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ANN-Based Mechanical Property Prediction of Bio-Fibre for Wind Turbine Blade Materials with FEM Validation

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Abstract. The increasing demand for renewable energy highlights the need for sustainable materials in wind turbine blade design. Conventional fiberglass blades, while effective, present environmental and disposal challenges, motivating the exploration of bio-composites as greener alternatives. This study aims to develop and validate an integrated framework that combines experimental validation, Finite Element Method (FEM) pre-screening, Artificial Neural Networks (ANN), and Rule of Mixtures (RoM) validation to evaluate the feasibility of bio-fibre wind turbine blades Mechanical properties of flax, hemp, sisal, jute, pineapple fiber, and resin are obtained from previously published experimental studies available in the literature, with resin content fixed at 90% and permutations generated for ANN training. Experimental tensile testing on a 90% resin–10% pineapple fiber composite yields 131 MPa, closely matching the permutation prediction of 118.6 MPa, confirming dataset reliability. FEM simulations are then employed to pre-screen potential maximum performance values within the dataset range, ensuring the physical feasibility of ANN input properties. Using these validated inputs, the ANN predicts feasible bio-composite compositions, which are further compared against RoM estimations. The results show that ANN predictions remain within a 7% deviation from RoM values, demonstrating consistency with micromechanical theory. This integrated framework highlights that FEM-based input screening enhances ANN prediction reliability, and pineapple-based bio-composites can serve as sustainable and technically viable alternatives for wind turbine blade applications.

Keywords: Artificial Neural Network (ANN), Finite Element Method (FEM), Bio-Composites, Pineapple Fiber, Wind Turbine Blades

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1. Introduction

The global push for renewable energy aims to mitigate fossil fuel depletion and climate change, with wind energy playing a pivotal role. As turbine blades grow in size, structural efficiency and material sustainability become critical design factors. Conventional fiberglass-based composites pose environmental and end-of-life recycling challenges, prompting the need for more sustainable alternatives [1].

Fiberglass-reinforced composites are difficult to recycle due to energy-intensive processes like pyrolysis [2] and mechanical recycling [3], compounded by complex environmental impacts [4] and recycling constraints [5], which often result in blades ending up in landfills as large-scale recycling remains limited. Life-cycle assessments indicate that carbon fiber production largely drives the global warming potential of blades, while natural fiber alternatives like flax and hemp may reduce emissions by around 6–8% [1].

Bio-composites, using natural fibers such as flax, hemp, jute, sisal, and pineapple leaf fiber, offer reduced environmental impact and improved biodegradability [6]. However, their variable mechanical properties, moisture sensitivity, and fatigue behavior pose technical challenges.

Previous studies either conduct FEM-based structural analysis of composite blades or investigate natural fiber feasibility for turbine components [7–9]. Yet, these often lack integrated predictive modeling and experimental validation. Current ANN approaches for composite materials rarely include pre-screening of input values via structural feasibility, reducing their practical reliability.

This study bridges that gap by integrating structural screening via FEM with ANN-based compositional prediction, backed by experimental tensile testing. Mechanical property permutations (with fixed 90% resin and varying fibers) are first vetted with FEM using high-performance values within the ANN training range. The ANN predicts optimal compositions, which are then subject to FEM analysis for deformation and stress verification. This integrated methodology enhances prediction credibility and demonstrates pineapple fiber–based bio-composites as a viable, sustainable alternative to fiberglass for wind turbine blades.

2. Methods

This study integrates experimental testing, finite element method (FEM) pre-screening, and artificial neural network (ANN) prediction to evaluate bio-composite wind turbine blades. The research begins with dataset generation through permutation of mechanical property data for flax, jute, hemp, sisal, and pineapple fiber combined with 90 percent resin content. Mechanical properties include tensile strength, tensile modulus, density, and fatigue strength, which are sourced from literature [10]. Experimental tensile testing is performed on a pineapple fiber–resin composite (90 percent resin and 10 percent pineapple fiber) to validate the permutation dataset. FEM pre-screening uses potential maximum performance values within the range of the ANN training dataset to ensure structural feasibility. The ANN predicts optimal fiber compositions, which are validated using the Rule of Mixtures. The overall methodology is illustrated in Figure 1.

