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Prediction of natural fiber composite mechanical properties with a multilayer artificial neural network

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Abstract

For environmental and cost reasons that have gained acceptance across the globe, natural fiber-reinforced composites have been adopted in all sorts of applications currently. However, these composites are a production challenges, such as poor adhesion between reinforcement and matrix. Consequently, a comprehensive Artificial Neural Network (ANN) framework to predict the mechanical properties of green composites, especially for Ultimate Tensile Strength (UTS) and Young's Modulus, is adopted, to reduce the experimental work issues. Since the mechanical properties of green bio-fibers for several key parameters of influence could well differ from one fiber to the next, bio-fiber prediction involves a high level of complexity. Therefore, this paper utilizes an Artificial Neural Network (ANN) framework with non-linear activation functions to predict the mechanical properties of natural fibers—specifically Ultimate Tensile Strength (UTS) and Young's Modulus—based on cellulose content, microfibrillar angle, and fiber diameter. The developed ANN system consists of three model techniques for predicting the mechanical properties of natural fiber composites; however, the 3-6-12-18-2 model has given results quite predictably. Results show that the ANN model could help raise the scientific

evaluation of green fibers and determine their suitability as a replacement material for effective green product output in future eco-friendly industries.

Keywords: Green composites materials; natural fibers; artificial neural network;
Cellulose content; mechanical performance

1. Introduction

As the old take-make-dispose mechanisms of the economy are morphed into a new circular and bio-based mode, natural fiber reinforced polymer (NFRP) materials have been thrown up onto the materials development map. Due to increasingly strict environmental regulations and recurrent and shocking spikes in oil prices, the automotive, construction, and aerospace sectors are all falling over themselves to try "green" composites as part of their load-bearing materials[1, 2]. As the stiffness of these composite materials can only be matched by that in traditional fibers—in terms of both force per gram and specific volume ratio—the general proposition for reinforcement of blends from wood fibers generally follows if not exactly: These properties influence the entire mechanical performance of green composites significantly; for example, increasing cellulose reinforcement fiber content can improve mechanical and thermal stability. Another example is that lower microfibrillar angles produce increasingly rigid mechanical performance in composites, while higher ones give softer ones[3-6]. In recent years, with environmental concerns becoming increasingly important, we also start to pay more attention to the suppliers of cellulosic fiber—of which there are many, for example, kenaf, cotton, jute, hemp etc. It is used in a wide range of products and composites. It is worth emphasizing that these fibers are valuable not so much for their use in the production of pulp or paper as for what happens afterwards, which is, without exception, down-cycling. In particular, the use of these fibers

as reinforcements in polymer composites has attracted this interest [7-11]. The result in Table 1 indicates that the mechanical properties of the natural fibers become different when they contain less cellulose in them, their microfibril angle changes, and if there is some enlargement of diameter from those which are generally utilized [12-17].

Table 1: Results of several experimental studies on natural fibers' mechanical properties

Fiber Type	Microfibrillar Angle (deg)	Cellulose content (Wt%)	Diameter (μm)	Ultimate tensile strength (MPa)	Young's modulus (GPa)
Cotton	32-35	82.7-95	10-45	400-980	6.2-20
Jute	8	61-71.5	20-200	320-800	8-78
Kenaf	7.1-15	45-57	65.2-77	400-938	61.4-128
Bamboo	8-11	35-74	14.0-88	270-862	17-89
Sisal	10 -22	66-78	8-200	363-700	9-38

However, the mechanical integrity of green composites is a complex interplay of variables which is incredibly difficult to predict. But the basic problem remains the poor interfacial adhesion between biofiber hydrophilic and resin matrices typically hydrophobic. With stress transfer prevented altogether, failure comes early[18, 19]. The authors have shed the light on the limitations of analytical modeling; artificial neural networks (ANNs) have become a revolutionary paradigm shift in predictive material science to overcome this limitation. Modeled after the way in which the brain processes information through biological neurons, ANNs can learn the concealed relationships within experimental data without requiring any explicit governing equation of physics. This is especially beneficial to our understanding of green composites, as any effect on ultimate tensile strength due to chemical processing can appear non-linear - it may even be linked with fiber aspect ratio.

Like biological neural networks, an artificial neuron in the ANN is linked to all others[20-25]. The neuron's output is computed as a nonlinear function of the sum of its inputs, and these summands are all represented by real numbers[26-30]. Indeed, the ANN is widely used in various disciplines such as, structural engineering, predicting concrete expansion, resource engineering, robotics applications, and composite material [31-37]. Artificial Neural Networks (ANNs) are able to handle high-dimensional datasets and to generate highly correlated predictive maps by using many different architectures, like the Multi-Layer Perceptron (MLP). Although previous work covered such broad fields as the general application of machine learning in composites, there remain ever-so serious questions needing debate: how do we model more specifically, for the improving of the choices of natural fibers for biomaterials in green systems. This study seeks to address this question by building an integrated ANN framework, trained on a vast array of experimentally datasets. It not only examines the optimization of the hidden layer structure to minimize the mean-square error (MSE), but it also evaluates the predictive capability of the multi-layer network across key fiber parameters to establish accurate design maps for green material composites.

