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Optimization of Milling Parameters for Hybrid Sisal-Cotton Fiber Reinforced Polymer Composites Using Taguchi Method

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ABSTRACT

The increasing demand for sustainable, lightweight, and high-performance components in the automotive sector has accelerated interest in natural fiber-reinforced polymer composites (NFCs). However, machining these materials poses formidable challenges due to their heterogeneous and anisotropic nature, frequently causing fiber pull-out, delamination, and matrix cracking that degrades surface quality. To address this issue, this study proposes an intelligent artificial neural network (ANN)-based framework integrated with genetic algorithm (GA) optimization and Taguchi methodologies to predict and optimize machining responses during CNC end milling of hybrid sisal-cotton fiber-reinforced epoxy composites.

The hybrid composites were fabricated using the cost-effective hand lay-up method following targeted chemical mercerization with 5% NaOH for cotton yarns and 8% NaOH for sisal fibers for 1 hour. Laminates with 10 and 30 wt% fiber mass fractions and random, bidirectional, and unidirectional configurations were characterized through tensile, compressive, flexural, and Charpy impact tests. CNC milling experiments were subsequently conducted using a Taguchi L9 orthogonal array by varying spindle speed (1000–2000 rpm), feed rate (100–300 mm/min), and depth of cut (1.0–2.0 mm). Levenberg-Marquardt backpropagation ANN models were developed to predict material removal rate (MRR) and average surface roughness (Ra).

Sample 1, configured with a 30 wt% fiber mass fraction and short (2 mm) random orientation, exhibited the highest tensile, compressive, flexural, and Charpy impact strengths of 62, 44, 336.91, and 0.738 N/mm², respectively. ANOVA revealed that feed rate was the dominant factor affecting MRR, contributing 65.85% ($P = 0.036$), whereas depth of cut predominantly influenced R_a , contributing 54.48% ($P = 0.023$), followed by spindle speed at 28.44% ($P = 0.0438$). Taguchi optimization identified 1000 rpm, 200 mm/min, and 1 mm as the optimal cutting conditions for surface smoothness, while validation demonstrated only 1.28% prediction error for R_a under optimized conditions. The proposed ANN-GA-Taguchi framework provides a robust and reliable approach for pre-machining simulation, process planning, and optimization, reducing dependence on costly and time-consuming physical trials and supporting sustainable manufacturing of hybrid NFCs.

Key Words: Milling, Artificial Neural Networks, Genetic Algorithm, Hybrid sisal-cotton fiber Reinforced polymer composite, Taguchi technique.

Manuscript Nomenclature & Abbreviations

Symbol / Abbreviation	Description	Unit
ANN	Artificial Neural Network	—
ANOVA	Analysis of Variance	—
ASTM	American Society for Testing and Materials	—
B	Width of the mechanical test specimen	mm
CFRP	Carbon Fiber Reinforced Polymer	—
CNC	Computer Numerical Control	—
D / DOC	Depth of Cut	mm
DF	Degrees of Freedom	—
E	Energy absorbed during impact fracture	J
F	Feed Rate	mm/min
FRP / FRPC	Fiber-Reinforced Polymer Composite	—
GA	Genetic Algorithm	—
H	Thickness of the mechanical test specimen	mm
Is	Impact Strength	J/mm ²
L	Span length during three-point bending	mm
Mbmax	Maximum Bending Moment	N·mm
Mf	Mass fraction of fibers	% / wt%
Mm	Mass fraction of the polymer matrix	% / wt%

MRR	Material Removal Rate	mm ³ /min
Mc	Total mass of the composite specimen	g
Mf	Mass of the fiber phase	g
Mm	Mass of the matrix resin phase	g
NaOH	Sodium Hydroxide (Caustic Soda)	—
NFC	Natural Fiber Composite	—
OA	Orthogonal Array	—
P-Value	Probability Value (Statistical Significance Indicator)	—
Ra	Average Surface Roughness	μm
S	Spindle Speed	rpm
S/N	Signal-to-Noise Ratio	dB
SR	Surface Roughness Polynomial Output	μm
UTM	Universal Testing Machine	—
Vf	Volume fraction of fibers	%
Wb	Section Modulus	mm ³
Wf	Weight/Mass fraction of fiber reinforcement	%
Abmax	Maximum Flexural Strength	N/mm ² / MPa

1. INTRODUCTION

Composite materials have garnered considerable attention across diverse industries due to their exceptional mechanical properties, such as high strength-to-weight ratio, corrosion resistance, fatigue durability, and design flexibility[1, 2]. These characteristics make composites highly suitable for applications demanding lightweight yet robust materials, including aerospace, automotive, and construction sectors. In particular, fiber-reinforced polymer composites (FRPCs) have revolutionized material engineering by combining the superior properties of fibers with versatile polymer matrices.

Among composite types, hybrid composites, those integrating two or more distinct fiber reinforcements have emerged as promising candidates for enhanced mechanical performance by synergizing the strengths and offsetting the weaknesses of individual fibers[3, 4]. Notably, the automotive industry's growing emphasis on sustainability and environmental stewardship has accelerated interest in natural fiber-based polymer composites (NFCs), which offer several advantages over synthetic fibers. Natural fibers such as cotton and sisal are renewable, biodegradable, lightweight, cost-effective, and require significantly less energy during production [5, 6]. This eco-friendly profile positions NFCs as attractive substitutes for

conventional synthetic composites, particularly in vehicle body panels where weight reduction directly translates into improved fuel efficiency and reduced emissions. However, the machining of composites, especially hybrid natural fiber composites poses formidable challenges primarily due to their heterogeneous and anisotropic nature. The machining process, such as end milling, can induce defects including fiber pull-out, delamination, matrix cracking, and excessive tool wear, all of which degrade surface quality and dimensional accuracy[7, 8]. The abrasive properties of natural fibers, combined with the complex fiber-matrix interactions, further complicate machining operations, demanding precise control of cutting parameters like speed, feed rate, and depth of cut to optimize component quality.

Fiber-matrix interfacial bonding is a critical factor influencing the mechanical integrity and machinability of natural fiber composites. Natural fibers are inherently hydrophilic; whereas most polymer matrices are hydrophobic, leading to weak interfacial adhesion and poor stress transfer[9, 10]. Chemical treatments such as alkali (mercerization) treatment are widely employed to improve fiber surface roughness, remove impurities like lignin and hemicellulose, and enhance fiber-matrix interlocking, thus improving composite strength and moisture resistance[11, 12]. Alongside fiber treatment, fiber orientation and hybridization significantly affect composite performance and machining behavior[13-17]. Manufacturing methods, including lay-up, filament winding, pultrusion, and injection molding, also influence composite microstructure and final properties [18-20]. While each technique offers unique advantages, ranging from shape complexity to production efficiency, the choice of process impacts fiber alignment, resin impregnation, and ultimately machinability.

Despite extensive research on synthetic fiber-reinforced composites, the machining of natural fiber-based hybrid composites remains underexplored, particularly with regard to optimizing cutting parameters for automotive-grade components. Most studies focus on improving composite mechanical properties through fiber treatment and hybridization[3, 9, 10], but less attention has been paid to understanding and modeling the machining forces, tool wear, and surface finish outcomes specific to hybrid natural fiber composites like cotton-sisal reinforced polymers. The variability in fiber properties, abrasive nature of natural fibers, and complex fiber-matrix interactions introduce substantial uncertainty in machining outcomes, creating a gap in predictive and optimization models. While the machining of synthetic fiber composites such as CFRP has been extensively studied, resulting in predictive models for cutting forces and surface integrity[21-23]. There is a notable lack of comprehensive research on machining hybrid natural fiber composites. Specifically, the relationship between machining parameters and resultant surface quality, dimensional accuracy, and tool wear in hybrid cotton-sisal fiber composites is

insufficiently understood. Moreover, despite the promise of Artificial Neural Networks (ANN) and other machine learning approaches for parameter optimization in machining processes[24, 25] , their application to hybrid natural fiber composites remains limited. This gap inhibits the wider adoption of eco-friendly hybrid composites in automotive manufacturing, where precision and quality standards are stringent.

The automotive industry is under increasing pressure to adopt sustainable materials without compromising component performance or production efficiency. Hybrid sisal-cotton fiber-reinforced polymer composites exhibit promising mechanical properties and environmental benefits but face challenges in machining due to their heterogeneous nature and abrasive fiber characteristics. Improper machining parameters can lead to poor surface finish, delamination, dimensional inaccuracies, and accelerated tool wear, undermining product quality and increasing manufacturing costs [26-28]. Currently, there is a lack of optimized machining guidelines tailored for these hybrid composites. The absence of predictive models that correlate machining conditions with output quality metrics hinders process control and scalability. Furthermore, limited use of advanced optimization techniques like ANN in this context restricts the ability to systematically refine machining parameters for enhanced productivity and sustainability.

Thus, the key problem addressed in this study is the optimization of machining parameters for hybrid cotton-sisal fiber-reinforced polymer composites used in automotive body panels to ensure superior surface finish, dimensional accuracy, and mechanical integrity, while minimizing tool wear and production costs. And in summary, optimizing machining processes for hybrid natural fiber composites has the potential to revolutionize automotive manufacturing by combining performance, cost-effectiveness, and sustainability. This study bridges critical gaps in machining knowledge and process control, paving the way for broader adoption of green composites in high-demand applications.

2. Experimental Sections

A thorough exploration is undertaken, covering the materials and experimental methods employed. This includes the matrix and fiber materials, composite preparation techniques, Taguchi analysis for experimental design, procedures for conducting milling operation.

2.1. Materials

The fabrication process has involved the combination of two constituent materials: the matrix material and the reinforcement material. Additionally, alkali treatment is done before fabrication of the composite. This treatment played a crucial role in enhancing the properties of the fiber.

