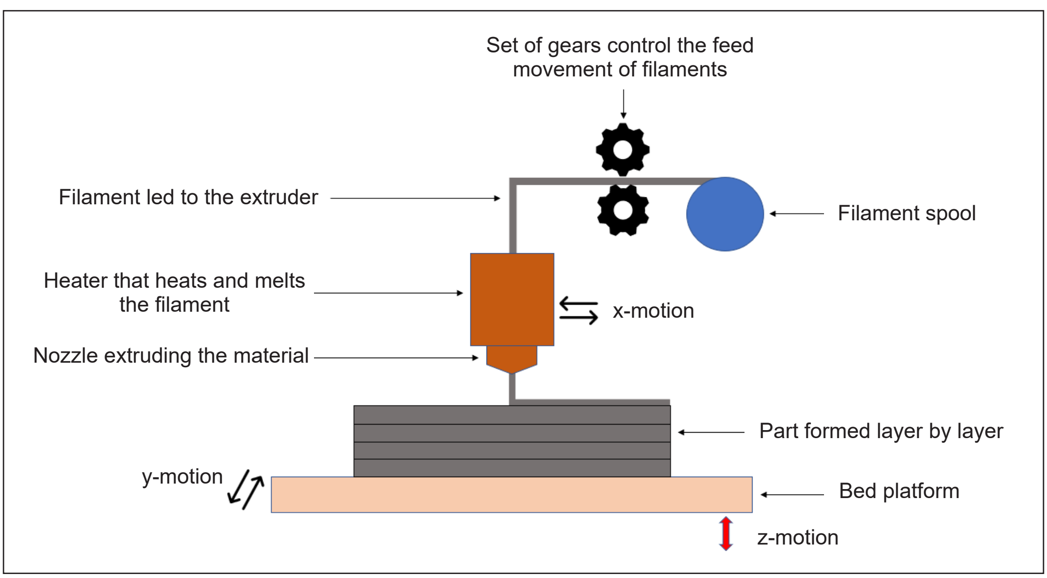


*Figure 1*. FDM process schematically

Filaments come in various materials, with bio-composite filaments being one option. Bio-composites consist of two distinct elements: (1) natural fiber and (2) matrix. Recent studies revealed that plant-based natural fibers are the most often used material in bio-composites. Plant-based natural fibers such as jute, flax, hemp, coir, and sisal are gaining popularity in the composite sector due to stricter laws concerning their usage. According to Noryani et al. (2018), plant-based natural fiber is far simpler to work with than animal or mineral fiber, making it ideal for experimental and installation settings. Table 1 shows that natural fiber can come from different types of cellulose, animals, and minerals. Every natural fiber category possesses distinct attributes that render it appropriate for diverse purposes. As an illustration, cotton is renowned for its inherent softness and breathability, wool is esteemed for its exceptional insulating properties, and silk is highly regarded for its rich tactile sensation.

A comprehensive comprehension of the origin and characteristics of diverse natural fibers is crucial in selecting appropriate materials for certain applications. The numerous advantages of these natural fibers include cheap cost, flexibility, high strength-to-weight ratios, low densities, high recycling rates, and minimum environmental effect. These have led to their widespread usage throughout the years (Safri et al., 2018). However, selecting suitable processing conditions to enhance the performance of the composites is essential when using natural fibers as reinforcing elements in conjunction with thermoplastics (Kabir et al., 2020; Ngo et al., 2018).

The essential part of the bio-composite manufacturing process is selecting the appropriate natural fiber. The characteristics of the material determine the choice of natural fiber. Natural fiber's effectiveness is heavily dependent on the plant's age. Fibers'

Table 1
*Sources of natural fibers*

| | Group | Fiber | Source |
|---|---|---|---|
| **Natural fibers** | Animal | Hair | Come from hairy mammals and animals |
| | | Avian | Feathers of birds |
| | | Silk | Dried saliva of bugs or insects |
| | Cellulose | Bast | Jute, Flax, Hemp, Ramies, Kenaf, Roselle, Mesta |
| | | Leaf | Sisal, Banana, Abaca, Pina |
| | | Seed | Kapok, Cotton, Luffa. Milkweed |
| | | Fruit | Coir, Oil palm |
| | | Wood | Softwood, Hardwood |
| | | Stalk | Rice, Wheat, Barley, Maize, Oat, Rye |
| | | Grass | Bamboo, Bagasse, Corn, Sabai, Rape, Esparto, Cancry |
| | Mineral | Asbestos cloth | Asbestos |
| | | Glass | Mixed silicates |

*Source:* Gholampour and Ozbakkaloglu (2020) chemical components varied depending on their origin, but cellulose, hemicellulose, and lignin were among the more prevalent ones (Xanthos, 2005). The internal structure of the cellulose fibers is shown in Figure 2. The fiber reinforcement's physical and chemical characteristics significantly impact the final bio-composite material's qualities. The composition of natural fibers is the primary factor in determining their mechanical qualities (especially the non-cellulosic components like hemicellulose, lignin, waxes, and pectin). Removing these non-cellulosic components from the fiber increases the composite material's mechanical strength since the bonding ability of the fiber and matrix is not hindered (Vigneshwaran et al., 2020). Due to their hydrophilicity, most natural fibers have poor bonding properties. These advantages may decrease the bio-mechanical composite's strength (Faruk et al., 2012). Natural fibers offer adequate reinforcements in the composite industry for a variety of applications, including those involving transportation, interior components, buildings, airplanes, and the construction sector (Alsubari et al., 2021; Amir et al., 2021; Asyraf et al., 2020; Hanan et al., 2020).

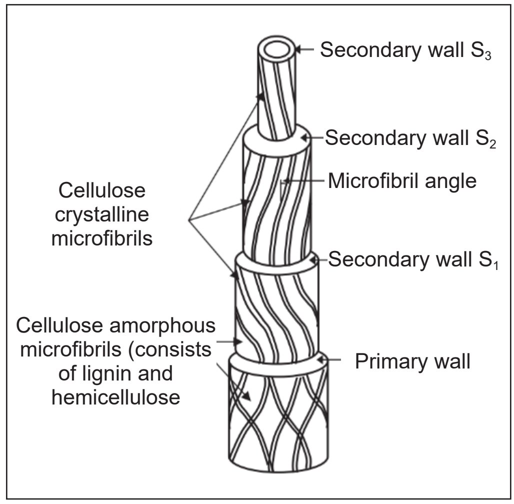


*Figure 2*. Diagrammatic representation of natural fiber composition (Kabir et al., 2012)

Developing eco-friendly FDM-based natural fiber-reinforced polymer bio-composites has drawn much interest from both industries and researchers. Natural fibers have been viewed as crucial components in the creation of a green and sustainable economy because of their low density, high specific strength and modulus, lighter weight, high affinity, and biodegradability in contrast to glass and other synthetic fiber-reinforced composite materials (Bi & Huang, 2022). In addition, they have drawn a lot of rivals and market platforms (Stoof et al., 2017). Le Duigou et al. (2020) claimed that faults (such as porosity and misalignment), mechanical hygro-thermal deterioration, and residual stress are produced during the manufacturing stages of semi-finished goods (filament), which affect the performance characteristics of composite materials. According to research by Šafka et al. (2016), ABS/Coconut bio-composites have a slightly higher modulus of elasticity (+16%) but much lower strength (-50%) and strain (-15%) when compared to a pure matrix. According to Dong et al. (2018), tensile strength decreased by 60%, Charpy impact strength decreased by 55%, and flexural strength decreased by 60%. PLA-based bio-composites tensile modulus, strength, and impact resistance are all impacted by the addition of cork powder (Daver et al., 2018).

A standard extrusion method using fibers and polymer creates the filament for FDM. More attention is being paid to the extrusion parameters used to make filaments. The filaments were hemp fiber, hemp hurds, bamboo fiber and powder, flax fiber, bagasse fiber, cork powder, cocoa shell, coconut fiber, cotton fiber, wood fiber, wood pulp, wood flour, Harakeke fiber, waste macadamia nutshell (Coppola et al., 2018; Depuydt et al., 2019; Liu et al., 2019; Milosevic et al., 2017; Montalvo Navarrete et al., 2018; Pop et al., 2019; Stoof et al., 2017; Stoof & Pickering, 2018; Xiao et al., 2019). According to Mazzanti et al. (2019), manufacturing filament is a crucial step in the FDM process, and defects at this stage (such as porosity) are passed on to the printed parts. Due to that, design engineers have a difficult choice when attempting to optimize the manufacturing process of a particular design by determining which materials to utilize among the many conceivable fiber and matrix combinations (Noryani et al., 2018).

The attributes of the finished composites rely on their components, for which some data are accessible; moreover, composites do not share the same features as metal-based materials. Thus, design engineers need to proceed with care when selecting materials. In addition, we may fine-tune the composites' attributes by modifying the constituent parts' properties. For this reason, material selection is essential to the manufacturing process since it may save high costs incurred during product design testing. The effectiveness of a substance may be evaluated using several different approaches, and it can be affected by a wide range of variables. The design engineer is responsible for deciding which composite material combinations best achieve the intended design goals. As a result, material selection is a crucial stage in the design process, necessitating attention to product specifications, budget, and ecological impact, as AL-Oqla and Salit (2017) stated.