2. Methodology

An Artificial Neural Network (ANN) usually has three main parts: an input layer, an output layer, and one or more hidden layers in between. The process starts with the input layer getting data from outside the system[38]. This data is then changed by the hidden layers before the final output is made[39, 40]. The neuron is the basic building block of this system, as seen in Figure 1. Every neuron works by taking inputs from the nodes before it,

scaling them by certain weights, and then using an activation function to compute the total and send a signal to the next layer.

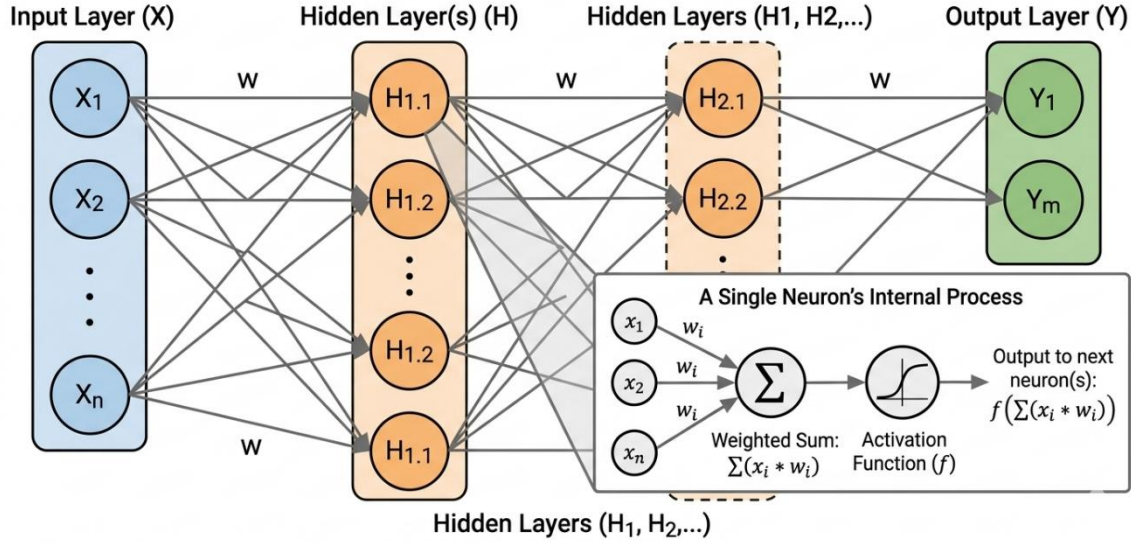


Figure1: The multilayered hierarchy of an ANN and the internal process of a neuron, including weighted summation and activation function application.

Neurons in multiple layers such that with the creation of an artificial neural network, it is capable of performing extremely complex operations from still others. For this purpose, three stimulus models made in the paper are built with the MATLAB environment simulating tensile stress and young modulus. The key components of these models are as follows: Increasing the number of hidden layers and the number of neurons in each layer. The three parameters that are fundamental to all models are the cellulose content, the microfibrillar angle (in degrees), and the diameter (in micrometers). In addition, they provide information on Young's modulus and ultimate tensile strength. By these principles, Model I has a first hidden layer with six neurons. However, as shown in Model II the number of hidden layers increases to two layers each containing six and twelve neurons,

respectively. To see whether the predicted mechanical performance improves at all, model III was created, with three hidden layers. In each layer there are six, twelve and eighteen neurons of Increasing numbers. Further, optimal for linking hidden and output layers, the Log-sigmoid transfer function carries each neuronal output signal to the subsequent layer in the simulation (Figure 2). Table 2 summarizes the models utilized in this work; Table 3 summarizes the Hyperparameters used in this work, to explicitly detail all training settings.

Table 2: Comparative ANN Network Architectures

Model type	Hidden Layers	Neurons in each hidden Layer	Transfer Function type
Model I	1	6	Log-sigmoid
Model II	2	6, 12	Log-sigmoid
Model III	3	6, 12, 18	Log-sigmoid

Table 3: Hyperparameters and settings for the artificial neural network (ANN) model.

Parameter	Value / Configuration
Optimization Algorithm	Levenberg-Marquardt (trainlm)
Weight Initialization	Uniform weight distribution
Initial Learning Rate	0.001
Performance Goal (MSE)	10^{-5}
Minimum Gradient	10^{-7}
Validation Checks	6 consecutive epochs
Maximum Training Epochs	380

However, equation 1 shows the mathematical formula of the log sigmoid function:

$$\text{logsig}(j) = \frac{1}{1+e^{-j}} \dots \dots \dots (1)$$

A well-known multi-layer neural network trained to positive infinity using the back-propagation technique is the Log-sigmoid. This function produces 0–1 output when the net input to the neurons goes from negative to positive infinity. In this study, a qualitative method is utilized: the weights between neurons in artificial neural networks are given random values at first. Then, these models (networks) start to train data, and so input values or categories are mapped to output results.