2.1.1. Matrix Material – Polymer Resin

In natural fiber-reinforced polymer composites, the matrix material plays a pivotal role in defining the composite's overall functionality and performance. The matrix acts as a continuous phase that surrounds and binds the reinforcement fibers together, providing structural integrity and protecting the fibers from mechanical and environmental damage. The choice of polymer resin as the matrix material is critical due to its influence on the composite's mechanical properties, durability, and manufacturability. Polymer resins are widely favored as matrix materials in natural fiber composites because of their excellent process ability, compatibility with natural fibers, and favorable mechanical properties. Acting as a binder, the polymer resin ensures that the reinforcing fibers are held in a uniform and stable configuration, preventing agglomeration or clustering of fibers that can compromise the composite's strength and performance. This uniform dispersion of fibers within the polymer matrix facilitates efficient stress transfer between the fibers and the matrix, thereby improving the composite's overall mechanical behavior, including tensile strength, stiffness, and impact resistance.

One of the key functions of the polymer matrix is to provide a protective barrier around the natural fibers. Natural fibers are hydrophilic and susceptible to moisture absorption, which can lead to swelling, degradation, and loss of mechanical integrity over time. The polymer resin encapsulates the fibers, shielding them from environmental factors such as moisture, chemical exposure, and ultraviolet (UV) radiation. This protection significantly enhances the operational lifespan of the composite by preserving the reinforcing fibers' structural and functional properties. Polymer resins also offer considerable flexibility in fabrication processes. Their good flow characteristics and curing behavior make them suitable for various composite manufacturing techniques such as compression molding, injection molding, and vacuum-assisted resin transfer molding (VARTM). These processing methods allow for efficient incorporation of natural fibers into the resin matrix, enabling the production of complex shapes and sizes with consistent quality and performance.

Another important advantage of polymer resins lies in their ability to be tailored to meet specific application requirements. For instance, thermosetting resins such as epoxy, polyester, and phenolic resins offer excellent mechanical strength, chemical resistance, and thermal stability

once cured. They form a rigid, cross-linked network that enhances composite rigidity and dimensional stability. While thermoplastic resins such as polypropylene (PP), polyethylene (PE), and polylactic acid (PLA) provide advantages in recyclability, impact resistance, and ease of reshaping or reprocessing. Their melt-process able nature enables efficient manufacturing and potential for reuse or recycling.

Moreover, polymer resins can be modified through additives or formulation adjustments to improve specific properties such as flame retardancy, UV resistance, or enhanced interfacial bonding with natural fibers. Surface treatments, coupling agents, and compatibilizers may be introduced to promote stronger adhesion between the hydrophobic polymer matrix and the hydrophilic natural fibers, thus maximizing mechanical interlocking and stress transfer efficiency. For this study, the polymer resins and mold releasing agents were procured from Tana Fiber Glass Industry S.C., a reputable supplier known for high-quality materials suitable for composite fabrication. The selection of these materials ensured a reliable baseline for processing natural fiber-reinforced composites with optimal mechanical and environmental performance. In summary, polymer resins are an essential component in the development of natural fiber composites, balancing process ability, compatibility with natural fibers, and mechanical performance. Their ability to protect fibers, transfer load efficiently, and be tailored for diverse applications makes them the preferred matrix materials in many composite manufacturing scenarios.

Table 1: Unsaturated polymer resins' mechanical properties; Source[29, 30].

Property	Unit
Density	1200 kg/mm ³
Thermal conductivity	0.17 W/m.°C
Tensile strength	70.3 – 103 MPa
Modulus of elasticity	2.06 – 4.41 GPa
Fracture toughness	0.6 (M.Pa.m0.5)

As illustrated in **Fig.S1**, the polymer resin used was EPOXYLY556, paired with Hardener HY951. EPOXYLY556 was chosen for its excellent mechanical properties, chemical resistance, and good process ability, making it ideal for natural fiber composites. Hardener HY951 acts as a curing agent, triggering cross-linking to form a strong, stable network. Together, they create a durable matrix that binds and supports natural fibers, enhancing the composite's strength and stability.

2.1.2. Mold releasing Agent

Mold-releasing agents play a critical role in composite manufacturing by enabling the easy separation of the finished part from the mold surface. These agents form a barrier that prevents adhesion between the composite material and the mold, facilitating clean demolding and preserving surface quality.

Types of Mold-Releasing Agents; (i) Wax-Based Agents: Commonly used due to their versatility, wax-based agents form a thin barrier on the mold surface. They provide reliable release performance and are suitable for a wide range of composite materials, (ii)Silicone-Based Agents: Ideal for complex molds and detailed parts, silicone-based agents offer excellent release properties and create a smooth, durable film that minimizes surface defects and (iii)Water-Based Agents: These environmentally friendly agents use water as a carrier

along with surfactants and emulsifiers. They are easy to apply, safe to handle, and compatible with various composite systems. In this study, as shown in **Fig.S2**, Honey Wax, a high-gloss paste supplied by Tana Fiber Glass Manufacturing was used as the mold release agent. Known for its ease of application and buffing, Honey Wax effectively reduces processing time while ensuring a clean release in the composite fabrication process.

2.1.3. Fiber Material- Sisal and Cotton

As illustrated in **Fig.1**, natural fibers, specifically sisal fiber and cotton fiber were utilized as reinforcements in the composite material. The matrix material, on the other hand, consisted of a polymer resin. Sisal fibers sourced from the leaves of the sisal plant were gathered in the Southern Region, Zeyse Woreda, Ethiopia, located in close proximity to Arbaminch town. The extraction of sisal fiber was carried out by using a knife to carefully separate the fibers from the sisal leaf. After the extraction process, the sisal fiber was left under the sun for duration of five hours to ensure the removal of any moisture content. The drying phase was essential to ready the sisal fiber for the subsequent stages in the fabrication process. The experimental density of the cured hybrid composite specimens slightly exceeded that of the neat unsaturated matrix (approx. 1200 kg/m^3). This structural increase is mathematically fully consistent and is directly attributed to the higher intrinsic densities of the constituent cellulosic reinforcement phases (extracted sisal fiber approx. 1450 kg/m^3 and processed cotton yarn approx. 1540 kg/m^3). This density variation confirms highly uniform resin matrix impregnation, efficient fiber wetting, and compact structural consolidation under the uniformly applied 60 kg physical compressive load maintained across the 24-hour initial curing cycle.



Fig.1: Processed Cotton Yarn (a) and Extracted Sisal Fiber (b)

2.1.4. Materials utilized to prepare the composite

A hybrid composite has been fabricated using the hand layup method, with sisal and cotton fibers as major constituents, along with epoxy resin (LY 556), hardener (HY 951), a releasing agent, a brush, a roller, PVC sheets, and tape.

3. Methods

3.1. Fiber Treatment Methods

Fiber treatment plays a crucial role in the composite manufacturing process by modifying the surface properties of natural fibers to enhance their adhesion to the polymer matrix. Improved interfacial bonding between fibers and the matrix directly contributes to superior mechanical properties and the overall performance of the resulting composite materials. Among various surface modification techniques, chemical treatments are commonly employed to alter the surface chemistry of fibers, thereby promoting better compatibility and adhesion with the matrix. In this study, alkali treatment using sodium hydroxide (NaOH) was selected due to its effectiveness in enhancing the fiber-matrix interface. Natural fibers were extracted from fully matured enset pseudo stems and sisal leaves. The extracted fibers were thoroughly washed with water to remove surface contaminants and dried under sunlight for 8 hours. Subsequently, the dried fibers were subjected to alkali treatment.

As shown in **Fig.2**, the alkali treatment involved immersing enset and sisal fibers in NaOH solutions of 5% and 8% concentrations, respectively, for 1 hour at room temperature. After the immersion period, the fibers were removed from the solution and rinsed multiple times with clean water to ensure the complete removal of residual alkali. The fibers were then left to air dry at room temperature for 24 hours, as recommended by [31]. Alkali treatment, also known as mercerization, is widely used in the textile and composite industries to improve the performance of both natural and synthetic fibers. This process typically involves immersion in an alkaline solution, commonly NaOH or potassium hydroxide (KOH) for a specific duration. The treatment alters the fiber surface by: (i) removing non-cellulosic components such as lignin, hemicellulose, pectin, waxes, and natural oils, (ii) increasing surface roughness, leading to better mechanical interlocking, (iii) introducing hydroxyl groups (-OH), which enhance chemical bonding with the

matrix, and (iv) improving moisture regain, dimensional stability, and dye ability. By eliminating surface impurities and modifying the fiber's chemical structure, alkali treatment significantly enhances the compatibility of fibers with polymer matrices, thus resulting in improved mechanical strength, adhesion, and durability in the final composite product.



Fig .2: Alkali treatment of the fiber

3.1.1. Alkali Compound for Fiber Treatment

As illustrated in **FigS3**, sodium hydroxide (NaOH), commonly known as caustic soda, is a white crystalline solid that readily absorbs moisture from the air. This highly versatile chemical is widely used across several industries, including the manufacture of paints, dyes, textiles, and in processes such as cotton processing and metal cleaning [32, 33]. The form of NaOH used in this context is shown in **Fig.S3**. In the textile and composite industries; sodium hydroxide is frequently employed for alkali treatment (also known as mercerization) of natural fibers. This chemical modification process enhances the interfacial bonding between fibers and polymer matrices by altering the fiber surface. The treatment improves fiber wettability, removes non-cellulosic substances, and introduces reactive hydroxyl (-OH) groups. Steps involved in Sodium Hydroxide Fiber Treatment: (i) preparation of NaOH Solution in which a sodium hydroxide solution is prepared by dissolving a specified quantity of NaOH pellets or flakes in distilled water while the concentration typically varies based on the fiber type and desired surface characteristics, (ii) immersion of Fibers that the natural fibers are completely submerged in the NaOH solution to ensure uniform exposure and reaction, (iii) soaking Period when the fibers are

left in the solution for a predetermined period, ranging from a few minutes to several hours depending on factors such as fiber composition, solution concentration, and intended surface modification, (iv) rinsing means, after treatment, the fibers are removed from the solution and thoroughly rinsed with water to eliminate residual alkali. Proper rinsing is critical to neutralize the fibers and avoid degradation or interference with subsequent processes and (v) drying in which the treated fibers are dried either in ambient air or using a drying oven to eliminate moisture, making them suitable for further use in composite fabrication or textile processing. The alkali treatment with sodium hydroxide modifies the fiber surface by removing impurities such as lignin, hemicellulose, waxes, and oils, increasing surface roughness, thereby improving mechanical interlocking with the matrix, and introducing hydroxyl groups, which enhance chemical bonding potential with polymer matrices. As a result, NaOH-treated fibers exhibit improved adhesion, enhanced mechanical properties, and greater compatibility in composite material applications.