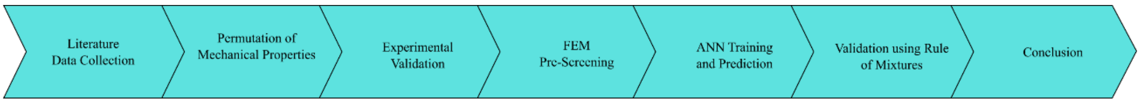


Figure 1. Flow Diagram of the Methodology.

2.1. *Experimental Testing (Validation of Permutation Dataset)*

The initial mechanical properties of the base materials are collected from literature [10], including flax, jute, hemp, sisal, pineapple fiber, and polyester resin. These properties, which consist of tensile strength, Young's modulus, density, and fatigue strength, are summarized in Table 1.

Table 1. Basic Mechanical Properties of Bio-Based Materials [10].

No	Material	Tensile Strength [MPa]	Tensile Modulus [GPa]	Density [g/cm^3]	Fatigue Strength at 10^6 Cycles [Mpa]
1	Flax	343 – 1035	28 – 100	1.45 – 1.55	115
2	Jute	393 – 773	25 – 55	1.35 – 1.45	85
3	Hemp	310 – 900	32 – 60	1.45 – 1.55	83
4	Sisal	248 – 483	9 – 28	1.40 – 1.45	101
5	Pineapple	118 – 466	4 – 27	1.44 – 1.56	68
6	Resin	60 – 85	2.5 – 4.0	1.1 – 1.4	35

Based on these properties, a dataset is generated through permutation by combining 90 percent resin with 10 percent fiber for each material. The resulting values are presented in Table 2, which provides the training dataset for the artificial neural network (ANN).

Table 2. A Dataset That Contains Several Data Points For Training An Artificial Neural Network (ANN) That Has Already Been Permuted.

No	Material	Percentages	Tensile Strength (MPa)	Tensile Modulus (GPa)	Density (g/cm^3)	Fatigue Strength (MPa)
1	Flax, Resin	10, 90	106.30	5.68	1.2070	43.00
2	Jute, Resin	10, 90	111.30	5.38	1.1970	40.00
3	Hemp, Resin	10, 90	103.00	6.08	1.2070	39.80
4	Sisal, Resin	10, 90	106.70	3.78	1.2020	41.60
5	Pineapple, Resin	10, 90	118.60	5.58	1.2180	38.30
…	…	…	...	...	...	...
3205	Flax, Jute, Hemp, Sisal, Pineapple, Resin	10, 0, 0, 0, 0, 90	106.34	5.49	1.2065	42.86

To ensure the validity of the permutation dataset, an experimental tensile test is performed on a pineapple fiber–resin composite with 90 percent resin and 10 percent pineapple fiber. The experimental testing serves as a benchmark to confirm that the dataset generated from literature-based permutations is consistent with real composite behavior, thereby reinforcing its suitability for ANN training.

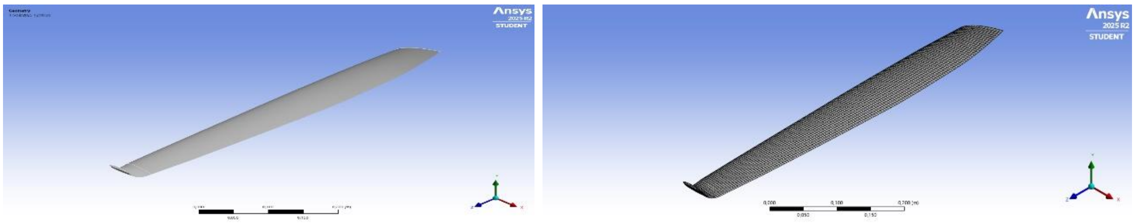
2.2. FEM Pre-Screening

Finite Element Method simulations are commonly used in the structural analysis to evaluate stress distribution and deformation under loading [11]. Finite Element Method (FEM) simulation in this study is conducted to pre-screen the dataset and ensure that the input values used for training the Artificial Neural Network (ANN) remain within a physically reasonable range. The simulation is performed using ANSYS Workbench (Static Structural module). The turbine blade is designed based on the Clark-Y foil, and the main geometric parameters are summarized in Table 3. This configuration is adapted from small-scale wind turbine blade designs reported in the literature [12].