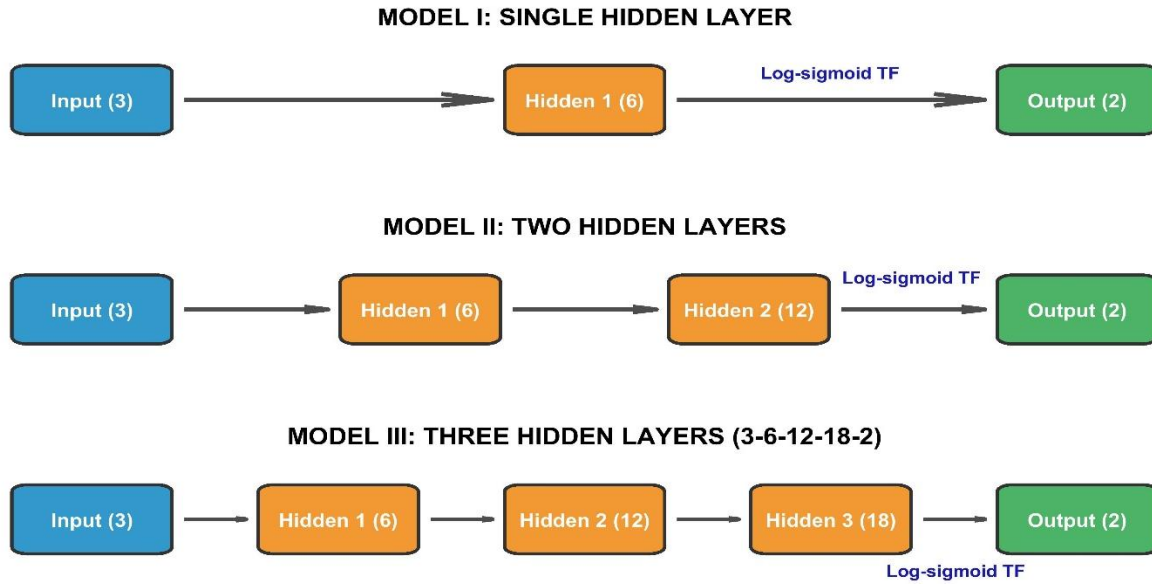


Figure 2: Schematic progression of Artificial Neural Network (ANN) architectures (Models I–III) simulated in the MATLAB environment.

3. Results and discussion

The generated Artificial Neural Network (ANN) models were trained and tested with a large database including $N = 300$ discrete experimental data points. The database was

gathered from extensive experimental research and published literature on natural fiber characterization [12-17]. A rigorous discretization of the stated experimental ranges for the input constituents (cellulose, microfibrillar angle, diameter) and the outputs (Table 1) was performed to create a one-to-one correlation between each synthetic input combination and its target. Each data point in this dataset is a discrete vector of the physical input features that directly mapped to the corresponding experimental output properties. The data collection includes five major natural lignocellulosic fibers which are Cotton, Jute, Kenaf, Bamboo and Sisal. Each data point in this dataset is a discrete vector of three physical input features, i.e. cellulose content (Wt%), microfibrillar angle (deg), and fiber diameter (micrometer), directly mapped to the corresponding experimental output properties, Ultimate Tensile Strength (UTS, MPa) and Young's Modulus (YM, GPa). Summary of the wide property ranges representative of the inherent variability of the samples set are reported in Table 1. Before training, the 300 dataset samples were randomly split into two independent halves of 70% ($n = 210$ samples) for model training and 30% ($n = 90$ samples) for model testing and validation to estimate the generalization capability.

The process began to have the method produce global output data, and then training this by networks performed for input. Backpropagation gradient descent, on the other hand, was the foundation of the training process because of its simplicity and efficacy, even in multi-layer networks. First, the input training values are fed into the algorithm, and then the network outputs are computed. This division into phases helps to comprehend the back-propagation technique. Also, the second step is to determine how much the calculated results depart from the target values. Third, retransmitting the mistake to adjust the layer weights.

ANN is applied here with the goal of analyze the mechanical property of fiber material from experimental data. The objective of these results is to compare the model with the experimental results of average tensile stress and Young's modulus. Tables 4–6 compared the calculated predictions from ANN results of tensile stress (TS) and young's modulus (YM) – for Models I, II and III, respectively.