3.2. Composite Fabrication Methods

Natural fibers from cotton and sisal were extracted, washed, sun-dried, and subjected to alkali treatment using sodium hydroxide (NaOH). The composites were fabricated using the hand lay-up method, selected for its simplicity and cost-effectiveness. The composite laminates were fabricated to dimensions of $300 \times 300 \times 8$ mm on a steel mold plate, using fibers treated with 5% and 10% NaOH solutions. Fiber orientations were varied across random, bidirectional, and unidirectional configurations to assess their influence on composite properties. A mixture of epoxy resin and hardener in a 10:1 weight ratio was used as the matrix material. The prepared resin was evenly poured onto the mold surface. A roller was used to distribute the resin, followed by the placement of fibers and polyester sheets. This process was repeated in layers until the desired laminate structure was achieved [34, 35]. To ensure thorough resin penetration into fiber porosities and improve fiber-matrix bonding, a load of 60 kg was applied to the mold and maintained for 24 hours. Post-compression, the samples were allowed to cure for 48 hours at room temperature to ensure full polymerization. As indicated in **Fig.3**, after curing, the composite sheets were cut into standardized test samples for mechanical and physical characterization.

Hand Lay-Up Process Overview: The hand lay-up technique is a widely adopted, low-cost method for fabricating fiber-reinforced polymer composites. It involves manual layering of fiber and resin in a prepared mold. The steps involved in this process are as follows; (1) mold preparation in which the mold surface was thoroughly cleaned and coated with a release agent to facilitate easy removal of the cured composite and prevent surface contamination, (2) material preparation that natural fibers (cotton and sisal) were cut to the required dimensions and arranged according to the desired orientation. To ensure proper wetting and bonding, fibers were pre-impregnated with the epoxy resin before lay-up, (3) Lay-Up Process in which the pre-impregnated fibers were manually placed in the mold, layer by layer, ensuring the elimination of air pockets and wrinkles. A roller was used during each layer to distribute the resin evenly and remove any trapped air, (4) Curing when once the lay-up process was complete, the composite laminate was compressed and allowed to cure under load. Curing was done at room temperature for 48 hours to achieve optimal mechanical properties and (5) trimming and finishing that after curing, excess edges were trimmed using a band saw, and the composite panels were sanded and finished to achieve the required shape and surface quality for testing.



Fig.3: Samples' fabrications

Table 2: Samples, Mass fraction, and fiber orientation

No of sample	Mass fraction	Fiber orientation	Fiber length
Sample one	30% fiber and 70 % of resin	Random	Short(2 mm)
Sample two	30% of fiber and 70% of resin	Bidirectional	Long
Sample three	10% of fiber and 90 % of resin	Unidirectional	Long
Sample four	10 % of fiber and 90% resin	Random	Short(3mm)

The composite specimens fabricated in this study had dimensions of 300 mm × 300 mm × 8 mm. All fabrication processes were conducted at the Arba Minch University Composite Materials Laboratory. As indicated in **Table 2**, for clarity and ease of reference, the fabricated composite samples are labeled and categorized based on fiber type, NaOH concentration, and fiber orientation (random, unidirectional, or bidirectional). The labeling scheme and naming convention are detailed in the subsequent sections.

3.3. Sample preparation for Testing of Composites

Table 3: Dimensions of mechanical property test samples

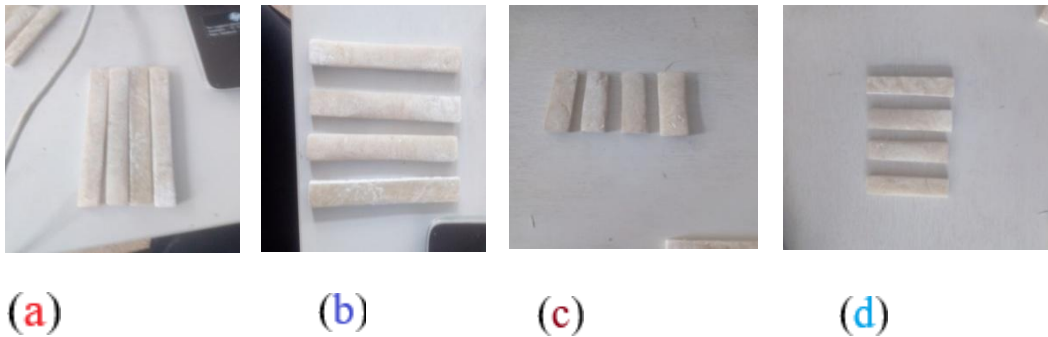
Sample name	Dimensions		
	Length	Width	Thickness
Tensile test sample	250	25	3.2
Flexural test sample	127	12.7	3.2
Compression test sample	80	15	4
Impact test sample	60	12.7	3.2

As illustrated in **Table 3**, mechanical characterization is a fundamental and crucial aspect of material testing that involves a comprehensive evaluation of various properties to understand how a material behaves under different loading conditions. This characterization process provides valuable insights into the mechanical performance and capabilities of a material, aiding in its selection for specific applications and ensuring structural integrity.

3.4. Tensile, Flexural, Impact , and Compression Test Samples Preparation

The mechanical performance of composite materials is assessed through tensile, flexural, impact, and compression testing. These standardized tests provide critical information about the strength, stiffness, toughness, and deformation behavior of materials under various loading conditions. As indicated in **Figs.4**; **(i) Tensile test sample preparation**-tensile strength represents the maximum stress a material can withstand while being stretched before breaking. Composite specimens were prepared by cutting according to the **ASTM D780** standard using a table saw. Testing was conducted using a **universal testing machine** rated for a maximum load of 400 kN. Four different composite configurations; **Sample 1, Sample 2, Sample 3, and Sample 4** were prepared with varying fiber combinations to study the influence of fiber content on tensile behavior [36], **(ii) Flexural test sample preparation**-flexural strength, or the modulus of rupture, measures a material's ability to resist deformation under bending. During testing, tensile and compressive stresses are induced on the convex and concave sides of the specimen, respectively. Specimens were cut as per **ASTM D790** and tested using a three-point bending fixture. The same four composite samples were used to evaluate and compare flexural performance, with a focus on the stress experienced by outermost fibers during bending [37-39], **(iii) Impact test sample preparation**-impact strength indicates a material's ability to absorb energy during sudden impact. This was measured using the **Charpy impact test apparatus**, with notched specimens prepared according to the **ASTM D256** standard. The test determines the amount of energy (in joules) absorbed by the specimen during fracture, reflecting its toughness and ability to withstand shock loading. All four composite samples were tested to assess their resistance to dynamic loads[40, 41] and **(iv) Compression test sample preparation**-Compression testing evaluates a material's resistance to compressive forces. Specimens were prepared in accordance with **ASTM D3410**, with dimensions of **80 mm (length) × 10 mm (width) × 4 mm (thickness)**. Each specimen was subjected to a gradually increasing

compressive load until failure, and the maximum load sustained was recorded as the compression strength. The test provides insights into the load-bearing capacity of the composites under axial compressive stress[42].



Figs.4: Tensile test specimens (a), Flexural test sample (b), Impact test specimens (c) and Compression test specimens (d)

3.5. Milling of Cotton-Sisal Fiber Reinforced Polymer Composite

Milling fiber-reinforced composites (FRP) is a critical process in manufacturing industries for shaping components, improving surface quality, and assembling complex structures. Despite its importance, milling FRP presents several challenges due to the heterogeneous nature of the materials. Common issues include **delamination**, **fiber pull-out**, **matrix cracking**, **surface roughness**, and **tool wear**, which are influenced by factors such as **fiber orientation**, **cutting parameters**, **tool geometry**, and **material properties**[24, 43]. **End milling**, particularly for **Carbon Fiber Reinforced Polymer (CFRP)**, is more complex due to CFRP's abrasive and heat-insulating properties. This can result in high cutting forces, fiber splintering, delamination, and rapid tool degradation. As a result, researchers have developed **predictive models for cutting force** to help optimize cutting conditions and minimize defects [23, 44]. For **natural fiber-reinforced composites**, such as **hybrid cotton-sisal-reinforced polymers**, **CNC milling** offers high precision and flexibility in shaping complex geometries. By applying machine learning techniques like **artificial neural networks (ANNs)**, optimal machining parameters (cutting speed, feed rate, depth of cut) can be predicted, improving surface finish, reducing material waste, and enhancing overall process efficiency. As illustrated in **Fig.5**, milling operations were conducted at **Ethio Technical and Vocational Training University**, using a CNC milling machine.



Fig.5: Milled Hybrid sisal-cotton FRPC sample

3.6. Specimen Preparation Methods

In preparing the composite material specimen for this work, the initial step involves establishing the volume and mass proportions for the matrix and fiber components. As illustrated in **Equas.S3**, following the calculations, the required composite material samples were then manufactured [45, 46]. Since $M_f = 30\%$ (0.3) and Mass of matrix $M_m = 70\%$ (0.7) for sample 1 and sample 2 and for sample 3 and 4 $M_f = 10\%$ (0.1) and Mass of matrix $M_m = 90\%$ (0.9).