Table 3. Turbine Blade Design Parameters

Parameter	Value
Airfoil profile	Clark-Y
Blade span	2.4 m
Chord length root	0.445 m
Chord length tip	0.15 m
Winglet Angle	30°

The turbine blade geometry is illustrated in Figure 2a, while the meshed model prepared for the simulation is shown in Figure 2b. The geometry is discretized using a tetrahedral mesh with adaptive sizing, medium resolution, and fine span angle control. The adopted mesh configuration is summarized in Table 4.



a. b.

Figure 2. a. Turbine blade geometry before meshing; b. Meshed turbine blade model

The determination of aerodynamic loads begins with the calculation of the Tip Speed Ratio (TSR), which relates the tangential speed at the blade tip to the incoming wind velocity. The TSR is defined in Equation (1) [13]:

$$\lambda = \frac{\omega R}{V} \tag{1}$$

where ω is the angular velocity (rad/s), R is the blade length, and V is the free-stream wind speed. Once the TSR is known, the relative velocity along the blade span, V_{rel}, can be determined and subsequently used to calculate the lift and drag forces. The lift force is obtained using Equation (2) [14]:

$$F_L = \frac{1}{2}\rho V_{rel}^2 C_L c R \tag{2}$$

while the drag force is determined using Equation (3) [15]:

$$F_D = \frac{1}{2}\rho V_{rel}^2 C_D c R \tag{3}$$

where ρ is the air density, C_L and C_D are the lift and drag coefficients, and c is the chord length.

The centrifugal force is applied as a distributed body load and is calculated using Equation (4):

$$F_{cent} = \rho_m A_{cross} \omega^2 R \tag{4}$$

where ρ_m is the material density, A_{cross} is the average cross-sectional area, ω is the angular velocity, and R is the blade length. The blade's self-weight is considered using Equation (5):

$$W = m \times g \tag{5}$$

where m is the blade mass obtained from the geometry and material density, and g is the gravitational acceleration (9.81 m/s²).

Table 4. Mesh settings for FEM simulation

Parameter	**Value**
Adaptive Sizing	Yes
Resolution	5 (medium)
Transition	Fast
Span angle center	Fine
Minimum edge length	7.6681 × 10^-2 m
Average surface area	2.4072 × 10^-2 m²
Bounding box diagonal	0.60949 m

The material properties assigned in the FEM simulation are chosen as potential maximum values that still fall within the dataset range derived from literature-based permutations used for ANN training. These values include a density of 1.218 g/cm³, Young's modulus of 6050 MPa, Poisson's ratio of 0.003, bulk modulus of 2.03×10^9 Pa, shear modulus of 3.02×10^9 Pa, tensile yield strength of 118 MPa, and fatigue strength of 42.5 MPa at 10^6 cycles. Since all parameters remain within the ANN dataset boundaries, the FEM setup ensures that the input data for ANN training are technically valid and avoid extreme or non-physical assumptions.

Boundary conditions are applied to represent the actual operating state of the blade. The blade root is constrained as a fixed support to simulate its attachment to the hub. The aerodynamic forces, namely the lift force F_L (Equation 2) and drag force F_D (Equation 3), are applied as surface pressures acting normal and tangential to the blade surface, respectively. The centrifugal force F_{cent} (Equation 4) is applied as a body force distributed radially along the blade span. In addition, the blade self-weight W (Equation 5) is applied as a gravitational load acting uniformly on the entire geometry.