Therefore, this study aims to use the multi-criteria decision-making (MCDM) strategy with the fuzzy analytical network process (FANP) technique to determine which bio-composite filament material would be ideal for the FDM process. These filaments are the most eco-friendly option since they can be used several times, recycled, and thrown away without harm. The FANP study considered their tensile strength, flexural strength, impact strength, and printability to choose which bio-composite filaments to utilize. Using SuperDecisions V3.X, the FANP material selection algorithm is implemented.

## MATERIALS AND METHODS

Material selection is significant in product development, manufacturing, and marketing stages. Nonetheless, the work is time-consuming and requires careful consideration because of several competing criteria. Material selection is often motivated by the need to enhance performance while minimizing costs; however, other variables, such as resistance to failure and reduced weight, may also be powerful motivators (Emovon & Oghenenyerovwho, 2020). If the wrong materials are used, it might be challenging to meet the needs of both consumers and producers. It may also cause an assembly to fail or a product's performance to degrade, harming productivity, profit, and an organization's credibility.

The MCDM technique is one of the most popular to solve the material selection problem. MCDM offers a systematic procedure that considers the decision criteria and the knowledge of the advantages and disadvantages of the decision-makers to assist in selecting the best choice from a group of options. MCDM tools like the analytical hierarchy process (AHP), the analytical network process (ANP), the Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR), the multi-attribute utility theory (MAUT), the Elimination and Choice Expressing the Reality (ELECTRE), the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), and the technique of ranking preferences by the similarity of the ideal solutions (TOPSIS) have all been used for materials research and development (Emovon & Oghenenyerovwho, 2020; Noryani et al., 2018). Using the several criteria for making a choice, each of which can be measured differently, the tools framework ranks the available options. Table 2 provides a comprehensive overview of several well-known MCDM tools, including information on their underlying decision-making principles, inventors, invention dates, advantages and disadvantages.

Table 2
*Comprehensive overview of MCDM*

| MCDM method | Decision-making philosophy | Inventor/ Year | Advantages | Disadvantages |
|---|---|---|---|---|
| AHP | Weighting criteria and options attain optimal results according to importance. Before sorting through possible solutions, the issue is often organized hierarchically. | Thomas Saaty, 1970 | There is no need for a separate instrument to calculate criterion weights. | Adding additional criteria and options makes the method more difficult to implement. |
| ANP | The hierarchical structure of AHP is transformed into a network consisting of components such as criteria, sub-criteria, and alternatives. Feedback and dependency links inside and between clusters connect all network elements. | Thomas Saaty, 1996 | Able to prioritize both dependent and independent needs. The outcomes are dependable and error-tolerant. The outcomes are reliable. | The prioritization process is complex. Tool support is needed to minimize the complexity and time consumption while prioritizing requirements. |
| VIKOR | Finding the best answer by contrasting choices based on how closely they resemble the ideal. | S. Opricovic, 1990 | An improved version of TOPSIS. | Conflicting situations provide challenging opportunities for developing and applying methods. |

Table 2 *(continue)*

| MCDM method | Decision-making philosophy | Inventor/ Year | Advantages | Disadvantages |
|---|---|---|---|---|
| **TOPSIS** | It uses distances between the positive and negative solutions to determine preferable ones. | Hwang and Yoon, 1981 | The process is simple, and the strategy for finding a solution does not change. | The assessment of Euclidean distance does not consider the connection between the criteria. Additionally, vector normalization could be needed to solve multidimensional problems. |
| **PROMETHEE** | It is an outranking strategy for solving decision-making problems considering the divergence of choice concerning decision criteria. | J. P. Brans and P. Vicke, 1982 | Score normalization is unnecessary. | A separate method is required for assessing criteria weight. A preference function must also be defined. |
| **ELECTRE** | Creates a solution by establishing an outranking connection between two possible choices. | Benayoun Roy, 1968 | They can give a solution in the absence of the required information. | The complicated assessment techniques involved make the approach computationally challenging without dedicated software. |

*Source:* Emovon and Oghenenyerovwho, 2020; Kumar et al., 2017

MCDM issues may be solved in several ways, including using the ANP technique. Thomas L. Saaty (1996) created it, using it extensively to solve MCDM issues across several disciplines. It considers a wide range of interactions, relationships, and feedback between higher and lower-level components and makes decisions based on the sometimes-unreliable preferences of humans. Saaty's ANP has two significant flaws, according to Ayağ and Yücekaya (2019): it is only helpful for simple choice situations and generates and manages a very asymmetrical judgment scale. Furthermore, the ANP technique ranks slightly imprecisely since it does not consider the uncertainty in translating one's judgment to a number. However, outcomes are heavily influenced by the decision-makers biased assessment, choices, and preferences. To address this shortcoming, "fuzzy ANP" has been suggested, using ANP pairwise comparisons and fuzzy logic.

In 1965, Zadeh created the first iteration of what would become known as a fuzzy set theory to solve the difficulties associated with the study of "fuzzy phenomena," which include issues of vagueness, ambiguity, and incompleteness (Mohaghar et al., 2012). The FANP approach fits the subjectivity of human judgment as it is conveyed in everyday language. Getting precise conclusions in pairwise comparisons may sometimes be elusive and unpractical (Senvar et al., 2018). Promentilla (2008) argued that acquiring accurate assessments in pairwise comparisons is difficult due to human judgments' complexity, ambiguity, and intrinsic subjectivity. When making a subjective evaluation, spoken judgments are more accessible or natural. Conventional qualification needs to work on explaining circumstances that seem complicated or complex to characterize adequately. Linguistic variables may be employed. Fuzzy-level language measures are shown in Table 3. It is important to note that the membership function of the linguistic scale is set by the three parameters of the symmetric triangular fuzzy number. In his 2011 article, Balmat explained how fuzzy set theory is an extension of classical set theory that helps solve numerous problems involving inaccurate and uncertain data works. Table 4 outlines the advantages and disadvantages of the theory of fuzzy sets.

There are few examples of research using the FANP method for product creation or choice in the existing literature (Zavadskas et al., 2016). Using the manufacturing of lithium-iron phosphate batteries as an example, Chen et al. (2015) combined a FANP method with interpretative structural modeling (ISM) to assess several new product

Table 3
*The linguistic scales with the fuzzy level scale*

| Gradients of language | Degree of significance | Fuzzy triangular scale | Triangle-shaped fuzzy-ratio scale | Details |
|---|---|---|---|---|
| **Equally important/ significant** | 1 | (1, 1, 1) | (1, 1, 1) | Two actions contribute similarly to the goal. |
| **Intermediate** | 2 | (1, 2, 3) | (1/3, 1/2, 1) | |
| **Moderately important/significant** | 3 | (2, 3, 4) | (1/4, 1/3, 1/2) | There is a minor advantage in one activity over another, according to experience and judgment. |
| **Intermediate** | 4 | (3, 4, 5) | (1/5, 1/4, 1/3) | |
| **Strongly important/ significant** | 5 | (4, 5, 6) | (1/6, 1/5, 1/4) | Based on one's knowledge, experience, and judgment, one activity is superior to another. |
| **Intermediate** | 6 | (5, 6, 7) | (1/7, 1/6, 1/5) | |
| **Very strongly important/significant** | 7 | (6, 7, 8) | (1/8, 1/7, 1/6) | Strong preference is shown toward one action over another. |
| **Intermediate** | 8 | (7, 8, 9) | (1/9, 1/8, 1/7) | |
| **Extremely important/ significant** | 9 | (9, 9, 9) | (1/9, 1/9, 1/9) | A fair assumption can be made that one course of action is preferable because of the overwhelming weight of information in its favor. |

Note that on a reciprocal scale, if nonzero values were given into the i activity above, compare it to activity j, and the j would have the typical value.
*Source:* Bathaei et al. (2019); Senvar et al. (2018)

Table 4
*Advantages and disadvantages of fuzzy set theory*

| Advantages | Disadvantages |
|---|---|
| Fuzzy logic considers uncertainty and the development of current understanding. | Creating a reliable fuzzy system is not always straightforward. |
| Fuzzy logic allows imprecise input. | It needs to be tested in a virtual environment before being employed in the real world. |
| Fuzzy logic permits a small number of rules to cover a wide range of complexity. | |

*Source*: Velasquez and Hester (2013); Balmat (2011)

development approaches. Based on a FANP assessment technique, Senvar et al. (2018) provided a strategy for choosing the best renewable energy investment project. Ayağ and Yücekaya (2019) suggested using the FANP and the grey relational analysis (GRA), two of the most used MCDM approaches, to assess various ERP software options. Many studies have recently focused on integrating QFD with MCDM and fuzzy logic. To establish essential technical qualities that would improve the quality of a suggested wheelchair, Mistarihi et al. (2020) combined the QFD model with the FANP technique.

The significance of the FANP method is shown by using two real-world examples involving the selection of materials for turbine blades, and the rankings of the available materials are provided. The first scenario involves evaluating the best material for a wind turbine blade out of five possibilities (steel, aluminum, e-glass, carbon, and aramid) based on five characteristics (stiffness, tensile strength, density, elongation at break, and minimum temperature) (Babu et al., 2006). In contrast, Thakker et al. (2008) evaluated the properties of eight materials: titanium alloy, nickel alloy, aluminum alloy, glass fiber-reinforced plastics, silicon nitride, copper alloy, stainless steel, and carbide across four dimensions to identify the optimal material for a wave energy turbine blade. Another case in point is the recommendation of FANP to choose the optimal material for a super-critical boiler by Maity and Chakraborty (2012a), who emphasized the need to consider the interplay and interdependencies of the many variables involved in this process.