Table 4: Comparison of Experimental and ANN-Predicted Mechanical Properties of Various Natural Fibers: Model I

Fiber Type	Microfibrillar Angle (deg)	Cellulose content (Wt%)	Diameter (µm)	TS (MPa)	Predicted TS (MPa)	YM (GPa)	Predicted YM (GPa)
Cotton	32-35	82.7-95	10-45	400-980	710.2–1300.1	6.2-20	11.2–40.5
Jute	8	61-71.5	20-200	320-800	690.7–1513.2	8-78	16.9–129.1
Kenaf	7.1-15	45-57	65.2-77	400-938	824–1872.1	61.4-128	100.7–188.4
Bamboo	8-11	35-74	14.0-88	270-862	500.9–1269.3	17-89	44.6–125.8
Sisal	10 -22	66-78	8-200	363-700	972.9–1108.2	9-38	20.7–68.3

Table 5: Comparison of Experimental and ANN-Predicted Mechanical Properties of Various Natural Fibers: Model II

Fiber Type	Microfibrillar Angle (deg)	Cellulose content (Wt%)	Diameter (µm)	TS (MPa)	Predicted TS (MPa)	YM (GPa)	Predicted YM (GPa)
Cotton	32-35	82.7-95	10-45	400-980	459.1–1102.4	6.2-20	8.8–30.8
Jute	8	61-71.5	20-200	320-800	390.7–988.5	8-78	11.5–91.6
Kenaf	7.1-15	45-57	65.2-77	400-938	483.4–1010.2	61.4-128	77.8–150.6
Bamboo	8-11	35-74	14.0-88	270-862	400.9–999.6	17-89	40.8–100.1
Sisal	10 -22	66-78	8-200	363-700	589.1–910.5	9-38	14.2–51.7

Table 6: Comparison of Experimental and ANN-Predicted Mechanical Properties of Various Natural Fibers: Model III

Fiber Type	Microfibrillar Angle (deg)	Cellulose content (Wt%)	Diameter (μm)	TS (MPa)	Predicted TS (MPa)	YM (GPa)	Predicted YM (GPa)
Cotton	32-35	82.7-95	10-45	400-980	408.9–1005.6	6.2-20	6.5–21.3
Jute	8	61-71.5	20-200	320-800	315.2–816.8	8-78	8.2–74.7
Kenaf	7.1-15	45-57	65.2-77	400-938	388.6–970.4	61.4-128	57.7–134.5
Bamboo	8-11	35-74	14.0-88	270-862	262.9–861.3	17-89	18.1–90.1
Sisal	10 -22	66-78	8-200	363-700	370.5–701.2	9-38	9.8–42.8

From Table 4, it can be shown that Model I (single hidden layer with 6 neurons) has significant predictive constraints and excessive overpredictions at the top bound. For example, the measured tensile strength of jute fibers is 320-800 MPa, but Model I predicts 690.7-1513.2 MPa, an overprediction at the top threshold. This mismatch highlights the intrinsic weakness of shallow neural network topologies in mapping complex, non-linear bio-composite characteristics. The network with only one hidden layer does not have the hyper-dimensional mapping power to separate the intricate interaction of low microfibrillar angles and large differences in fiber diameter adequately. Therefore, the shallow network has large variance and unrestricted gradient propagation, resulting in unrealistic extrapolation.

This limitation highlights why deeper, multi-layered architectures (Model III) are essential to constrain prediction boundaries within physical limits. Clearly, these results demonstrate

that Model III has the best accuracy among these models; the predicted ANN data are very close to the experiment ones. This, in fact, is due to using a multi-hidden layer with large number of neurons. Figures 3 and 4 display the relative error results of model III, which shows small levels of deviations.