3.6.1. Determination of Volume and Mass fraction for Milling Sample Preparation

The specimen dimensions were determined considering factors like the number of slots created by the end mill cutters, the diameter of the end mill cutters, and the gaps between slots. In this study, each sample will undergo a total of 9 milling operations, using end mill cutters with a 20mm diameter and a 10mm gap between two slots. The specimen dimensions are as follows: 250mm in width, 70mm in length, and 10mm in thickness. To find the volume of the specimen, the length, width, and thickness are multiplied together. As indicated in **Equas.S4**, composite specimen's volume, and mass of the composite (m_c) have been computed and hence for sample 1 ($m_f = M_f \times m_c = 0.3 \times 217 \text{ g} = 65.1 \text{ gram}$) and for sample 2 ($m_m = M_m \times m_c = 0.7 \times 217 \text{ g} = 151.9 \text{ gram}$) while for sample 3 ($m_f = M_f \times m_c = 0.1 \times 217 \text{ g} = 21.7 \text{ gram}$) and for sample 4 ($m_m = M_m \times m_c = 0.9 \times 217 \text{ g} = 195.3 \text{ gram}$).

3.6.2. Determination of Volume and Mass Fractions for Mechanical Testing of Composite Samples

As presented in **Equation (S5)**, the accurate determination of volume fraction (V_f) and mass fraction (W_f) is essential in the preparation of composite material samples for mechanical characterization. These parameters ensure the correct proportioning of the reinforcement phase (e.g., fiber) and the matrix phase (e.g., resin), which significantly influences the overall mechanical behavior of the composite. Consistency in V_f and W_f calculations is particularly critical for comparative analysis across different mechanical tests, including compression, flexural, impact, and tensile strength evaluations. For compression strength testing, the total composite volume was set at 33.6 cm^3 , with a total mass of 45 g. Two sets of samples were prepared: Samples 1 and 2 (30 wt% fiber): Fiber mass: $m_f=13.5 \text{ g}$ and matrix mass: $m_m=31.5 \text{ g}$ whereas Samples 3 and 4 (10 wt% fiber): Fiber mass: $m_f=4.5 \text{ g}$ and Matrix mass: $m_m=40.5 \text{ g}$. For flexural strength testing, the composite volume and mass were 29 cm^3 and 35.96 g, respectively: Samples 1 and 2: Fiber mass: 10.788 g and Matrix mass: 25.17 g while Samples 3 and 4: Fiber mass: 3.357 g and Matrix mass: 30.195 g. For impact strength evaluation, the composite volume was 28 cm^3 with a mass of 34.72 g: Samples 1 and 2: Fiber mass: 10.42 g and Matrix mass: 24.3 g. And Samples 3 and 4: Fiber mass: 3.472 g and Matrix mass: 31.248 g. For tensile strength testing, the sample volume was 18.75 cm^3 , and the mass was 23.25 g: Samples 1 and 2: Fiber mass: 6.975 g and Matrix mass: 16.275 g and Samples 3 and 4: Fiber mass: 2.375 g and Matrix mass: 20.925 g. The determination of these values using **Equation (S5)** enables controlled sample fabrication, ensuring uniformity and repeatability across test specimens. This approach supports reliable interpretation of the composite's mechanical properties and allows for meaningful comparison between different reinforcement ratios and loading conditions.

3.7. Characterizations and Conditions

Mechanical properties of the specimens are tensile, compression, flexural strength, and impact resistance, which were evaluated at Bishoftu Defense Engineering College. Compression and flexural tests were conducted using a 50 kN capacity machine (**Figs. S3**), while impact resistance was measured using a Charpy tester. Tensile strength was assessed with a Universal Testing Machine (UTM) by applying a uniaxial load until failure.

3.8. Optimization Using Integrated ANN-GA

The integrated ANN-GA approach combines Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) to optimize complex problems efficiently[47, 48]. ANNs inspired by the human brain, model nonlinear relationships and predict solution quality[24, 49-51]. GAs use evolutionary operators like selection, crossover, and mutation to explore large solution spaces [52, 53]. In this approach, the ANN acts as the fitness function evaluator within the GA, enhancing solution evaluation accuracy[47, 48]. The GA iteratively evolves candidate solutions, guided by ANN-based fitness scores[54, 55]. This integrated method improves optimization speed and effectiveness, especially for stochastic processes like CNC milling [53]. ANN training involves algorithms such as Levenberg-Marquardt for minimizing errors [54, 55]. As presented **Fig.6**, overall, ANN-GA provides a robust framework for optimizing machining parameters and other complex tasks compared to traditional methods.

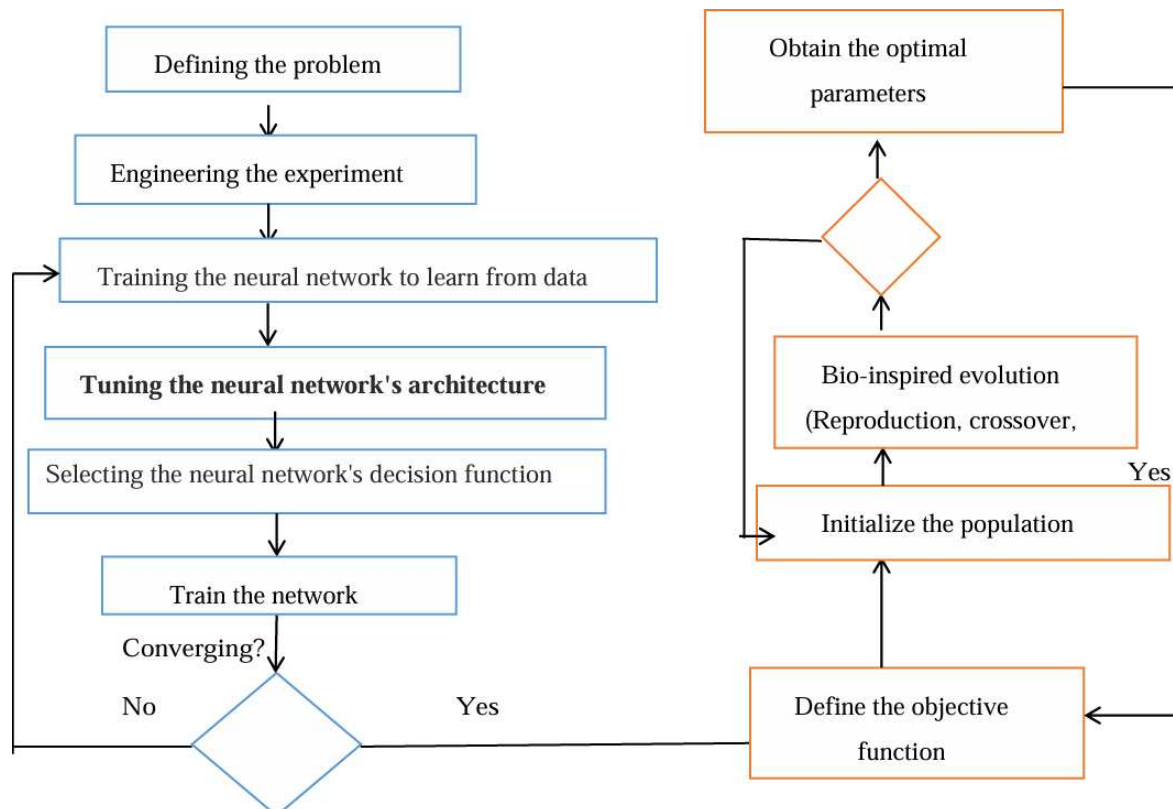


Fig.6: The combined Artificial Neural Network (ANN) and Genetic Algorithm (GA) Methodology for modeling and forecasting Material Removal Rate (MRR) and surface roughness

3.9. Experimental Design Approach for Milling

In this work, the milling experiments for sisal fiber-reinforced composites were designed using Taguchi techniques, originally developed by Dr. Genichi Taguchi, a renowned Japanese engineer [56]. Taguchi methods are widely used in machining to enhance productivity and quality while reducing costs and processing times. As illustrated in **Table S1**, they employ orthogonal arrays (OA) to systematically explore the effects of multiple parameters with a minimal number of experiments, facilitating the identification of optimal control factor settings[57]. The optimization process targets key control variables that influence machining outcomes, aiming to determine their ideal combinations to achieve desired response qualities[58, 59].

3.9.1. Taguchi's Approach to Milling Operation Design

Following Taguchi's structured methodology[60], the milling of sisal-cotton fiber-reinforced polymer composites on a CNC milling machine involved several key steps:(i)define objectives and adverse effects- the main objective was to analyze how input parameters influence milling responses during end milling of fiber-reinforced composites, (ii)identify control and noise factors -as indicated in **Table S2**, the primary control factors affecting milling quality were spindle speed, feed rate, and depth of cut [26, 61]. Noise factors, which are unpredictable variables that were also considered. Surface roughness and material removal rate were selected as critical output responses due to their importance in machining fiber composites[62], (iii) set objective function-define the task for optimization based on quality attributes, (iv) select parameter levels- three levels each for spindle speed (1000–2000 rpm), feed rate (100–300 mm/min), and depth of cut (1–2 mm) were chosen, consistent with prior studies, (v)choose orthogonal array-as presented in **Table S3**, an appropriate OA was selected to minimize experimental runs while enabling effective analysis of factor effects[63, 64] and (vi) conduct milling operations-using a Fanuc CNC milling machine, the end milling experiments were performed as per the OA design, with CNC programs developed for precise tool path control. The milling procedure involved preparing rectangular specimens, setting reference points for the CNC axes, and executing the milling runs under varied parameter combinations.