Several published works have attempted to include the FANP method in the product development/selection process; however, customer needs-to-engineering characteristics mapping has yet to be made, and a single criteria decision-making strategy has always been used. The primary contribution of this work is that it is the first to apply the FANP method to pick bio-composite materials, specifically FDM filaments. SuperDecision V3.X's algorithm was used to determine the weighted average of each pairwise comparison matrix.

Data collection is crucial to every research project since it yields information. The information provided should be as thorough as possible to provide accurate results. The data on the criteria and sub-criteria were all gathered from reliable sources as a result. The methodology steps are shown in Figure 3. The following phases were involved in implementing the suggested FANP model. The first phase was to specify the primary objective and available alternatives for choosing the best bio-composite material for filaments that comply with the FDM process specifications. The information chose the possibilities for bio-composite filament materials from previous studies that were readily available. After that, the mechanical properties analysis from several technical references was used to establish the FANP model's criteria. Natural fiber is crucial in producing bio-composite filaments with improved mechanical qualities, including tensile strength, flexural strength, impact strength, toughness, durability, and hardness (Rajendran Royan et al., 2021).

The second phase was choosing the essential material selection criterion. To do this, a questionnaire that included the material's primary selection criteria was created and distributed to experts. The critical criteria were categorized based on the findings of the first phase, and the experts suggested the final criteria for the second session. Experts then organized the last criteria, connections, and interdependencies between the elements for use in the FANP model. The FANP model was created in three phases (Figure 4).

Professor Saaty made the first proposal for the ANP in 1996. For ANP to be able to study systems with impact and feedback, the concepts of indirect priority and supermatrix

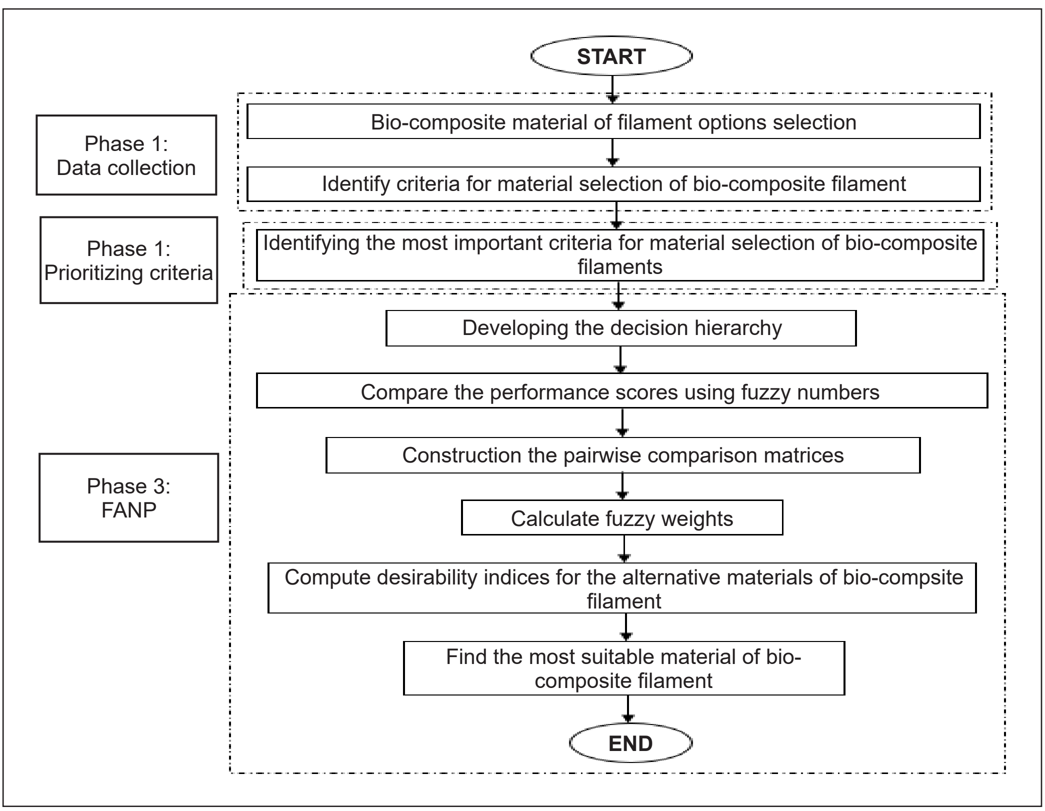


*Figure 3*. The fundamental structure of the best-suggested model of a bio-composite filament for use in material selection

are brought into play (Maity & Chakraborty, 2012b). There are two layers in an ANP network: control and network. Goals and independent principles, or only one objective, are included in the control layer. Groups of objects that communicate with one another make up the network layer.

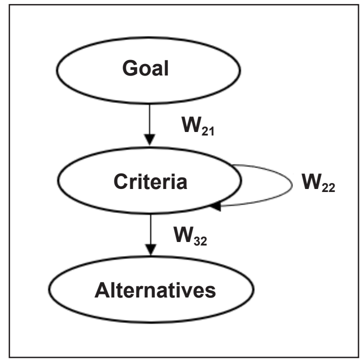


*Figure 4*. The proposed FANP model

The FANP expands upon the conventional approach suggested in this study. How the comparison matrix is constructed and solved is the primary distinction between FANP and ANP. The enhanced technique generates the linguistic variable-fuzzy number table as the basis for the fuzzy comparison matrix. The fuzzy preference programming (FPP) algorithm calculates the weight vector using the suggested FANP approach. Following are the steps that can be utilized to analyze the predicted performance of various kinds of bio-composite filaments using the FANP method:

### Step 1: Creating the Fuzzy Comparison Matrix

It was assumed that there was only one target *G* in the control layer and that there were *N* element groups ($C_1$, $C_2$, …, $C_N$) in the network layer. Experts, *k* were asked to evaluate the relative effects of elements $SC_{i1}$, $SC_{i2}$, …, $SC_{in}$ in group $C_i$ ($i$ = 1, 2, …, N) on elements $SC_{jl}$ ($l$ = 1, …, $n_j$), with $SC_{jl}$ as the primary criterion and target *G* as the secondary criterion. From what the *k* experts said, a fuzzy judgment matrix was made. Each element was first shown as a linguistic variable. Then, the formula in Table 3 turned it into a triangular fuzzy number. The fuzzy comparison matrix then looked like what is shown in Table 5.

Table 5
*Fuzzy comparison matrix*

| $SC_{jl}$ | $SC_{i1}$ | $SC_{i2}$ | … | $SC_{in\mathrm{i}}$ |
|---|---|---|---|---|
| $SC_{i1}$ | $e_{i11}$ | $e_{i12}$ | … | $e_{i1n}$ |
| $SC_{i2}$ | $e_{i21}$ | $e_{i12}$ | … | $e_{i2n}$ |
| . | | | . | . |
| . | | | . | . |
| . | | | . | . |
| $SC_{in\mathrm{i}}$ | $e_{in1}$ | $e_{in2}$ | … | $e_{inn}$ |

*Source:* Pang et al. (2021)

### Step 2: Calculate the Comparative Synthetic Matrix

Expert opinions were put together in this work using an average geometric method. This medium eliminated the effect of combining opinions on the reliability of the comparison matrix. In $C_i$ ($i$ = 1, 2, …, N), the elements $SC_{iu}$ and $SC_{iv}$ were compared, and the results were shown as ($l_{iuv}$, $m_{iuv}$, $u_{iuv}$). Using the fuzzy number's lower limit, $l_{iuv}$, as an example, below is the formula for determining $l_{iuv}$ (Equation 1):

$$l_{\mathrm{iuv}} = (\overset{(1)}{l_{\mathrm{iuv}}}\, x\, \overset{(2)}{l_{\mathrm{iuv}}}\, x \ldots x\, \overset{(k)}{l_{\mathrm{iuv}}})^{1/k} l_{\mathrm{iuv}} = (l_{\mathrm{iuv}}\, x\, l_{\mathrm{iuv}}\, x \ldots x\, l_{\mathrm{iuv}})^{1/k} \quad [1]$$

**Step 3: Compute the Weight Vector Using the FPP Technique**

The weight of elements $SC_{iu}$ and $SC_{iv}$ were denoted by $w_u$ and $w_v$, respectively. Equation 2 determines the membership degree of ($w_u$ / $w_v$), and $s_{iuv}$ stands for the unity between the solution weight and expert opinion.