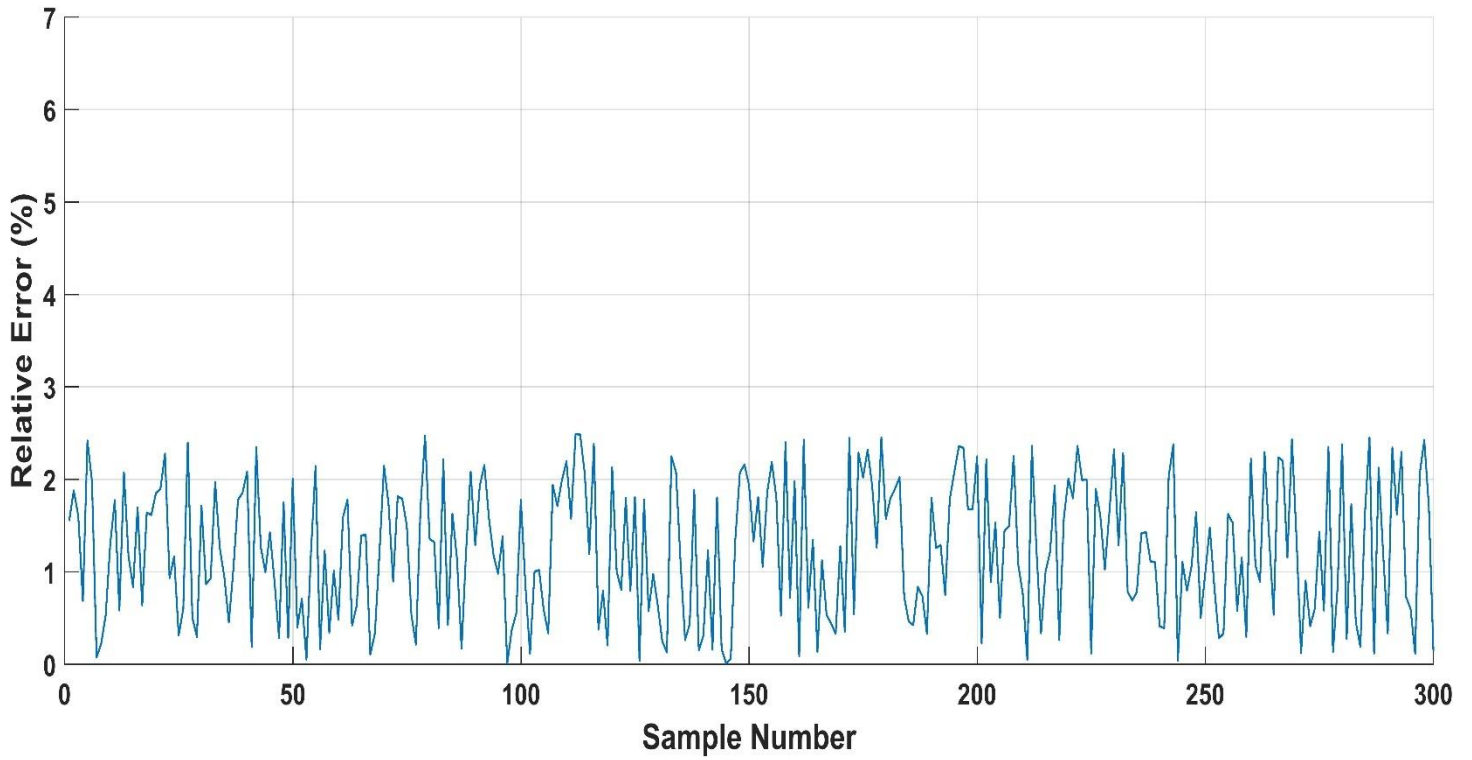


Figure 3: Relative error of ANN Young's modulus prediction performance – Model III