2.3. Artificial Neural Network (ANN) Modeling and Prediction

Artificial Neural Networks (ANN) are computational models inspired by the human brain that are widely used in engineering for modeling complex relationships between input and output variables [16]. In the context of wind turbine blade analysis, ANN can learn from experimental or simulated data to predict material properties or performance metrics with high accuracy, even when nonlinearities and interactions among variables are present [17]. Artificial Neural Network (ANN) in this study is designed to predict the composition percentage of bio-composite materials for wind turbine blades. To ensure quality and consistency in model training, normalization is first applied to the input features [18]. This step equalizes the scale of different mechanical properties preventing any single attribute from disproportionately influencing the learning process.

The network architecture consists of an input layer with four neurons representing tensile strength, Young's modulus, density, and fatigue strength. Two hidden layers with 64 neurons each are applied to capture nonlinear relationships between the mechanical properties and the material composition. Rectified Linear Unit (ReLU) activation functions are employed in the hidden layers to enhance learning efficiency, while a linear activation function is used in the output layer. The ReLU activation is mathematically defined in Equation (6) [19] as:

$$f(x) = \max(0, x) \tag{6}$$

The output layer contains five neurons, corresponding to the predicted percentage of flax, jute, hemp, sisal, and pineapple fibers. The overall structure of the ANN is presented in Figure 3.

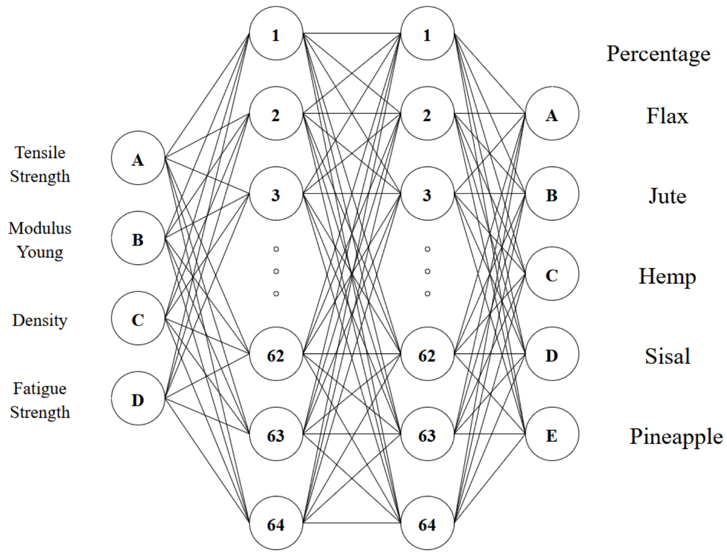


Figure 3. The structure of ANN

The model is trained using the Adam optimizer with Mean Squared Error (MSE) and Mean Absolute Error (MAE) as the evaluation metrics. These metrics provide a comprehensive assessment of the model's prediction accuracy by quantifying the gap between predicted and actual values. MSE highlights larger deviations through squaring, while MAE represents the average error magnitude [20]. Training is performed over sufficient epochs with an appropriate batch size to ensure convergence while maintaining computational efficiency. To improve the robustness of the model evaluation, a five-fold cross-validation strategy is applied [21]. Furthermore, the ANN predictions are validated against the Rule of Mixtures to ensure consistency with established composite material theory.

2.4. Rule of Mixtures Validation

To further validate the performance of the Artificial Neural Network (ANN) model, the predicted mechanical properties of bio-composites are compared with theoretical estimations obtained from the Rule of Mixtures (ROM). The Rule of Mixtures (RoM) is a widely adopted micromechanical model that provides first-order estimations of composite properties based on fiber and matrix volume fractions [22]. Although RoM has limitations in capturing factors such as fiber orientation, voids, and misalignments [23], it remains a useful benchmark for validating ANN predictions. In this study, RoM serves as a theoretical reference to ensure that the ANN-predicted compositions yield physically reasonable properties within an acceptable engineering margin. Specifically, it is applied to calculate tensile strength, Young's modulus, density, and fatigue strength of the bio-composites, as shown in Equation (7) [24]:

$$P_c = V_f P_f + V_m P_m \tag{7}$$

where P_c is the composite property, V_f and V_m are the volume fractions of the fiber and matrix, respectively, and P_f and P_m are the corresponding material properties.