$$s_{\mathrm{iuv}}\left(\frac{w_{\mathrm{u}}}{w_{\mathrm{v}}}\right) = \begin{cases} \dfrac{(w_{\mathrm{u}}/w_{\mathrm{v}}) - l_{\mathrm{iuv}}}{m_{\mathrm{iuv}} - l_{\mathrm{iuv}}}, & \dfrac{w_{\mathrm{u}}}{w_{\mathrm{v}}} \le m_{\mathrm{iuv}} \\ \dfrac{u_{\mathrm{iuv}} - (w_{\mathrm{u}}/w_{\mathrm{v}})}{u_{\mathrm{iuv}} - m_{\mathrm{iuv}}}, & \dfrac{w_{\mathrm{u}}}{w_{\mathrm{v}}} \ge m_{\mathrm{iuv}} \end{cases} s_{\mathrm{iuv}}\left(\frac{w_{\mathrm{u}}}{w_{\mathrm{v}}}\right) = \begin{cases} \dfrac{(w_{\mathrm{u}}/w_{\mathrm{v}}) - l_{\mathrm{iuv}}}{m_{\mathrm{iuv}} - l_{\mathrm{iuv}}}, & \dfrac{w_{\mathrm{u}}}{w_{\mathrm{v}}} \le m_{\mathrm{iuv}} \\ \dfrac{u_{\mathrm{iuv}} - (w_{\mathrm{u}}/w_{\mathrm{v}})}{u_{\mathrm{iuv}} - m_{\mathrm{iuv}}}, & \dfrac{w_{\mathrm{u}}}{w_{\mathrm{v}}} \ge m_{\mathrm{iuv}} \end{cases} \quad [2]$$

**Step 4: Create the Unweight Supermatrix**

The weight vector $(w_{\mathrm{i1}}{}^{(jl)}, w_{\mathrm{i2}}{}^{(jl)}, \ldots, w_{\mathrm{ini}}{}^{(jl)})^{\mathrm{T}} w_{\mathrm{i1}}{}^{(jl)}, w_{\mathrm{i2}}{}^{(jl)}, \ldots, w_{\mathrm{ini}}{}^{(jl)})^{\mathrm{T}}$ of the judgment matrix was constructed. In this case, the column vector denoted the weight vector of the impacts of components $SC_{jl}$ ($l$ = 1, …, $n_j$) in $C_i$ on elements $SC_{i1}$, $SC_{i2}$, …, $SC_{ini}$. They observed that the submatrix $W_{ij}$ was computed using Equation 3.

$$W_{\mathrm{ij}} = \begin{bmatrix} w_{\mathrm{i1}}{}^{(j1)} & w_{\mathrm{i1}}{}^{(j2)} & \cdots & w_{\mathrm{i1}}{}^{(jn_{\mathrm{j}})} \\ w_{\mathrm{i2}}{}^{(j1)} & w_{\mathrm{i2}}{}^{(j2)} & \ldots & w_{\mathrm{i2}}{}^{(jn_{\mathrm{j}})} \\ \vdots & \ldots & \ddots & \vdots \\ w_{\mathrm{ini}}{}^{(j1)} & w_{\mathrm{ini}}{}^{(j2)} & \cdots & w_{\mathrm{ini}}{}^{(jn_{\mathrm{j}})} \end{bmatrix} W_{\mathrm{ij}} = \begin{bmatrix} w_{\mathrm{i1}}{}^{(j1)} & w_{\mathrm{i1}}{}^{(j2)} & \cdots & w_{\mathrm{i1}}{}^{(jn_{\mathrm{j}})} \\ w_{\mathrm{i2}}{}^{(j1)} & w_{\mathrm{i2}}{}^{(j2)} & \ldots & w_{\mathrm{i2}}{}^{(jn_{\mathrm{j}})} \\ \vdots & \ldots & \ddots & \vdots \\ w_{\mathrm{ini}}{}^{(j1)} & w_{\mathrm{ini}}{}^{(j2)} & \cdots & w_{\mathrm{ini}}{}^{(jn_{\mathrm{j}})} \end{bmatrix} \quad [3]$$

$W_{ij}$ = 0 if the elements in $C_i$ did not affect $C_j$. The following formula was the unweighted supermatrix, W, made up of the sub-matrix (Equation 4):

$$W = \begin{array}{c c} & \begin{array}{cccc} 1 \ldots. n_1 & 1 \ldots. n_2 & \ldots. & 1 \ldots. n_N \end{array} \\ \begin{array}{c} 1 \ldots. n_1 \\ 1 \ldots. n_2 \\ \cdots \\ 1 \ldots. n_N \end{array} & \begin{bmatrix} W_{11} & W_{12} & \ldots & W_{1\mathrm{N}} \\ W_{21} & W_{22} & \ldots & W_{2\mathrm{N}} \\ \vdots & \cdots & \ddots & \vdots \\ W_{\mathrm{N}1} & W_{\mathrm{N}2} & \ldots & W_{\mathrm{NN}} \end{bmatrix} \end{array} \quad (4)$$

**Step 5: Create the Weighted Supermatrix $\overline{WW}$ and Determine the Weighing Matrix A**

$W$ still has to be column normalized even if the sub-matrix $W_{ij}$ had already been done. On element group $C_j$ ($j$ = 1, 2, …, N), the influence degree of element group $C_i$ ($i$ = 1, 2, …, N) was compared. A fuzzy comparison matrix was created using target G as the criteria and element group $C_j$ (j = 1, 2, …, N) as the sub-criterion. The FPP method created the weight vector for the judgment matrix $(a_1^{(j)}, a_2^{(j)}, \dots, a_N^{j})^{\mathrm{T}}\ (j = 1, 2, \dots, N).a_1^{(j)}, a_2^{(j)}, \dots, a_N^{j})^{\mathrm{T}}\ (j = 1, 2, \dots, N)$. The weight of the element group $C_i$ ($i$ = 1, 2, …, N) impact on element group $C_j$ ($j$ = 1, 2, …, N) was shown in this case by the column vector. A computation was conducted, which is noteworthy (Equation 5), to generate the weighting matrix.

$$A = \begin{array}{c} C_1 \\ C_2 \\ \cdots \\ C_N \end{array} \begin{bmatrix} a_1^{(1)} & a_1^{(2)} & \cdots & a_1^{(N)} \\ a_2^{(1)} & a_2^{(2)} & \cdots & a_2^{(N)} \\ \vdots & \cdots & \ddots & \vdots \\ a_N^{(1)} & a_N^{(2)} & \cdots & a_N^{(N)} \end{bmatrix} \tag{5}$$

**Step 6: Compute the Super-weighted Matrix, $\overline{\boldsymbol{W}} = (\boldsymbol{a}_{\boldsymbol{i}}^{(\boldsymbol{j})}\boldsymbol{W}_{\mathrm{ij}}).\overline{\boldsymbol{W}}\boldsymbol{a}_{\boldsymbol{i}}^{(\boldsymbol{j})}\boldsymbol{W}_{\mathrm{ij}})$**

**Step 7: Determine the Limit Supermatrix**

Assuming there were $T$ indications at the network layer, a one-step priority ordering can be represented by the element $w_{pq}$ in $\overline{W}$,$w_{pq}\,\overline{W}$, which indicated the degree to which indicator $p$ ($p$ = 1, 2, …, $T$) influenced indicator $q$ ($q$ = 1, 2, …, $T$). Another way to determine $p$'s influence on $q$ is using the two-step priority formula $\sum_{k=1}^{T} w_{pk}\, w_{kq}, \sum_{k=1}^{T} w_{pk}\, w_{kq}$, where $p$ and $q$ are vectors. If there is a limit matrix $\overline{W}^{\infty} = \lim_{t\to\infty} \overline{W}^{t}, \overline{W}^{\infty} \lim_{t\to\infty} \overline{W}^{t}$, then the column vector in $\overline{W}^{\infty}\overline{W}^{\infty}$ is the weight vector of all indicators in the network layer aiming for $G$.

**Step 8: Compute the Total Worth Assessment**

Experts were polled to rate potential unit schemes in terms of T indicators using this method. The final assessment value was calculated by multiplying the weight vector by the experts' ratings.

Sensitivity analysis has been increasingly prevalent in engineering and research, as it is considered an essential procedure for evaluating the feasibility of a model or approach (Ionescu-Bujor & Cacuci, 2004). Conducting a sensitivity analysis of the FANP approach is crucial to ascertain the stability of the derived order of preference. According to Saltelli et al. (2005), sensitivity determines the extent to which a certain model, whether numerical or otherwise, is influenced by its input factors. Li et al. (2013) conducted a sensitivity analysis on the criteria weights for the TOPSIS technique used to evaluate water quality. Their findings suggest that the TOPSIS approach is suitable for this purpose, as it demonstrates sensitivity to changes in the criteria weights. The stability of the derived order of preference for this study was assessed using a similar technique, with a little adjustment in the criteria weights. The weights assigned to the criterion were manipulated to evaluate the sensitivity of the FANP analysis. In this context, a perturbation is defined as introducing a disturbance of the criteria weights $\omega_k$, where k ranges from 1 to $n$. The perturbed criteria weights are denoted as $\acute{\omega}_k$. The relationship between $\omega_k$ and $\acute{\omega}_k$ is formally expressed as the unitary ratio $\beta_k$. This study employed seven variations of the $\beta_k$ method, with $\beta_k$ values of 0.01, 0.02, 0.05, 0.1, 0.2, 0.5, and 1.0. Following the adjustment of weights resulting from adopting $\beta_k$, a reevaluation of performance scores and rankings was conducted, allowing for a comparative analysis. The criteria weights were systematically manipulated over time, resulting in disruptions. Subsequently, the resulting variations in rankings were examined for each case.