4. RESULT AND DISCUSSIONS

4.1. Results of composite mechanical property testing

The results of composite mechanical property testing revealed the material's strength, stiffness, and durability characteristics, demonstrating its suitability for structural applications. To ensure result accuracy, the hybrid sisal-cotton fiber-reinforced polymer composite underwent multiple tests for tensile, compression, flexural, and impact strengths. Each test was performed four times to ensure reliability and statistical significance. Repetition helped identify anomalies and improved overall consistency. This rigorous testing provided a comprehensive and robust understanding of the composite's mechanical performance. As indicated in the **Table 4**, the tensile properties of the composite specimens, more specifically, samples 1, 2, 3, and 4 were assessed. Stress and elongation were measured during the testing, and the data obtained was used to make graphs that showed how the two variables related to one another.

Table 4: Results of Tensile test

Sample /specimen	Tensile strength (N/ mm^2)
1	62 N/ mm^2
2	55 N/ mm^2
3	56 N/ mm^2
4	53 / mm^2

Based on the results, the following observations were made: (i) **sample 1**, with random fiber orientation and higher fiber content (30%), showed the highest tensile strength. The random orientation enabled more even stress distribution, and the higher fiber content provided greater reinforcement,(ii) **sample 2**, with bidirectional fiber orientation and the same composition as Sample 1, exhibited slightly lower tensile strength. The bidirectional layout likely led to localized stress concentrations, reducing overall strength,(iii)**sample 3**, featuring unidirectional fiber orientation and lower fiber content (10%), demonstrated tensile strength similar to Sample 2. Although reinforcement was limited to one direction, the alignment partially compensated for the reduced fiber content and (IV) **sample 4**, with random fiber orientation and the same composition as Sample 3, showed the lowest tensile strength. While the random orientation

allowed for stress distribution, the low fiber content significantly weakened the sample. In summary, tensile strength varied due to differences in fiber orientation and content. Higher fiber content and random orientation generally resulted in superior tensile strength, highlighting their combined effect on mechanical performance. The tensile measurement processes using the machine are illustrated in **figure 7**(a and b).



Fig.7: Tensile tested sample ;(a) Tensile testing machine (b) The sample after taste

As shown in **Figure 8**, all four samples exhibited a linear elastic region at the beginning of the stress-strain curve, indicating reversible deformation. The yield point was clearly visible for Samples 1 and 2. The plastic deformation region was relatively short for all samples, suggesting a rapid transition from elastic to plastic behavior.

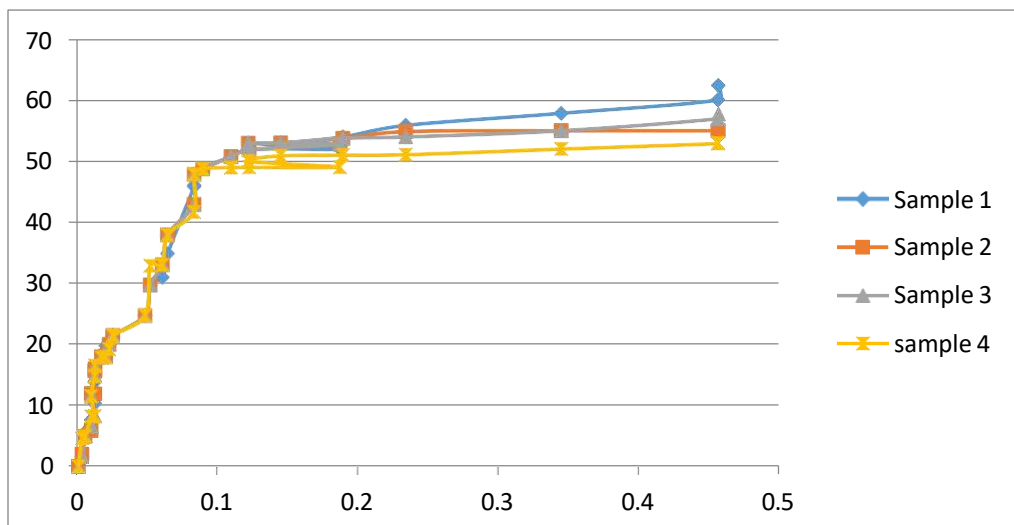


Fig.8: Stress strain graph for tensile strength

Using different formulae and their relationships; Section modulus (Wb) $Wb = \frac{B \times H^2}{6}$,

Maximum bending Moment (Mbmax) $Mbmax = \frac{F_{max} \times L}{4}$ and Flexural Strength ($\delta bmax$)

$\delta bmax = Mbmax = \frac{Mbmax}{Wb}$, Flexural strength was calculated using the following formula:

Flexural strength = $(3 \times F_{max} \times L) / (2 \times B \times H^2)$ where B = Width of specimen, H = Thickness of the specimen, Fmax = Maximum applied force and L = Span length, the following results have been obtained;

Table 5: Result of flexural strength test

Sample /specimen	Flexural strength (N/ mm ²)
1	336.91 N/ mm ²
2	307.62N/ mm ²
3	278.32 N/ mm ²
4	292.97 N/ mm ²

Based on the results as shown above **Table 5**, the following was observed: (a) **sample 1**, with random fiber orientation and higher fiber content (30%), exhibited the highest flexural strength, (b) **sample 2**, with bidirectional fiber orientation and the same composition as Sample 1, showed slightly lower flexural strength, (c) **sample 3**, featuring unidirectional fiber orientation and lower fiber content (10%), had lower flexural strength than Samples 1 and 2 and (d) **sample 4**, with random fiber orientation and the same composition as Sample 3, displayed flexural strength between Samples 2 and 3. The processes of Flexural strength tested specimens indicated in **figure 9** below.



Fig.9: Flexural strength tested specimens: (a) Flexural testing machine and the sample (b)

Tested sample

Flexural strength was generally higher compared to other mechanical properties. This disparity likely resulted from the bending force in flexural tests, which distributed stress across the cross-section and promoted more uniform load-bearing. In contrast, tensile tests applied force in one direction, causing stress concentrations and lower overall strength [65, 66]. Additionally, fiber orientation significantly influenced flexural performance, as fiber arrangements provided extra resistance to bending forces, enhancing strength.

Table 6: Result of impact test

No	Sample name	Absorbed Energy in (J)	Rise Angle in degree
1	1	30	77
2	2	25	88
3	3	28	82
4	4	27	84

Table 7: Impact strength test result

Sample number	Fiber	Thickne ss(mm)	Widt h (mm)	Area (a) mm^2	Average actual energy absorbed (k)	Impact strength I_s (k/a ²) J/mm^2
1	Hybrid sisal-cotton	3.2	12.7	40.6	30	0.738
2	Hybrid sisal-cotton	3.2	12.7	40.6	25	0.6157
3	Hybrid sisal-cotton	3.2	12.7	40.6	28	0.689
4	Hybrid sisal-cotton	3.2	12.7	40.6	27	0.665
Average		3.2	12.7	40.6	27.5	0.676

Table 6 showed the energy absorbed by the specimens during the impact test. Samples 2 and 4 absorbed less energy than samples 1 and 3. This difference was attributed to the hybrid

composites' dual fiber arrangement, which hindered crack propagation and enhanced energy absorption. Sample 1 demonstrated the highest energy absorption, indicating superior impact resistance. The dual fiber arrangement in the hybrid composites improved crack resistance, increasing energy absorption capacity. This highlighted Sample 1's potential for high-impact applications. **As depicted in Table7**, impact strength was calculated using the formula $IS = \frac{E}{w.t}$ where w is the specimen's breadth and t is its thickness, and E is the amount of energy that was absorbed in joules to break the specimen. Stresses in a material must be equally distributed throughout the object in order for it to have increased impact strength. The impact energy absorbed by the material is typically measured using a notched sample.



Fig.10: Impact strength tested specimens: (a) Charpy impact testing machine (b) sample

Table 8 : Compression test result

Sample /specimen	Compression strength (N/ mm^2)
1	44 N/ mm^2
2	39N/ mm^2
3	40 N/ mm^2
4	4 / mm^2

As shown in Figs 9, 10 and Table 8 presented the compression test results, showing: (i) **sample 1** exhibited the highest compression strength of 44 N/ mm^2 , with 30% sisal-cotton fibers in a random arrangement. The random fiber distribution enhanced load-bearing capacity,(ii)**sample 2** showed a compression strength of 39 N/ mm^2 , with 30% fibers in a bidirectional arrangement. This slightly lower strength was likely due to fiber alignment variations; (iii) **sample 3** had

compression strength of 40 N/mm², with 10% fibers in a unidirectional arrangement. Despite lower fiber content, fiber alignment along the load direction maintained comparable strength to sample 2 and (iv) **sample 4** showed 39 N/mm² compression strength, with 10% fibers in a random arrangement. The random fiber layout caused more variation in strength. The stress-strain curves (figure below) revealed a linear elastic zone at the start for all samples, indicating reversible deformation. The yield points were clearly visible, marking the onset of plastic, irreversible deformation. Ranking the samples by yield point, ultimate strength, and failure strain: **As illustrated in fig. 11 and 12** below, sample 1 ranked highest, followed by Samples 2, 3, and 4, respectively. Sample 1 was thus the strongest and most ductile among them.



Fig.11: Compression strength tested sample: (a) Compression tested sample (b) The sample while being tested

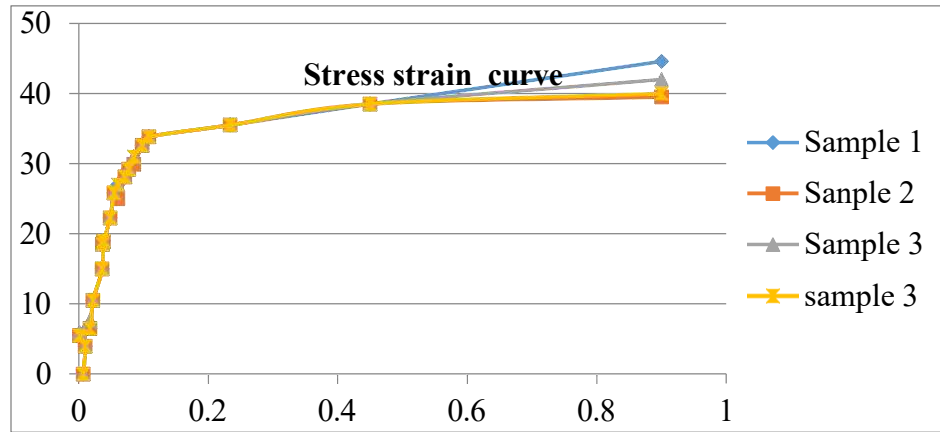


Fig.12: Stress –Strain curve for compression strength

4.2.Evaluating Mechanical Properties in Comparison with Existing Literatures

The mechanical properties of the proposed hybrid sisal-cotton fiber-reinforced polymer composites were evaluated against existing literature to assess their suitability for car body panels, which demand high compression, flexural, and impact strengths.