The ANN-predicted values are subsequently compared with the ROM-estimated values to evaluate their consistency. A close agreement between the two approaches indicates that the ANN model is capable of generating predictions that align with established micromechanical theory, thereby reinforcing the reliability of the proposed method.

3. Results and Discussion

This section presents the outcomes of experimental validation, finite element method (FEM) pre-screening, artificial neural network (ANN) prediction, and Rule of Mixtures (ROM) validation. The results are discussed sequentially to ensure the reliability of the dataset, the feasibility of FEM inputs, and the consistency of ANN predictions with established micromechanical theory.

3.1. Experimental Results and Validation

The experimental validation is conducted to confirm the reliability of the permutation-based dataset used for ANN training. Among the tested specimens, the 90% resin + 10% pineapple fiber composition is selected as the benchmark for validation, since it directly corresponds to the dataset permutation. All specimens are prepared according to ASTM D638 standards, ensuring consistent geometry and comparability.

Figure 4a shows the dog-bone specimens prepared for tensile testing, including fiberglass–resin, braided pineapple fiber–resin, and unbraided pineapple fiber–resin. Although several types are fabricated, the validation focuses specifically on the pineapple–resin composite with a 1:9 fiber-to-resin ratio. The post-test condition is presented in Figure 4b, where the pineapple–resin specimens exhibit ductile failure patterns, reflecting the influence of natural fibers.

a. b.

Figure 4. a. Dog-bone specimens for tensile testing; bottom to top: fiberglass–resin, unbraided pineapple–resin, braided pineapple–resin; b. Post-tensile test specimens showing failure patterns; bottom to top: fiberglass–resin, braided pineapple–resin, unbraided pineapple–resin

The tensile strength predicted by the permutation dataset for the pineapple–resin composition is 118.60 MPa, while the experimental result yields 131 MPa. Table 5 presents the comparison.

Table 5. Comparison between dataset prediction and experimental testing.

Material Composition	Tensile Strength (Dataset)	Tensile Strength (Experimental)
90% Resin + 10% Pineapple	118.60 MPa	131.00 MPa

The difference between dataset prediction and experimental testing is approximately 10.5%. This deviation is acceptable, given the natural variability of bio-based fibers and testing uncertainties. Figure 5 illustrates this comparison, highlighting that the permutation-based dataset provides a sufficiently accurate approximation of real composite behavior.

This validation confirms that the dataset construction approach is robust and reliable, providing a sound basis for ANN training in predicting the performance of bio-composite materials for wind turbine blade applications.

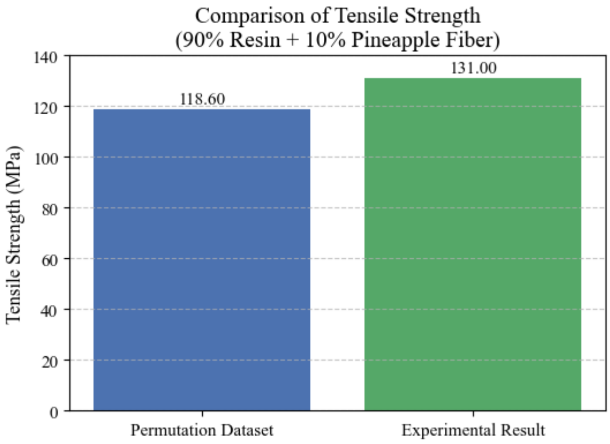
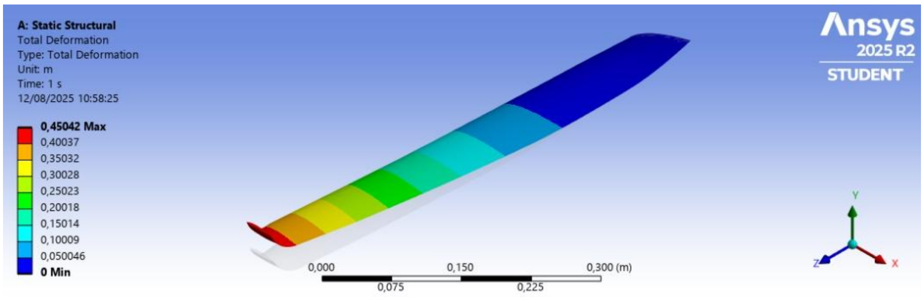


Figure 5. Tensile strength comparison between dataset prediction and experimental testing for 90% resin + 10% pineapple fiber composite.