## RESULTS AND DISCUSSION

Fabricating bio-composite filament entails adding reinforcement and matrix ingredients to a printed filament. Here, the matrix material will be one of the 3D printed polymeric materials, such as PLA, ABS, and nylon, and the reinforcing material may be continuous or discontinuous fibers. While the matrix shields the reinforcing material from toxic environments like abrasion, the reinforcement provides filament strength and stiffness. According to Matsuzaki et al. (2016), the choice of matrix and reinforcing materials should be made in a manner that both are compatible in terms of physical adhesion, chemical inertness, and comparable thermal expansion coefficients. Because there are so many different materials, choosing the ideal one requires the design engineers to spend significant time and money. As a result, FANP may be regarded as the most practical method to tackle this issue since it can handle the interactions and interdependencies between the selection criteria under consideration. Therefore, the relevant decision matrix in Table 6 was created to apply the FANP technique to this bio-composite filaments material selection issue and demonstrate its viability.

Table 6
*Decision matrix for bio-composite filaments material selection problem*

| SI No. | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| **A1** | 20.9 | 36.5 | 12586.6 | 760 |
| **A2** | 19.2 | 39.2 | 12291.3 | 840 |
| **A3** | 20.7 | 42.4 | 6568.4 | 800 |
| **B1** | 37.9 | 68.2 | 10084.8 | 760 |
| **B2** | 27.8 | 39.5 | 4913.4 | 840 |
| **B3** | 33.9 | 49.7 | 11485.9 | 988 |
| **C1** | 20.6 | 14.4 | 31293 | 852 |
| **C2** | 16.4 | 12.1 | 25963.2 | 918 |
| **D1** | 21.5 | 18.2 | 30852.9 | 852 |
| **D2** | 20.4 | 16.7 | 31683 | 918 |

This selection matrix includes ten bio-composite filaments and four main selection criteria. The values of all criteria in Table 6 are derived from data acquired from conducted assessments. Table 7 lists the specifics of these four selection criteria.

Table 7
*Criteria for bio-composite filaments material selection*

| Properties of bio-composite filament materials | Symbol |
|---|---|
| Tensile strength, MPa | C1 |
| Flexural strength, MPa | C2 |
| Impact strength, kJ/m² | C3 |
| Printability, mm | C4 |

The interfacial adhesion between the resin and fibers profoundly influences the tensile characteristics of bio-composites. Both physical and chemical modifications of the fiber and resin can improve the tensile characteristics of composites. The tensile characteristics of bio-composites are susceptible to the fiber volume fraction in the matrix resin (Gholampour & Ozbakkaloglu, 2020). When the volume percentage of the fibers is increased below the optimal amount, the load is distributed to more fibers. The matrix can support the applied stress even after the fibers have fractured. The tensile characteristics of composites typically increase with increasing fiber volume percentage. However, some studies have indicated otherwise. This fiber volume fraction can increase the composite's tensile strength (Ku et al., 2011). One of the most critical measures of a composite's durability is its flexural stiffness, which indicates how well it can withstand deformation when bent (Faruk et al., 2012). The composite material's modulus and moment of inertia are significant in determining its flexural characteristics. Optimal fiber composition in bio-composites has the potential to increase their flexural strength. Defects in the wetting of fibers may cause stress concentration areas in composites, which reduces the flexural strength as the fiber content grows further. Composites' flexural modulus also improves as their fiber content rises.

Bio-composites' behavior is very sensitive to the degree of bonding between the matrix and fiber. Bio-composites rely heavily on this characteristic during their useful lives. Techniques of modification can be used to enhance the impact characteristics of bio-composites. Bumps, collisions, and falling items or debris may all contribute to impact loading. Compatibility of bonding, fiber pull-out, energy absorption, and adhesiveness are all factors that affect the impact resistance of composites. The quality of an FDM print job depends on the filaments' feedability or how easily they can be fed into the printing head and melted there (Nasereddin et al., 2018). The filament in FDM printers is fed by being pushed between two counter-rotating gears. The printing head may jam if the filament is too fragile to resist the mechanical stress of compression and pressing. It will wrap as it is moved forward, reblocking the head if it is too pliable.

Alternative bio-composite filament materials are listed in detail in Table 8. Powdered kenaf (*Hibiscus cannabinus*) fibers and ABS pellets made from 100 % pure ABS were provided. Han et al. (2022) employed kenaf fibers with a mean length of 120 μm. The 1.75 mm diameter filament was produced by compounding kenaf fiber and ABS pellets in an HTGD-20 twin screw extruder. Different kenaf fiber-reinforced ABS (KRABS) composite volume percentages were used: 0%, 2.5%, 5%, 7.5%, and 10%.

The sugar palm fiber (*Arenga Pinnata*) was sourced from Jempol, Negeri Sembilan's rainforests on the western peninsular of Malaysia (Nasir et al., 2022). Sugar palm plants were used to create SPF after being cut into 1/3-centimeter pieces; the long fiber was washed under running water to remove leftover dirt and filth. Polylactic acid (PLA) was employed as the polymer matrix with a 1.24 g/cm$^3$ density. Pellets of Ingeo™ Biopolymer

2003D (pure, 100% PLA), Acetic acid (glacial), methanol, sodium hydroxide pellets for EMSURE® analysis and 3-Aminopropyl triethoxysilane were provided. Lab Tab Engineering Company Ltd., located in Muang, Samutprakarn, Thailand, supplied the twin screw extruder used for the extrusion process, which rotated at 70 rpm and included 26 mm twin screws with a 40:1 L/D. A sugar palm fiber/PLA (SPF/PLA) composite sample was fed into the barrel of a twin-screw extruder. Before entering the twin screw, the mixing mechanism thoroughly combined the SPF particles and PLA pellets, which were transported to the melting chamber and extruded via a die.

There is potential for recycling and reusing wood fibers, with industry sectors like woodworking and papermaking being the sources. Pine grove and tongue wood are the primary types of scrap wood generated by SME furniture factories (Nahfis et al., 2022; Azali et al., 2022). Plastic manufacturing tiny 2 mm pellets were purchased as a source of recycled PP polymer that was separated into three fiber loadings of 1%, 3%, and 5% for wood dust and sized between 1.5–1.75 mm. Recycled wood PP polymer (r-WoPPC) was produced utilizing a LABTECH twin screw extruder, resulting in composites of covalently linked fiber with polymers in filament form suitable for FDM commercial use. Coir, or coconut fiber, is a natural fiber extracted from coconut husk and processed into bales after washing.

The fibrous husk (mesocarp) of the coconut (*Cocos Nucifera*) on the coconut palm, which is a member of the palm family (Palme), is processed to produce coconut fiber, which is classified as a fiber/fibrous substance (Reddy, 2013). The number 5 in the resin identification code indicates that polypropylene can be recycled ( Ariffadzilah et al., 2022). The matrix and fibers work together to produce a biodegradable material that is both ecologically friendly and recyclable; this filament is made from polypropylene reinforced with coconut fiber. The coconut husk was selected because it is readily available and has desirable fiber characteristics, as determined by surveys of the local populace in Malaysia.

For use in the FANP model, a complete set of criteria was established, together with their interconnections and dependencies. The finalized FANP model consisted of three distinct components (Figure 5). The remaining dependencies in the model between the control criteria and the hierarchy network between the four fundamental criteria and the alternatives are shown in Figure 6.

The decision matrix from Table 6 was transformed into the fuzzy decision matrix from Table 9 using the triangular fuzzy

Table 8
*Bio-composite filament materials*

| Fiber | Polymer | Fiber loading (%) | Symbol |
|---|---|---|---|
| **Kenaf** | ABS | 2.5 | A1 |
| | | 5 | A2 |
| | | 7.5 | A3 |
| **Sugar palm** | PLA | 2.5 | B1 |
| | | 5 | B2 |
| | | 7.5 | B3 |
| **Wood dust** | r-PP | 3 | C1 |
| | | 5 | C2 |
| **Coconut husk** | PP | 3 | D1 |
| | | 5 | D2 |