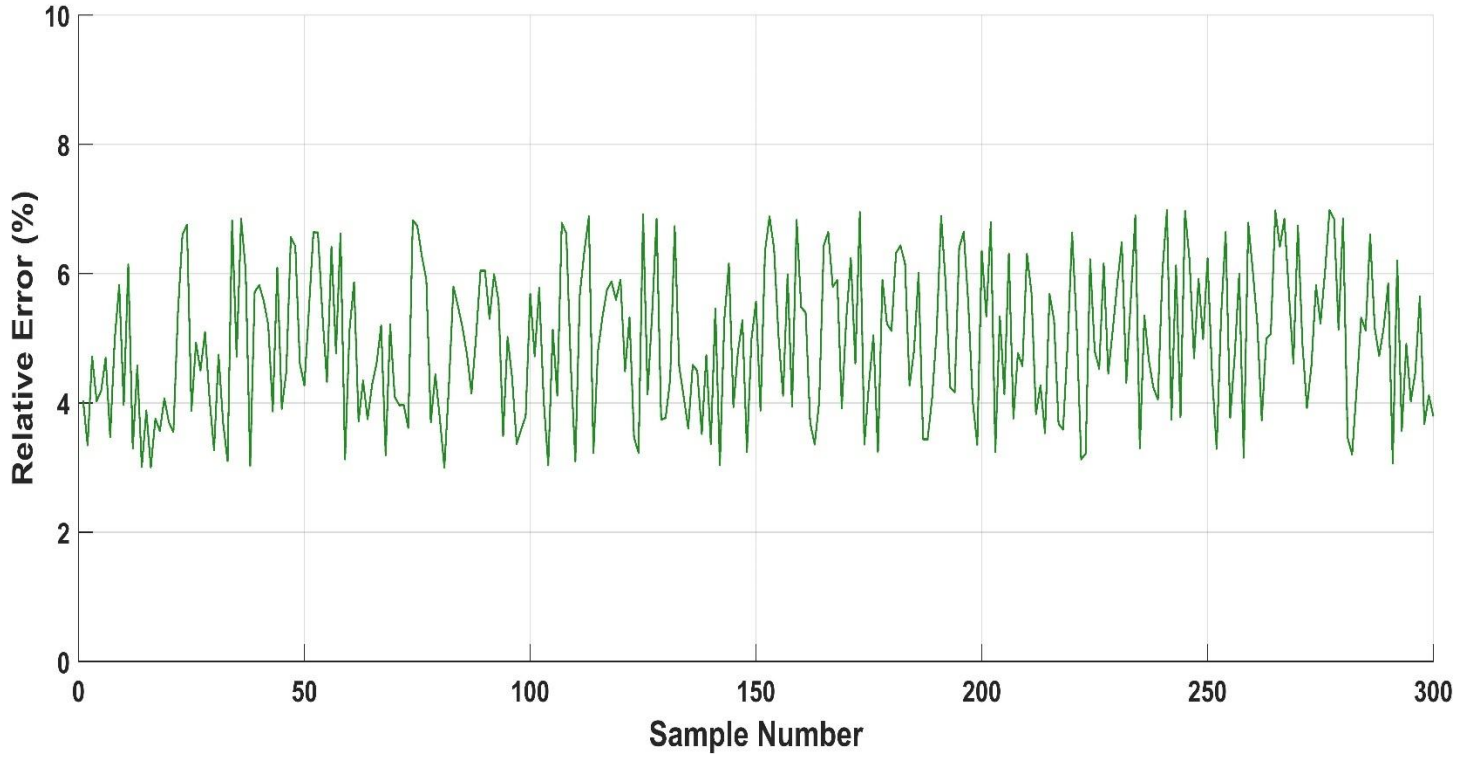


Figure 4. Relative error of ANN tensile stress prediction performance – Model III.

As mentioned, the tensile strength is the target variable i.e., output from the model for the columns of the data set against many permutations of inputs, which is seen in figures 5 through 7. One can clearly see that the predicted outcomes are obviously very close to that of the actual experimental outcomes as expected, thus validating the created predictive models in this work.

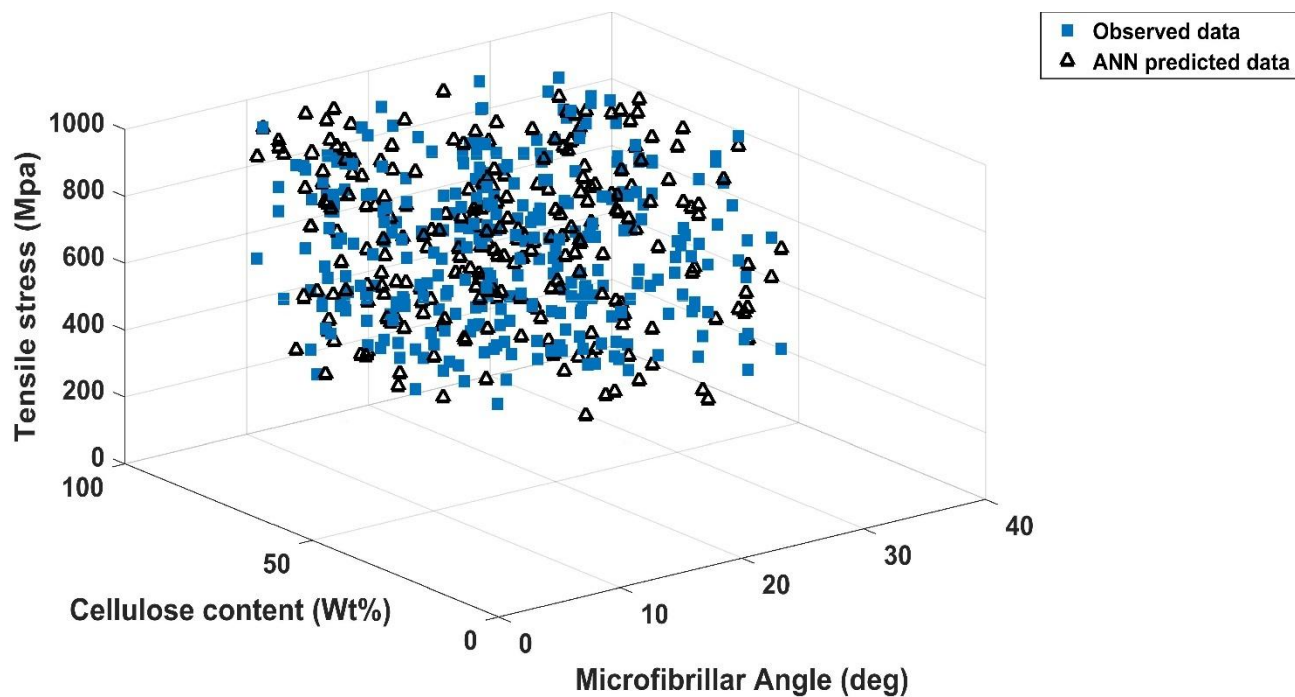


Figure5: A 3D scheme showing the relationship between the two input predictors, Microfibrillar angle and Cellulose content, and the tensile strength output.