Table 9: Evaluation of mechanical characteristics

Matrix	Fiber	Orientat ion	Ra tio	Tensile(MPa)	Compressi on(MPa)	Flexural (MPa)	Impact(J/ mm^2)	Reference
Epoxy (LY 556)	Hybrid sisal- cotton	Random	30 /7 0	56.5	44.8	303.9	0.676	Current work
Polyeste r resins	Hybrid sisal-cotton	Random	10 /9 0	-	18	190	0.0179	[67]
GP epoxy	Sisal fiber epoxy- reinforced	Random	30 /7 0	-	23.2	189.36	0.01067	[68]
GP Epoxy	Flax –sisal epoxy composite	Random	30 /7 0	68.40	45.64	145.7	0.2581	[69]
Epoxy (LY 556)	Hybrid flax- banana	Random	30 /7 0	68.9	24	169.14	0.25812	[70, 71]
Epoxy (LY 556)	Hybrid sisal and flax	Random	30 /7 0	-	23.5	61	0.5073	[72]
Epoxy	Sisal-fiber epoxy composite	Unidirect ional	40 /6 0	-	23	72	0.7881	[73]

Table 9 compared these properties with those of commonly used natural fiber-reinforced composites. The results demonstrated that the proposed composite exhibited sufficient potential for the intended application. The analysis combined Taguchi methodologies with Artificial Neural Networks (ANN) and Genetic Algorithms (GA). **Analysis Using Taguchi has been conducted and hence** surface roughness and material removal rate (MRR) during machining were influenced by several variables. This study focused on three controllable factors: spindle speed, feed rate, and depth of cut (DOC), while cutting tool settings remained constant due to uniform tool material. Experiments were performed on three samples per setting, totaling 27 trials. A CNC milling machine was used, machining composite work pieces sized 250 mm × 70 mm × 10 mm.

Table 10: Result of experimental data

Experiment number	(Ra) (μm)				(MRR) mm^3/min
	S1	S2	S3	Average	
1	1.23	1.19	1.07	1.163	2000
2	1.35	1.27	1.22	1.28	6000
3	1.22	0.87	1.44	1.176	12000
4	1.13	0.93	0.99	1.0167	3000
5	1.55	1.05	1.25	1.283	8000
6	1.73	0.47	1.11	1.103	6000
7	1.57	1.32	1.74	1.543	4000
8	0.68	1.53	1.33	1.18	4000
9	1.32	1.41	2.02	1.583	9000

Minitab's full factorial design was used to determine the number of tests and cutting conditions. The experimental results are presented in **Table 10**.

4.2. Influence of machining parameters on the rate of Material removal using statistical analysis involving Regression for MRR

Statistical regression analysis revealed that machining parameters such as cutting speed, feed rate, and depth of cut significantly influence the material removal rate (MRR), with feed rate showing the strongest positive correlation. Regard to the Influence of Machining Parameters on Material Removal Rate (MRR), regression analysis was used to determine the relationship between input parameters and MRR based on experimental data [73, 74]. A linear regression model was developed to quantify the effects of spindle speed (S), feed rate (F), and depth of cut (D) on MRR. The resulting regression equation was:

$$\text{MRR} = -4649 - 0.921S + 30.00F + 4000D$$

$\text{MRR} = -4649 - 0.921S + 30.00F + 4000D$

Table 11: MRR experimental result vs. predicted

Trials	Experimental result	Predicted result	Predicted Error value (%)
1	2000	2350.079	17.5
2	6000	6430	7.1
3	12000	11430	4.75
4	3000	3061.6	2.053
5	8000	8061.6	0.77
6	6000	7061.6	17.69
7	4000	4509	12.725
8	4000	3509	12.275
9	9000	8509	5.45

Using this equation, the predicted values and their discrepancies were calculated and compared with experimental results, as shown in **Table 11** above. Evaluation of the Signal to Noise Ratio for MRR, Taguchi introduced the concept of 'signal' as the target value (mean) for the response, with 'noise' representing the undesired value (deviation, SD). To identify parameters deviating from the experimental value, Taguchi utilizes the S/N ratio, which varies based on the objective function: lower is better, nominal is optimal, and higher is better[75]. Removal rate larger is better is used. According to Taguchi larger is better is given by the formula: Larger is better: $S/NL = -10 \log_{10} (\sum(y^2/n))$. The influence of the selected process parameters on the Material Removal Rate (MRR) was evaluated using the experimentally obtained MRR values.

Table 12: The results for material removal rate

Trial	V	F	DOC	MRR
1	1000	100	1	2000
2	1000	200	1.5	6000
3	1000	300	2	12000
4	1400	100	1.5	3000
5	1400	200	2	8000
6	1400	300	1	6000
7	2000	100	2	4000
8	2000	200	1	4000
9	2000	300	1.5	9000

Table 13: Material Removal Rate Signal-to-Noise Ratio Assessment

MRR	SNR(db)
2000	66.0206
6000	75.5630
12000	81.5836
3000	69.5452
8000	78.0618
6000	75.5630
4000	72.0412
9000	72.0412
	79.0849

As shown in **Tables 12 and 13**, the Material Removal Rate (MRR) results are presented; while the main effect plots for the Signal-to-Noise (S/N) ratio in **Figure 13** illustrates how the process parameters are correlated with MRR. Notably, spindle speed exhibits no significant influence on MRR. However, the analysis reveals a direct correlation between feed rate, depth of cut, and MRR specifically, increasing the feed rate and depth of cut leads to a higher material removal rate, whereas decreasing these parameters results in a reduced MRR.

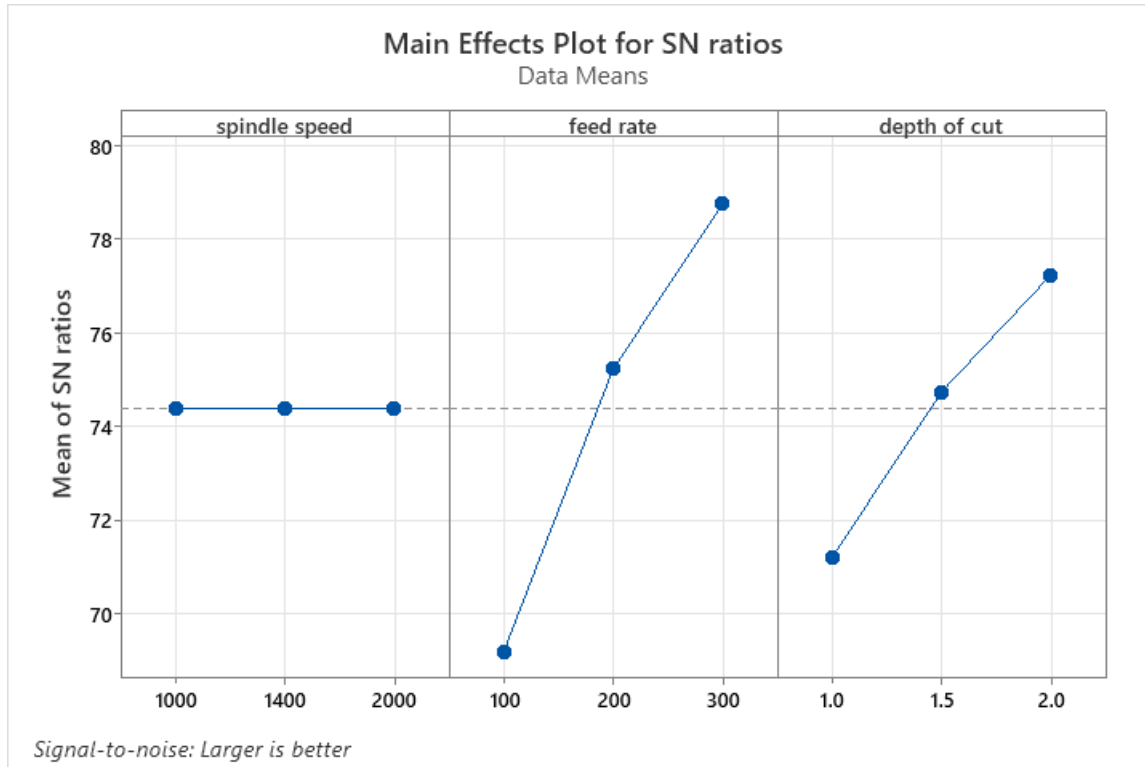


Fig.13: Analysis of Input Factors and Their Impact on MR

4.3. Utilizing ANOVA to examine the material removal rate

ANOVA analysis demonstrated that machining parameters, particularly feed rate and depth of cut have a statistically significant effect on the material removal rate (MRR), highlighting their critical role in optimizing machining performance.