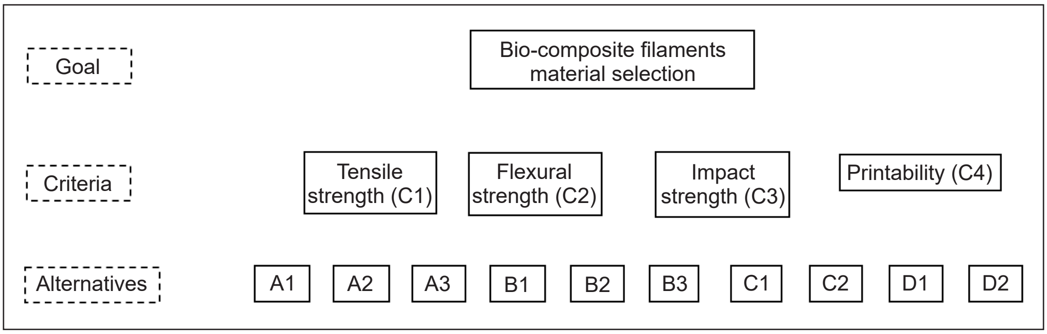


*Figure 5*. FANP model

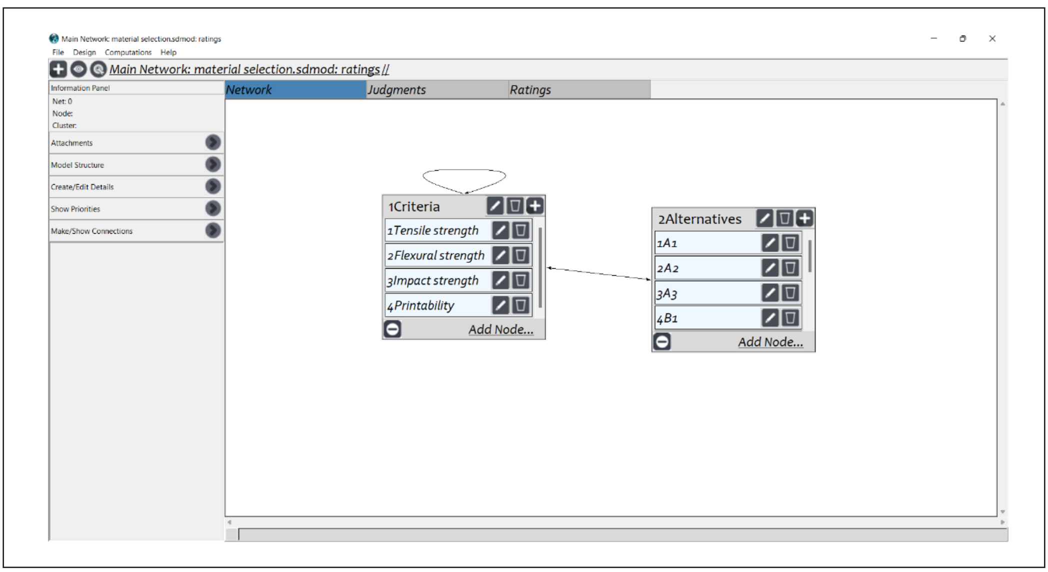


*Figure 6*. Network structure of the bio-composite filament material selection problem

Table 9
*Fuzzy decision matrix for bio-composite filament material selection problem*

| SI. No. | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| **A1** | (15.3, 20.9, 24.6) | (29.1, 36.5, 47.4) | (6099.4, 12586.6, 18816) | (600, 760, 1000) |
| **A2** | (11.6, 19.2, 26.4) | (25.8, 39.2, 46.8) | (8219.9, 12291.3, 20697.8) | (600, 840, 1000) |
| **A3** | (18.2, 20.7, 21.7) | (36.2, 42.4, 46.3) | (4819.4, 6568.6, 7964.3) | (600, 800, 1000) |
| **B1** | (28.2, 37.9, 43) | (60.9, 68.2, 82.6) | (7432.9, 10084.8, 13517.4) | (600, 760, 1000) |
| **B2** | (14.9, 27.8, 37) | (29.8, 39.5, 51.4) | (2354.4, 4913.4, 8135.4) | (600, 840, 1000) |
| **B3** | (23.7, 33.9, 61.2) | (27.6, 49.7, 63.8) | (9128.4, 11485.9, 15300) | (960, 988, 1000) |
| **C1** | (19.4, 20.6, 22.4) | (5.3, 14.4, 18.7) | (8108.1, 31293, 89172.4) | (750, 852, 970) |
| **C2** | (13.7, 16.4, 17.3) | (2.4, 12.1, 23.1) | (12483.9, 25963.2, 40092.5) | (800, 918, 1000) |
| **D1** | (18, 21.5, 25.8) | (13.3, 18.2, 25.8) | (18984.4, 30852.9, 43386.4) | (750, 852, 970) |
| **D2** | (17.1, 20.4, 24) | (15.1, 16.7, 20) | (3004.6, 31683, 46133.3) | (800, 918, 1000) |

membership function to solve the bio-composite filament material selection issue via the FANP approach. Priority vectors were created by constructing a pairwise comparison matrix for the selection criteria under consideration, as illustrated in Table 10. There was a clear hierarchy of material properties, with impact strength and printability of the potential material coming in first, then flexural strength.

After this, four pairwise comparison matrices of criteria were built to consider the interdependency connection between the four selection criteria (Figures 7, 8, 9 and 10). It is necessary to use the priority vectors of the pairwise comparison matrices for various criteria to create the supermatrix, highlighting the significance of the other criteria.

Table 10
*Various criteria pairwise comparison matrix*

| Criteria | C1 | C2 | C3 | C4 | Priority vector |
|---|---|---|---|---|---|
| **C1** | (1, 1, 1) | (1/3, 1/2, 1) | (1/4, 1/3, 1/2) | (1/4, 1/3, 1/2) | 0.106 |
| **C2** | (1, 2, 3) | (1, 1, 1) | (1/4, 1/3, 1/2) | (1/4, 1/3, 1/2) | 0.151 |
| **C3** | (2, 3,4) | (2, 3, 4) | (1, 1, 1) | (1, 1, 1) | 0.371 |
| **C4** | (2, 3, 4) | (2, 3, 4) | (1, 1, 1) | (1, 1, 1) | 0.371 |

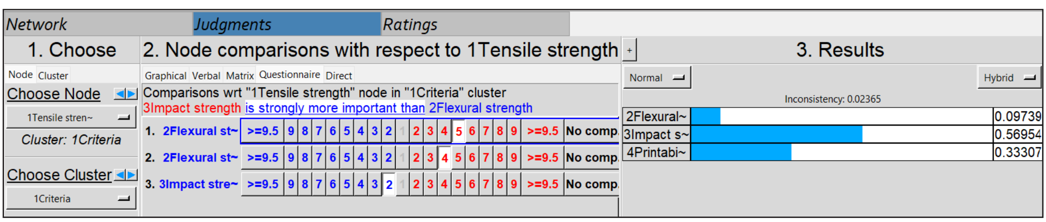


*Figure 7*. Comparison matrix for 'tensile strength' that compares several criteria in terms of their pairwise similarities and differences

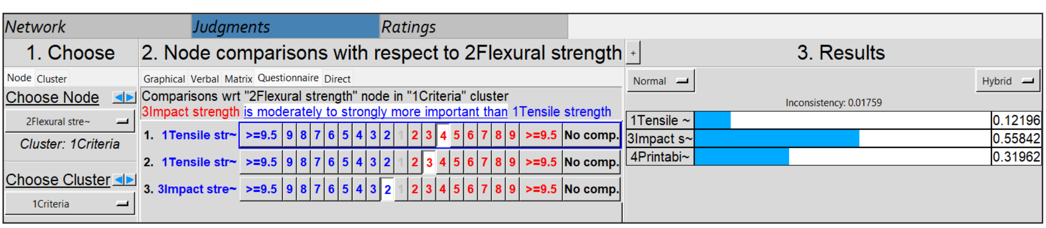


*Figure 8*. Matrix of pairwise comparisons based on several measures of 'flexural strength'

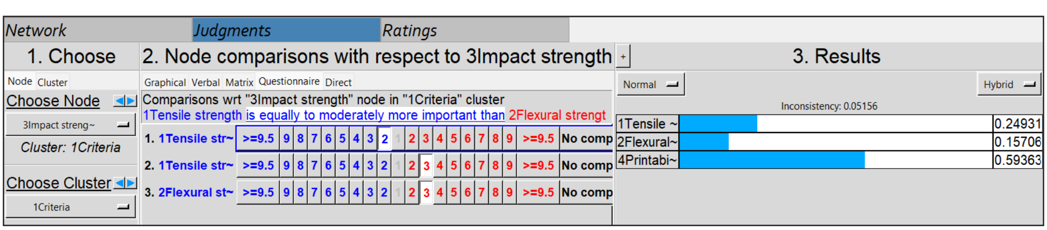


*Figure 9*. Impact strength comparison matrix with any criteria

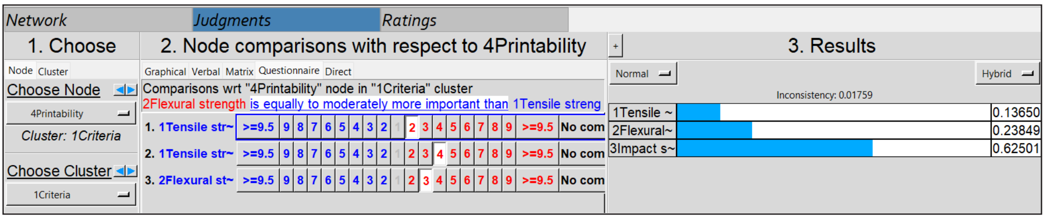


*Figure 10*. Various printability measures are compared in a pairwise matrix

Pairwise comparison matrices were built for the materials under consideration to determine the nature of the interdependency between the alternatives, with each matrix displaying the relevance of a particular criterion. In this step, the unweighted supermatrix was figured out when all comparisons and weighting produced were completed (Table 11).

Before determining the limit, the unweighted supermatrix should be reduced to a matrix with each column sum equalling unity. This matrix is then referred to as a stochastic column matrix. The normalized or weighted supermatrix was made by multiplying stochastic matrices several times in a row until the column in each block settles and becomes the same (Table 12).

A limited supermatrix is made by multiplying each block until the columns are stable and identical. It is necessary to normalize them to keep the unweighted supermatrix's columns' randomness. Then, the overall priorities can be decided by setting the normalized supermatrix to a limiting power. Each element in a row was ranked according to significance by the value that defined it. It was found that the selection issue was affected by the best option that met the greatest priority overall, which was also the selection criteria with the highest priority overall. The limited supermatrix would be obtained using the normalized supermatrix's 19$^{th}$ power. The limited supermatrix can be seen in Table 13.