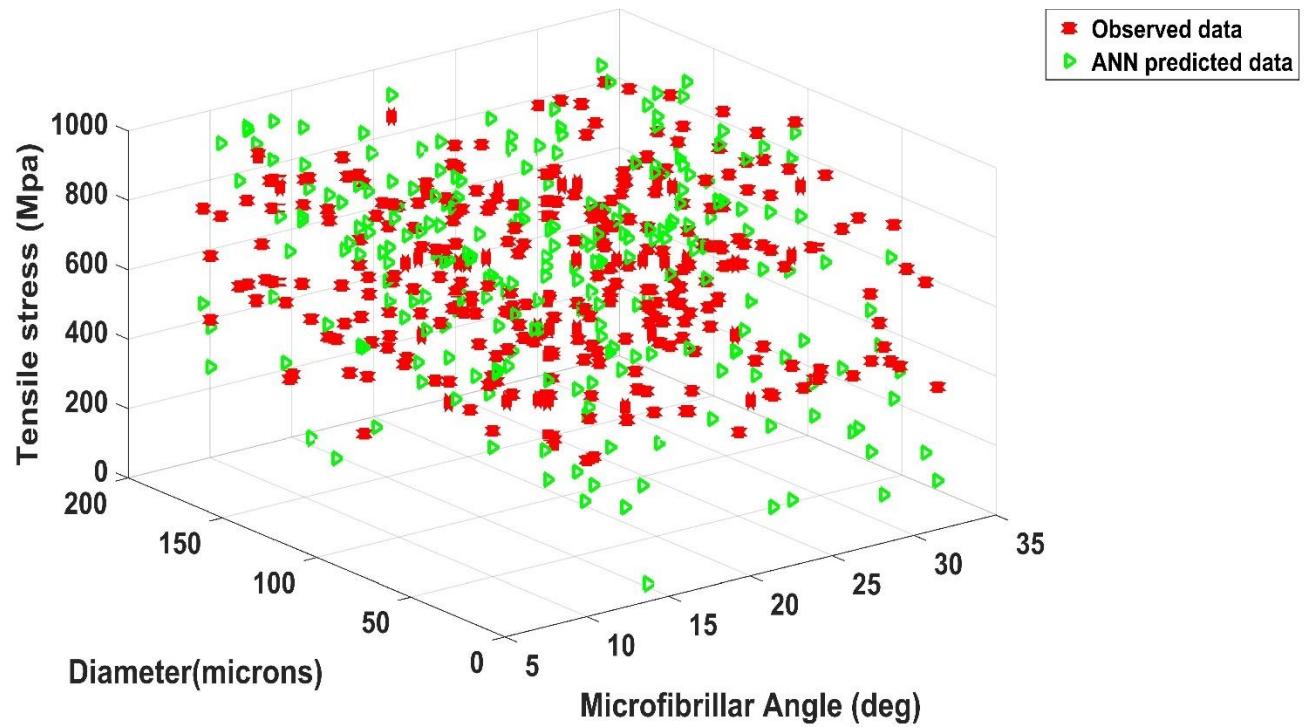


Figure6: A 3D scheme showing the relationship between the two input predictors, Microfibrillar angle and fiber diameter, and the tensile strength output.