Table 14: Interpreting ANOVA Findings for Material Removal Rate

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle speed	2	2000000	2.44%	2000000	1000000	1.00	0.500
Feed rate	2	54000000	65.85%	54000000	27000000	27.00	0.036
Depth of cut	2	24000000	29.27%	24000000	12000000	12.00	0.077
Error	2	2000000	2.44%	2000000	1000000		
Total	8	82000000	100.00%	82000000			

Table 15: Optimal combination of the parameters

Optimal parameters	Surface roughness actual	Surface roughness predicted	Predicted value (%)	Error
Spindle speed	-	12 000	11666.7	2.755
Feed rate	300mm/min			
Depth of cut	2mm			

An Analysis of Variance (ANOVA) was conducted to evaluate the influence of input parameters on the Material Removal Rate (MRR). As presented in **Tables 14 and 15**, the results demonstrated that MRR was predominantly affected by the feed rate, which accounted for 65.85% of the total variation. This was followed by the depth of cut (29.27%) and spindle speed (2.44%). A P-value below 0.05 for the feed rate indicated a statistically significant effect on MRR, whereas spindle speed exhibited the least influence. In conclusion, both feed rate and depth of cut had significant impacts on MRR, contributing 65.85% and 29.27% to the overall variation, respectively, while spindle speed contributed marginally, with only 2.44%.

The residual plots for MRR were analyzed to evaluate the adequacy of the fitted model and to detect any potential issues within the data, as illustrated in **Figure 14**. The normal probability

plot indicated that the residuals were approximately normally distributed, with only a few outliers. The fits versus residuals plot showed a random scatter of residuals around zero, suggesting no discernible patterns or model misspecification. The histogram further confirmed that the residuals followed an approximately normal distribution, with minor deviations. Additionally, the residuals versus order plot revealed no evident trends or systematic variation over time. Overall, the residual analysis supports the conclusion that the fitted model is appropriate and adequately represents the data. While a few outliers are present, they are not expected to significantly affect the validity of the model or its predictive capability.

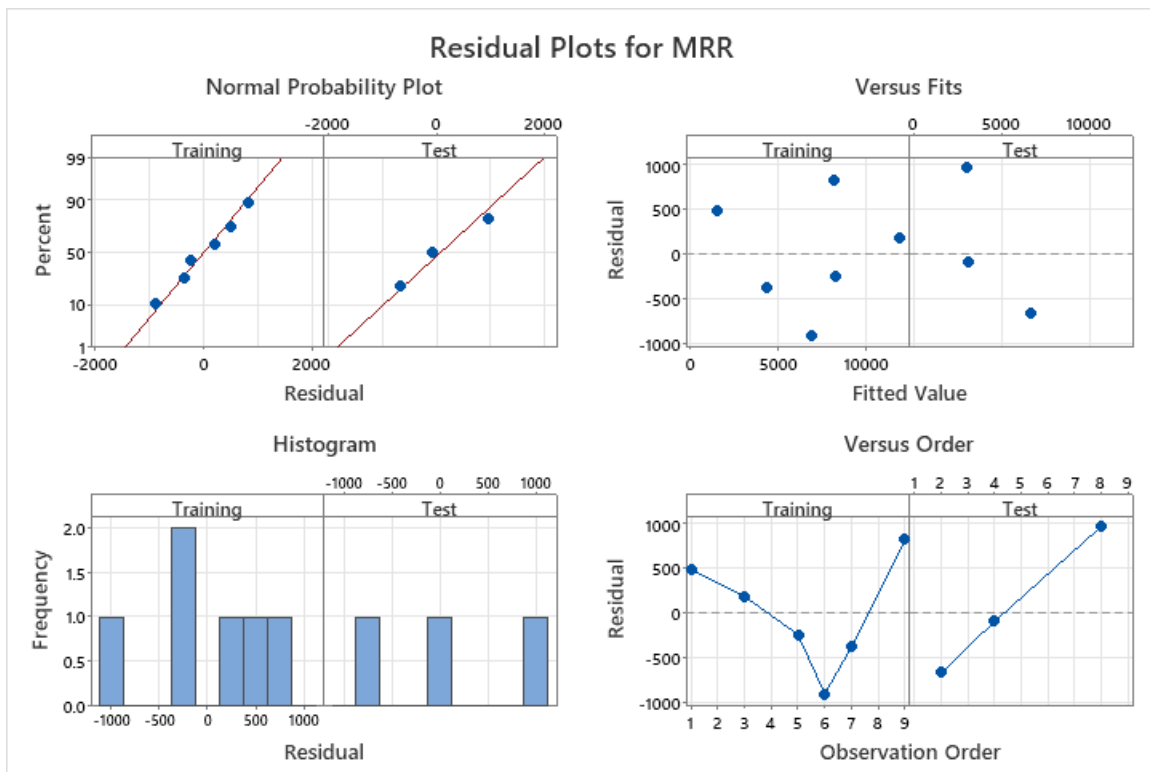


Fig 14: Residual plot for MRR

4.4. Influence of Machining Parameters on Surface Roughness: Statistical Analysis Using Regression

Regression analysis showed that machining parameters, especially cutting speed and feed rate, significantly affect surface roughness, with higher feed rates leading to increased roughness levels.

Table 16: Actual vs. Predicted value for surface roughness

Trials	Experimental result Ra(μm)	Predicted Ra(μm)	error Predicted value (%)
1	1.163	1.1085	4.68
2	1.2800	1.2415	3.07
3	1.176	1.3396	13.91
4	1.0167	1.01	5.2
5	1.283	1.2134	5.42
6	1.103	1.234	11.87
7	1.543	1.0372	32.7
8	1.180	0.8754	25.81
9	1.583	1.5911	2.07

As shown in **Table 16**, in formulating the mathematical model for surface roughness of milled slots, the input machining parameters are considered to explore their relationship with surface roughness during the milling of the composite. The guiding equation is derived through linear regression analysis. Using the measured surface roughness data, a linear polynomial model equation is generated to represent the influence of various milling parameters, using the formula; $SR = 1.156 - 0.000256 S + 0.000232 F + 0.185D$. In this context, **SR** represents surface roughness measured in μm.

4.5. The Signal-Noise Ratio Evaluation for Surface roughness

The Signal-to-Noise ratio analysis was conducted to evaluate the influence of machining parameters on surface roughness, aiming to identify the optimal settings that minimize variability and enhance process stability. A "smaller-the-better" criterion was applied, as lower surface roughness values indicate improved surface quality. It was computed using $S/NL = -10\log_{10} (\sum(y^2/n))$ formula.

Table 17: Result for experimental value of surface roughness

Number of trials	V	F	DOC	(Ra) (μm)
1	1000	100	1	1.163
2	1000	200	1.5	1.28
3	1000	300	2	1.176
4	1400	100	1.5	1.0167
5	1400	200	2	1.283
6	1400	300	1	1.103
7	2000	100	2	1.543
8	2000	200	1	1.18
9	2000	300	1.5	1.583

In this analysis, the preference for a lower surface roughness that aligned with the "smaller-the-better" criterion was established to achieve an optimal surface finish. MINITAB statistical software was utilized to evaluate the influence of the selected machining parameters on the surface roughness of the milled composite sample. The study was conducted within the framework of Taguchi's method, using experimental data presented in **Table 17**.

Table 18: Signal to Noise ratio for surface roughness

Surface roughness(μm)	SNR(db)
1.163	-1.31159
1.280	-2.14420
1.180	-1.43764
1.525	-3.66540
1.283	-2.16453
1.103	-0.85151
1.543	-3.76732
1.180	-1.43764
1.580	-3.97314

Table 19: Optimal combination of machining parameters

Optimal parameters	Surface roughness actual	Surface roughness predicted	Error
Spindle speed 1000	1.0167	1.0297	1.28%
Feed rate 200			
Depth of cut 1			

As illustrated in **Tables 18, 19** and **figure 15**, surface roughness is positively correlated with spindle speed. This is attributed to the increased friction between the cutting tool and the work piece at higher spindle speeds, which generates more heat and may lead to material burnout and a rougher surface finish[45, 76]. Conversely, feed rate negatively impacts surface quality, as higher feed rates tend to produce rougher surfaces. This effect is primarily due to the formation

of built-up edges, resulting from the resistance encountered by the cutting tool, which contributes to surface deterioration[77]. Additionally, the influence of depth of cut on surface roughness is non-linear; surface smoothness initially decreases with an increase in depth of cut, but beyond a certain point, it begins to improve. Based on the analysis, the optimal combination of cutting parameters for achieving the smoothest surface finish is a spindle speed of 1000 rpm, a feed rate of 200 mm/min, and a depth of cut of 1 mm.

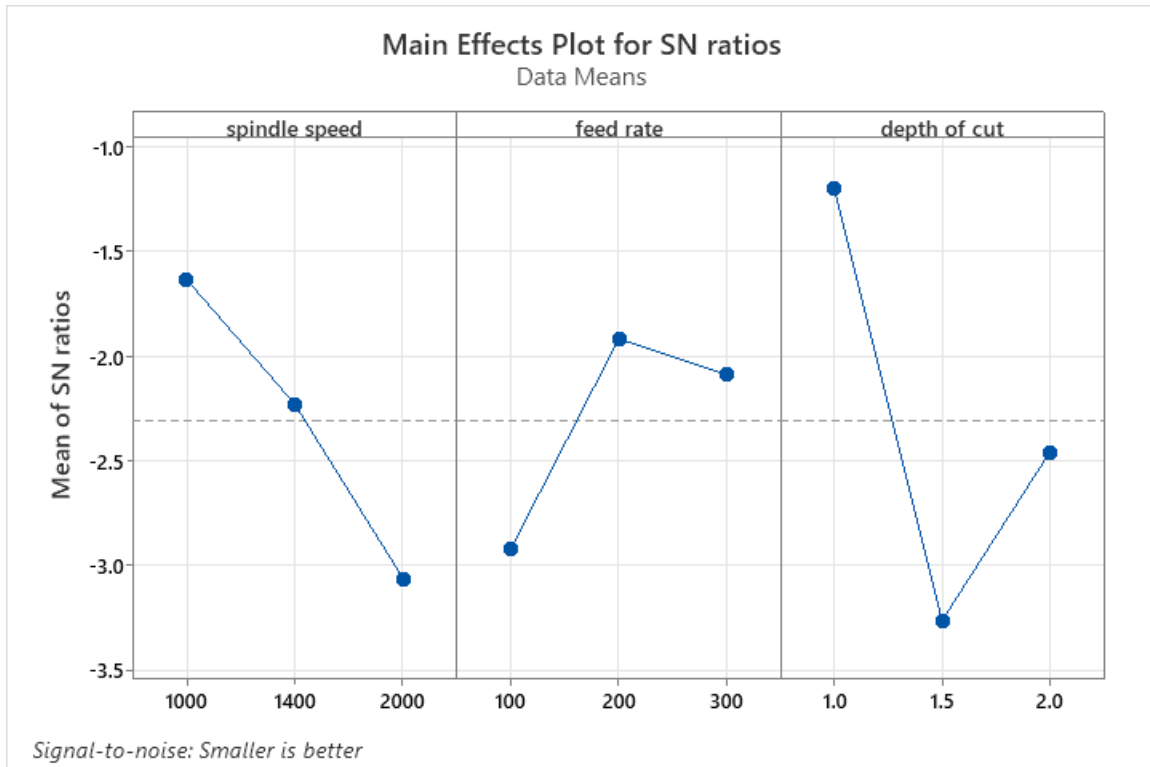


Fig. 15: Effect of machining parameter on surface roughness

4.6. Utilizing ANOVA to Examine Surface Roughness

An Analysis of Variance (ANOVA) was performed to assess the statistical significance and contribution of machining parameters is spindle speed, feed rate, and depth of cut on surface roughness. This analysis aimed to identify the most influential factors affecting surface quality during the milling of the composite material.