The supermatrix is boosted to a high enough power until convergence occurs. The supermatrix was then increased to limit power to be $W^{2n+1}W^{2n+1}$, yielding a steady-state outcome, with *n* being an arbitrarily huge number that included all interactions. The next step was to choose the choice with the highest overall relevance. The absolute priority for alternatives was presented, and the alternative with the most significant value was selected as the best alternative to normalizing every column in the restricted supermatrix. Table 14 normalized values of the alternatives demonstrated that SPF/PLA 7.5 wt.% with 19.80% importance was the best material for bio-composite filaments in the FDM process. In other words, SPF/PLA 7.5 wt.% with 20% importance was chosen as the best bio-composite filament material of FDM for the egg carton packaging project after the FANP method was used for the issue under consideration. The sequence of the criteria according to the priority is shown in Figure 11.

Table 11
*The unweighted supermatrix*

| Clusters | Nodes | C1 | C2 | C3 | C4 | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criteria** | C1 | 0 | 0.122 | 0.2493 | 0.1365 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 |
| | C2 | 0.0974 | 0 | 0.1571 | 0.2385 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 |
| | C3 | 0.5695 | 0.5584 | 0 | 0.625 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | | 0.305 |
| | C4 | 0.3331 | 0.3196 | 0.5936 | 0 | 0.2469 | 0.2469 | 0.2469 | 0.2469 | 0.2469 | 0.2469 | 0.2469 | 0.2469 | 0.2469 | 0.2469 |
| **Alternatives** | A1 | 0.0741 | 0.0785 | 0.0579 | 0.0174 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | A2 | 0.0376 | 0.0923 | 0.0596 | 0.0524 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | A3 | 0.0614 | 0.1039 | 0.0248 | 0.0274 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | B1 | 0.2499 | 0.3847 | 0.0407 | 0.0174 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | B2 | 0.1358 | 0.0923 | 0.0178 | 0.0524 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | B3 | 0.2295 | 0.1624 | 0.0358 | 0.3775 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C1 | 0.0523 | 0.0213 | 0.2218 | 0.059 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0.0263 | 0.0193 | 0.1341 | 0.1687 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | D1 | 0.0864 | 0.0238 | 0.2037 | 0.059 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | D2 | 0.0469 | 0.0217 | 0.2037 | 0.1688 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 12
*The weighted supermatrix*

| Clusters | Nodes | C1 | C2 | C3 | C4 | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criteria** | C1 | 0 | 0.061 | 0.1274 | 0.0683 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 |
| | C2 | 0.0487 | 0 | 0.0785 | 0.1192 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 | 0.1131 |
| | C3 | 0.2848 | 0.2792 | 0 | 0.3125 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 | 0.305 |
| | C4 | 0.1665 | 0.1598 | 0.2968 | 0 | 0.2769 | 0.2769 | 0.2769 | 0.2769 | 0.2769 | 0.2769 | 0.2769 | 0.2769 | 0.2769 | 0.2769 |
| **Alternatives** | A1 | 0.037 | 0.0392 | 0.0289 | 0.0087 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | A2 | 0.0188 | 0.0461 | 0.0298 | 0.0262 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | A3 | 0.0307 | 0.052 | 0.0124 | 0.0137 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | B1 | 0.1249 | 0.1923 | 0.0204 | 0.0087 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | B2 | 0.0679 | 0.0461 | 0.0089 | 0.0262 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 12 *(continue)*

| Clusters | Nodes | C1 | C2 | C3 | C4 | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | B3 | 0.1147 | 0.0812 | 0.0179 | 0.1887 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C1 | 0.0262 | 0.0106 | 0.1109 | 0.0295 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0.0131 | 0.0096 | 0.067 | 0.0844 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | D1 | 0.0432 | 0.0119 | 0.1019 | 0.0295 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | D2 | 0.0234 | 0.0108 | 0.1019 | 0.0844 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 13
*The limit supermatrix*

| Clusters | Nodes | C1 | C2 | C3 | C4 | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criteria** | C1 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 | 0.1494 |
| | C2 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 | 0.0869 |
| | C3 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 | 0.2308 |
| | C4 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 | 0.1996 |
| **Alternatives** | A1 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 | 0.0174 |
| | A2 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 | 0.0189 |
| | A3 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 | 0.0147 |
| | B1 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 | 0.0418 |
| | B2 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 | 0.0214 |
| | B3 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 |
| | C1 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 | 0.0363 |
| | C2 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 | 0.0351 |
| | D1 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 | 0.0369 |
| | D2 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 | 0.0448 |

Table 14
*The final outcomes*

| Alternatives | Ideals | Limited values | Real values | Ranking |
|---|---|---|---|---|
| **A1** | 0.263090 | 0.017362 | 0.052086 (5.2%) | 9 |
| **A2** | 0.286758 | 0.018924 | 0.056772 (5.7%) | 8 |
| **A3** | 0.222665 | 0.014694 | 0.044083 (4.4%) | 10 |
| **B1** | 0.633646 | 0.041816 | 0.125448 (12.5%) | 3 |
| **B2** | 0.324771 | 0.021433 | 0.064298 (6.4%) | 7 |
| **B3** | 1.00000 | 0.065993 | 0.197978 (19.80%) | 1 |
| **C1** | 0.550412 | 0.036323 | 0.108970 (10.9%) | 5 |
| **C2** | 0.532019 | 0.035109 | 0.105328 (10.5 %) | 6 |
| **D1** | 0.558969 | 0.036888 | 0.110664 (11.1%) | 4 |
| **D2** | 0.678726 | 0.044791 | 0.134373 (13.4%) | 2 |

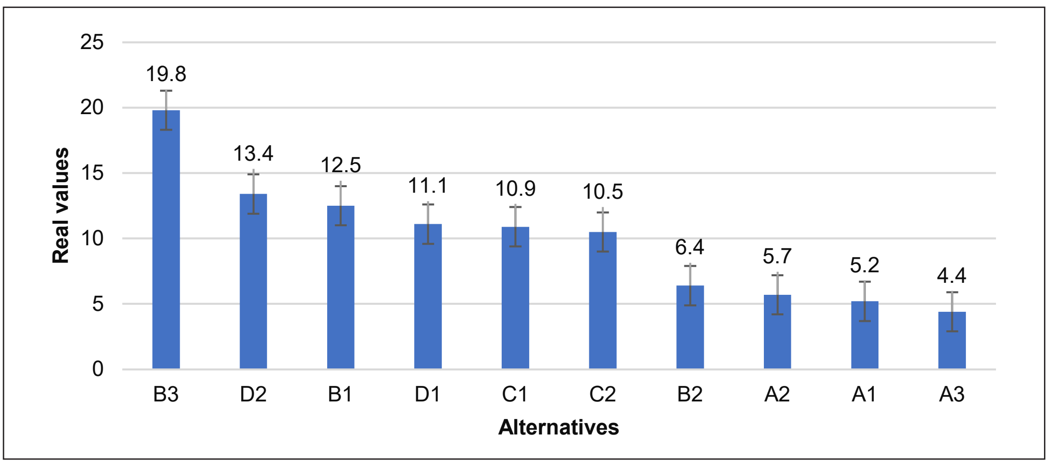


*Figure 11*. Priorities of the criteria

MCDM is a systematic and analytical approach that considers various criteria or factors to assess and compare alternatives. Within the framework of material selection, various aspects may come into play, including but not limited to cost, durability, environmental impact, and additional considerations. MCDM facilitates a methodical evaluation and prioritization of many possibilities, considering predetermined criteria. Fuzzy logic pertains to handling ambiguity and imprecision within the context of decision-making. In the realm of material selection, it is common for factors to lack specific definitions or ease of quantification. The notion of fuzziness enables the depiction of imprecise or unclear data, rendering it appropriate for addressing the inherent vagueness in decision-making scenarios seen in the actual world.

The integration of MCDM with fuzzy theory serves to augment the decision-making process. Fuzzy logic can accommodate the inherent uncertainties present in the criterion, but MCDM offers a structured approach for concurrently managing several criteria. The use of this integration facilitates a more accurate portrayal of decision-making situations. In conclusion, integrating MCDM with fuzzy theory offers a viable and efficient framework for addressing the intricate challenges associated with material selection. This methodology recognizes and confronts the ambiguities and many factors inherent in making decisions, resulting in more knowledgeable and resilient choices regarding material selection.