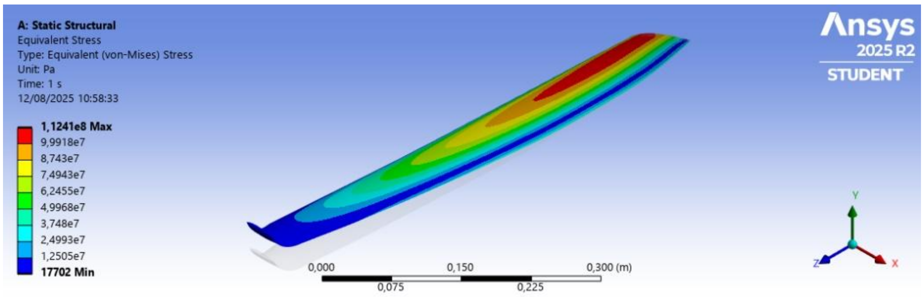
3.2. FEM Pre-Screening

The FEM simulation is conducted by applying the boundary conditions formulated in Section 2.2. The computed values for aerodynamic and structural loads are: lift force $F_L \approx 714.16$ N, drag force $F_D \approx 8.18$ N, centrifugal force $F_{cent} \approx 110.18$N, and blade self-weight $W \approx 3.65$N. These loads are applied as surface pressures (for F_L and F_D), a distributed body force (for F_{cent}), and gravitational load (for W).

The structural response shows a maximum total deformation of 0.45042 m and a maximum equivalent von Mises stress of 1.1241×10^8 Pa. The deformation contour is presented in Figure 6a, while the von Mises stress distribution is shown in Figure 6b. The deformation predominantly occurs at the blade tip, whereas stress concentration is highest at the blade root, which aligns with the expected mechanical behavior of rotating blades under aerodynamic and centrifugal loading.



a.



b.

Figure 6. a. Total deformation contour of turbine blade; b. Von Mises stress distribution of turbine blade

The pre-screening FEM yields a tip deformation of 0.450 m and a peak von Mises stress of 1.12×10^8 Pa. Relative to Ahmed et al. (2023) [25], who report 0.635 m deformation and 43.7 MPa stress for a composite blade (0.876 m and 39 MPa for aluminium), our deformation is ~29% lower whereas the peak stress is ~2.6× higher. The discrepancy is attributable to differences in blade geometry, boundary-condition implementation (surface pressure vs. point/distributed loads), and material parameters. Despite these differences, the results remain within a physically plausible range for small-scale blades and are therefore suitable as pre-screening inputs to ANN.

3.3. Artificial Neural Network (ANN) Prediction Results

The artificial neural network (ANN) is trained using the permutation-based dataset introduced in Section 2.1, with prior screening by FEM to ensure realistic input values. The model performance is evaluated using mean squared error (MSE) and mean absolute error (MAE), as shown in Figure 7. The training and validation curves indicate a stable convergence, with the validation error closely following the training error, confirming that the model generalizes well without significant overfitting.