Table 20: Statistical analysis in to Ra variability using ANOVA

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle speed	2	0.077668	28.44%	9.356	0.077668	22.15	0.0438
Feed rate	2	0.043108	15.78%	11.601	0.043108	12.29	0.075
Depth of cut	2	0.148774	54.48%	16.758	0.148774	42.42	0.023
Error	2	0.003507	1.28%	1.379	0.003507		
Total	8	0.273056	100.00%				

As shown in **Table 20**, an analysis of variance (ANOVA) was conducted to evaluate the influence of input machining parameters on surface roughness. The results revealed that surface roughness is predominantly affected by depth of cut, contributing 54.48% to the variation, followed by spindle speed (28.44%) and feed rate (15.78%). The corresponding p-values for spindle speed (0.0438), feed rate (0.075), and depth of cut (0.023) indicate that all three parameters significantly influence surface roughness, with p-values for spindle speed and depth of cut falling below the standard significance level of 0.05. Although the p-value for feed rate is slightly above 0.05, it still suggests a notable influence. The minimal error percentage of 1.28% confirms the reliability and acceptability of the results, emphasizing the dominant role of depth of cut in determining surface finish quality.

The residual plots were analyzed to evaluate the adequacy of the fitted regression model and to identify any potential anomalies in the data, as illustrated in **Figure 16**. The normal probability plot indicated that the residuals were approximately normally distributed, with only a few minor outliers. The residuals versus fits plot displayed a random scatter around zero, suggesting constant variance and the absence of systematic patterns. The histogram further confirmed the near-normal distribution of residuals, again with minimal outliers. Additionally, the residuals versus order plot revealed no discernible trend, indicating stability over the sequence of data collection. In general, the minor scatter deviations and isolated outlier points observed in the lower-bound quadrants of the residual versus order plots (Fig. 14 and Fig. 16) are entirely representative of the microstructural heterogeneity inherent to multi-component hybrid natural fiber architectures. Local minor variations in localized fiber bundle packing, microscopic void distributions, and shifting instantaneous tool-fiber cutting angles during high-speed CNC end milling introduces predictable stochastic force variations. These minute experimental boundary fluctuations do not degrade the global predictive stability, functional convergence, or mathematical

adequacy of the developed linear regression, Analysis of Variance (ANOVA), or back propagation artificial neural network frameworks.

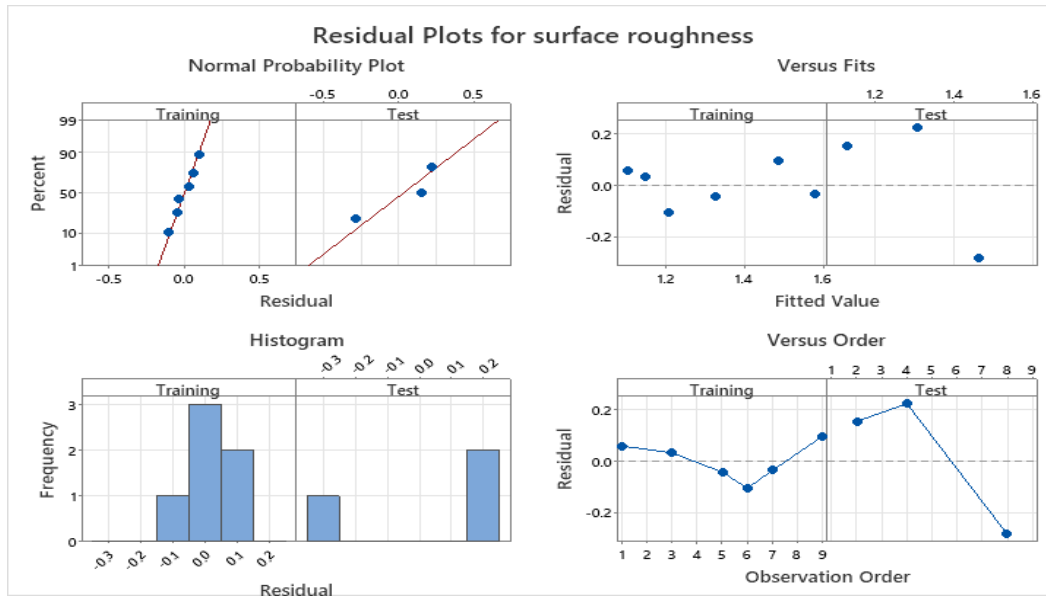


Fig. 16: Residual, probability, and fit plot

5. Conclusion

This study successfully established a comprehensive, sustainable, and intelligent manufacturing framework for the processing of hybrid natural fiber-reinforced polymer composites (NFCs) designed for high-performance automotive structural applications. Hybrid sisal-cotton fiber epoxy composites were successfully engineered utilizing targeted chemical pre-treatments, structurally profiled, and optimized via an integrated Taguchi, Artificial Neural Network (ANN), and Genetic Algorithm (GA) methodology. The critical findings and quantitative metrics derived from this research are concluded as follows: (i) Interfacial Enhancement and Structural Integrity: Alkaline mercerization treatment using sodium hydroxide (5% NaOH for cotton yarn and 8% NaOH for sisal fibers) successfully eliminated structural surface impurities, including lignin, hemicellulose, and waxes. This surface modification promoted superior mechanical interlocking, resulting in robust fiber-matrix interfacial adhesion, (ii) Mechanical Superlative Performance: Extensive mechanical characterization proved that Sample 1 (comprising a 30 wt% fiber mass fraction configured in a short, 2 mm random orientation layout) yielded optimal load distribution and structural performance. Quantitative maximum values achieved include a tensile strength of 62 N/mm², compression strength of 44 N/mm², a flexural strength of 336.91 N/mm², and a Charpy impact strength of 0.738 J/mm². Comparison with existing literature validated that this hybrid composite possesses the prerequisite structural properties needed to replace carbon-intensive materials in vehicle body panels, (iii) Material Removal Rate (MRR) Dynamics:

Within the CNC end-milling operations, Analysis of Variance (ANOVA) identified feed rate as the dominant parameter governing material removal rate, accounting for an explicit 65.85% contribution to total process variation ($P < 0.05$). This was followed by depth of cut at 29.27%, whereas spindle speed exhibited a marginal contribution of only 2.44%. The derived empirical linear regression model accurately verified that maximizing the feed rate (300 mm/min) and depth of cut (2.0 mm) maximizes bulk productivity,(iv) Surface Roughness (Ra) Optimization: Surface quality was predominantly controlled by depth of cut, which contributed 54.48% to the total variance ($P = 0.023$), followed closely by spindle speed at 28.44% ($P = 0.0438$) and feed rate at 15.78%. To suppress tool friction, built-up edge formations, and localized thermal degradation, Taguchi's 'smaller-the-better' signal-to-noise (S/N) criterion isolated the absolute optimal cutting configuration for maximum smoothness: a spindle speed of 1000 rpm, a feed rate of 200 mm/min, and a depth of cut of 1 mm, and (v) Predictive Framework Fidelity: The integrated intelligent ANN model demonstrated remarkable predictive stability and high fidelity when mapping non-linear machining interactions. Validations between the experimentally observed values and the simulated soft-computing predictions yielded minimal error indices, notably falling down to 1.28% error for surface roughness predictions under optimized conditions. Normal probability, residual histogram, and versus-fits scatter plots collectively confirmed that the statistical model assumptions are robust, completely adequate, and free from structural misidentifications.

In summary, this intelligent optimization framework successfully reduces the manufacturing sector's dependence on energy-intensive, costly, and time-consuming physical prototyping trials. By allowing reliable pre-machining simulation and parameter selection, this work significantly enhances process planning efficiency and material conservation, paving the way for the automated tracking and smart control of sustainable natural-fiber composites within manufacturing industries.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this research paper.

Authorship Contribution Statement

Yodit Esayas Ayele: Conceptualization, Methodology, Writing and Original Draft as initial PI.

Semegn Cheneke Lemessa: Software, Validation, Formal Analysis.

Melese Yalew Ayalew: Supervision, Project Administration, Writing – Review & Editing.

Tadele Ageru Alemu: Investigation, Data Curation, Resources, Writing, Review, Editing and corresponding author.

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Tessera Alemneh Wubieneh: Visualization, Investigation, Writing and and Original Draft as collaborator.

Data Availability Statement

The raw statistical profiles, experimental milling measurements, trained Artificial Neural Network weight values, and underlying datasets generated during this study are available from the corresponding authors upon reasonable request.

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