In order to do the sensitivity analysis of the FANP approach, a study was undertaken to examine the impact of altering the unitary ratio of the fuzzy criteria weights. Figure 12 illustrates the sensitivity of the ranking of each bio-composite filament material to disturbances caused by variations in criteria weights for FANP techniques. The radar

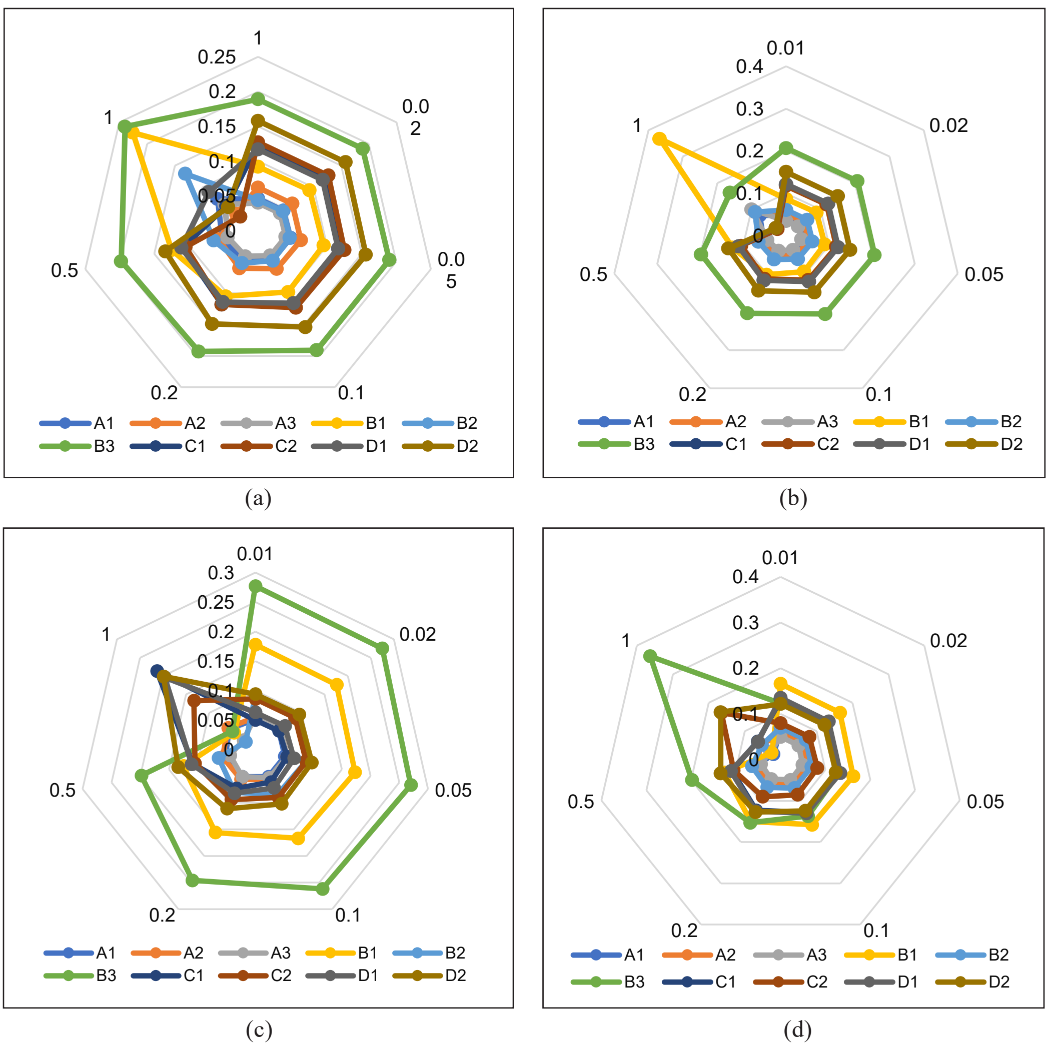


*Figure 12*. Ranking of the bio-composite filaments material with induced disturbance on the FANP-derived weights of (a) tensile strength, (b) flexural strength, (c) impact strength, and (d) printability

diagrams represent variable $\beta$ by utilizing radii on the chart, while the ranking is conveyed by the distances observed within these radii.

In Figure 12(a), it can be shown that the relative ordering of the ten bio-composite filament materials began to undergo alterations when the value of $\beta_1$ reached 0.2. The rankings of all materials were modified due to a change in the weighting of criteria for tensile strength. Following the value of $\beta_1$ being set to 0.5, it was seen that the variability in rankings became more pronounced. It can be attributed to the rapid increase in the weights assigned to the criteria of tensile strength as $\beta_1$ increased. Slight fluctuations in the ranking were noted for A2, B3, and D1 bio-composite filaments. The remaining bio-composite filaments exhibited sensitivity to changes in the weightage assigned to tensile strength. The sensitivity of the FANP study was examined by employing similar methodologies to assess the influence of varying weights on flexural strength, impact strength, and printability. Figure 12(b) demonstrates that the disruption imposed on the flexural strength weights resulted in consistent rankings of the bio-composite filaments material up to a value of $\beta_2$ = 0.2. Subsequently, a marginal alteration in the hierarchy of B1 bio-composite filament occurred, reaching a value of $\beta_2$ = 0.50. after that, there was a noticeable alteration in the ranking score of the B1 bio-composite filament. The rest of the filaments were also sensitive to the weight variation of flexural strength.

According to Figure 12(c), it can be observed that the B1, B3, C1, C2, D1, and D2 bio-composite filaments exhibited a high level of sensitivity to the disturbance caused by variations in impact strength weights. Conversely, the A1 and A2 bio-composite filaments displayed no sensitivity to such disturbances. The ranks of all the filaments exhibited consistency up to a value of $\beta_3$ equal to 0.2. Figure 12(d) illustrates that all the filaments exhibited a degree of sensitivity to the perturbation caused by changes in printability weights. The filaments' rankings remained unchanged until $\beta_4$ reached a value of 0.1. subsequently, a progressive shift in the bio-composite filament ranks occurred as a result of a significant alteration solely in the ranking of the B3 bio-composite filament. B3 filament exhibits a significantly greater level of printability than alternative filaments. As the value of $\beta_4$ increased, there was a corresponding increase in the weight assigned to printability. Consequently, an enhancement was observed in the ranking of the B3 filament. The summary of sensitivity analysis results can be seen in Table 15.

The B3 fiber composite was chosen as the optimal material for enhancing the strength of bio-composite filaments used in fused deposition modeling technology, specifically for egg carton packaging. Furthermore, it was revealed that B1 and D2 fiber composite exhibited a high frequency of occurrence within the top three ranks. In contrast, A2, A3, and C1 consistently ranked among the lowest three in all scenarios. Based on the findings, it was determined that A3 exhibited the lowest level of preference among bio-composite filaments when utilized as in FDM technology, specifically with regard to the designated design purpose.

Table 15
*Summary of sensitivity analysis results based on four circumstances*

| Rank | Original results | Increment of "Tensile strength," $\beta_1$=1.0 | Increment of "Flexural strength," $\beta_1$=1.0 | Increment of "Impact strength," $\beta_1$=1.0 | Increment of "Printability," $\beta_1$=1.0 |
|---|---|---|---|---|---|
| #1 | B3 | B3 | B1 | C1 | B3 |
| #2 | D2 | B1 | B3 | D2 | D2 |
| #3 | B1 | B2 | A3 | D1 | C2 |
| #4 | D1 | D1 | A2 | C2 | C1 |
| #5 | C1 | A1 | B2 | A2 | D1 |
| #6 | C2 | A3 | A1 | A1 | A2 |
| #7 | B2 | C1 | D1 | B3 | B2 |
| #8 | A1 | D2 | D2 | B1 | A3 |
| #9 | A2 | A2 | C1 | A3 | B1 |
| #10 | A3 | C2 | C2 | B2 | A1 |

## CONCLUSION

This study addresses the issues of selecting a bio-composite filament material by presenting a methodology based on FANP. This methodology takes into account both quantitative and qualitative aspects in the evaluation of bio-composite filament material options. The conventional ANP technique facilitates feedback among hierarchical levels and is a comparatively recent approach demonstrating superiority over the AHP method. The scale utilized consists of nine points. The use of the nine-point scale pairwise comparison in the standard ANP may not adequately and appropriately reflect the accurate assessment of decision-makers due to ambiguity and uncertainty surrounding their evaluations. Due to this rationale, the integration of conventional ANP with fuzzy logic was pursued. The utilization of the FANP entails more effort than the fuzzy AHP due to the necessity of constructing several pairwise comparison matrices based on triangular fuzzy numbers for a typical research investigation. Conversely, the advantage of utilizing the FANP lies in its ability to capture potential interdependencies that may arise inside decision hierarchies. Hence, unlike the fuzzy AHP, the FANP provides a more reliable solution.

The findings of this study are significant for future research endeavors. The integration of MCDM approaches is of utmost importance when considering the selection of materials. This claim is supported by previous studies investigating alternate methods for selecting materials, going beyond the conventional mean and variance approach. The main aim of the present study was to introduce a new approach for assessing many elements involved in the material selection process. This study also carries implications for professionals, policymakers, and individuals in leadership positions. Evaluating and choosing materials can be understood as a methodical approach that encompasses several steps, including identifying criteria, determining their relative significance, applying the criteria using the FANP technique, and subsequent analysis of the results. This method holds substantial promise for use in a range of real circumstances. Engineering, management, and invention professionals can apply this study's metrics, research structure, and technique to make well-informed decisions regarding selecting ideal industrial stock materials.

Exploring other MCDM models to facilitate material selection may benefit future investigations. It would enable a comparative comparison of their outcomes in relation to the present study's findings. In addition, factor analysis and confirmatory factor analysis can be utilized to define precise criteria for selecting materials. In conclusion, future research efforts may utilize flexible decision-support systems, such as software based on MCDM, to comprehensively assess all aspects related to the choice of materials. In summary, the FANP methodology demonstrates greater benefits in selecting bio-composite filament materials when a thorough assessment of several parameters is taken into account, along with the possible impact of interconnections among these elements. The study outcomes indicate that using SPF/PLA 7.5 wt.% fiber loading in FDM is a recommended strategy for producing egg carton packaging. The assignment of the highest position to prioritize impact strength can be attributed to its crucial significance in package design. Further research is needed to enhance the effectiveness of the proposed FANP technique through an in-depth examination of various bio-composite materials and the numerous aspects that require careful attention.

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