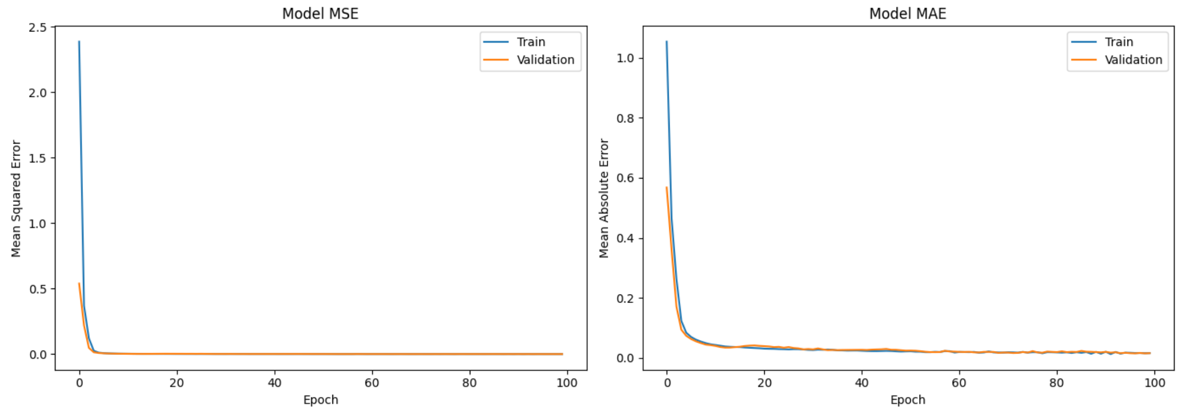


Figure 7. Training and validation loss curves of the ANN model evaluated using mean squared error (MSE) and mean absolute error (MAE), indicating stable convergence and good generalization.

Using the input properties obtained from FEM pre-screening (tensile strength = 118 MPa, Young's modulus = 6050 MPa, density = 1.218 g/cm³, fatigue strength = 42.5 MPa), the ANN predicts the corresponding material composition. The results are summarized in Table 6, which presents the weight percentages of each fiber and resin. The prediction demonstrates the ability of the ANN to function as an inverse design tool, where validated mechanical properties from FEM are mapped back into feasible bio-composite compositions.

Table 6. Predicted material composition from ANN based on FEM pre-screened properties

Flax (%)	**Jute (%)**	**Hemp (%)**	**Sisal (%)**	**Pineapple (%)**	**Resin (%)**
6.27	0.00	0.00	0.00	3.73	90.00

3.4. Rule of Mixture Validation

The ANN predictions are validated by comparing the corresponding material properties with theoretical estimations obtained using the Rule of Mixtures (RoM), as described in Section 2.4. Table 7 summarizes the comparison between the FEM input values and RoM re-estimations for tensile strength, Young's modulus, density, and fatigue strength. The deviations between the FEM input and the RoM validation are calculated using Equation (7):

$$Deviation\ (\%) = \frac{|P_{RoM} - P_{FEM}|}{P_{FEM}} \times 100 \tag{7}$$

Table 7. Comparison between ANN prediction and RoM validation

Property	FEM Input	RoM Validation	Deviation (%)
Tensile Strength	118 MPa	110.89 MPa	6.0
Young's Modulus	6.05 GPa	5.64 GPa	6.7
Density	1.218 g/cm³	1.21 g/cm³	0.6
Fatigue Strength	42.5 MPa	41.24 MPa	3.0

The results show that the RoM-based values closely follow the FEM input properties, with deviations remaining below ~7%. This agreement indicates that the compositions predicted by the ANN produce material properties that are consistent with micromechanical theory. Consequently, the validation confirms that the ANN not only provides numerically reliable predictions but also maintains physical feasibility, reinforcing its suitability for bio-composite applications in wind turbine blade design.

4. Conclusion

This study establishes a comprehensive methodology for designing and assessing bio-composite wind turbine blades by integrating experimental validation, Finite Element Method (FEM) pre-screening, Artificial Neural Network (ANN) prediction, and Rule of Mixtures (RoM) validation. The framework's robustness is demonstrated as experimental tensile tests on a 10% pineapple fiber composite validate the dataset for ANN training, showing only a 10.5% deviation, while FEM pre-screening ensures the physical plausibility of all input properties, such as a max tip deformation of 0.45 m and a peak von Mises stress of 1.12×108 Pa. The trained ANN subsequently proves effective as an inverse design tool, accurately mapping desired mechanical properties back to feasible bio-composite compositions. The physical meaningfulness of these predictions is confirmed by their strong alignment with established RoM micromechanical theory, with all deviations remaining below 7%. Therefore, this integrated approach provides a reliable and comprehensive framework for exploring sustainable material alternatives, confirming ANN as a powerful tool for inverse design in renewable energy systems.

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