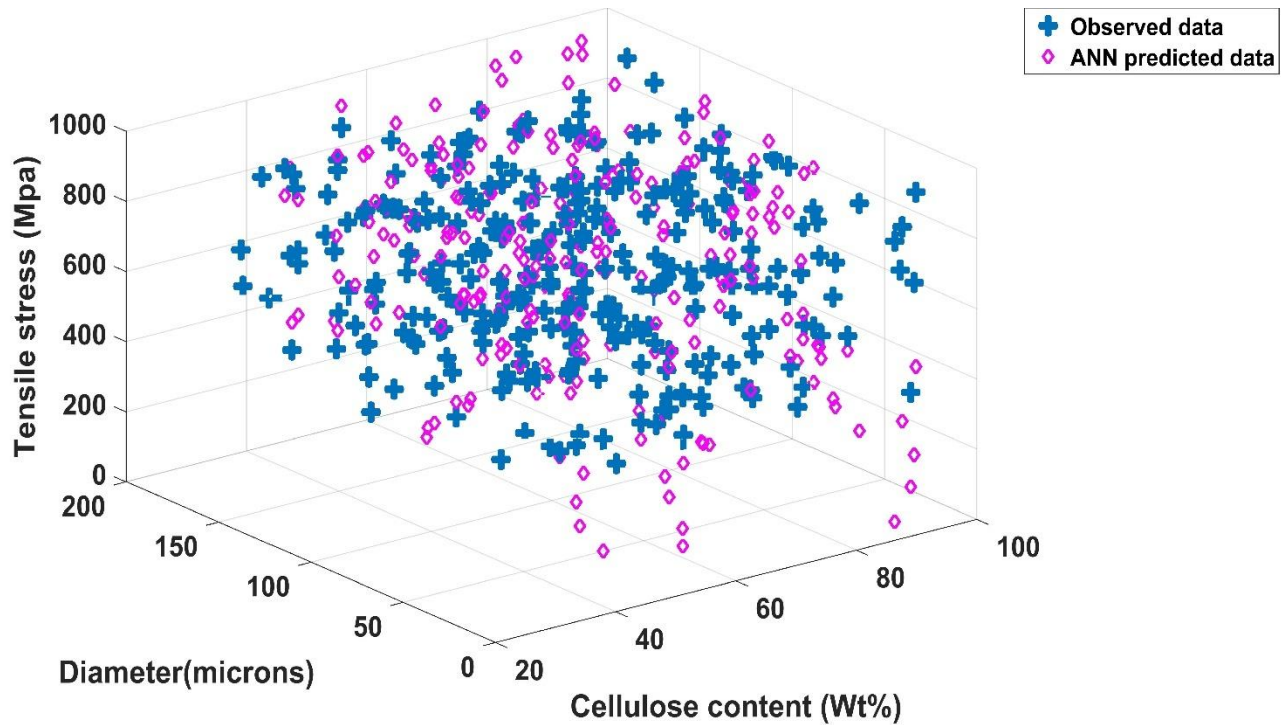


Figure7: A 3D scheme showing the relationship between the two input predictors, fiber diameter and Cellulose content, and the tensile strength output.

On the other hand, figures 8-10 show how the predicted ANN outcomes are obviously very close to that of the actual experimental outcomes, for the second time – in the case of young's modulus.

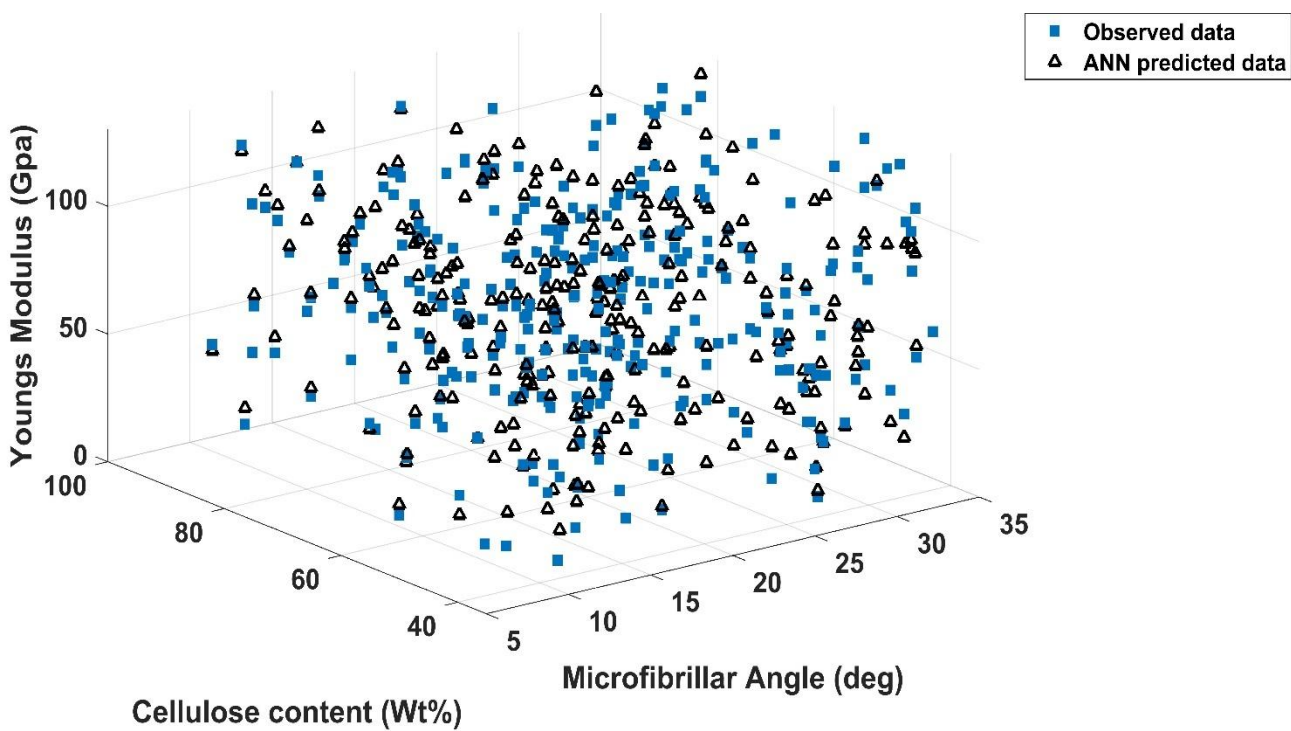


Figure8: A 3D scheme showing the relationship between the two input predictors, Microfibrillar angle and Cellulose content, and the young's modulus output.

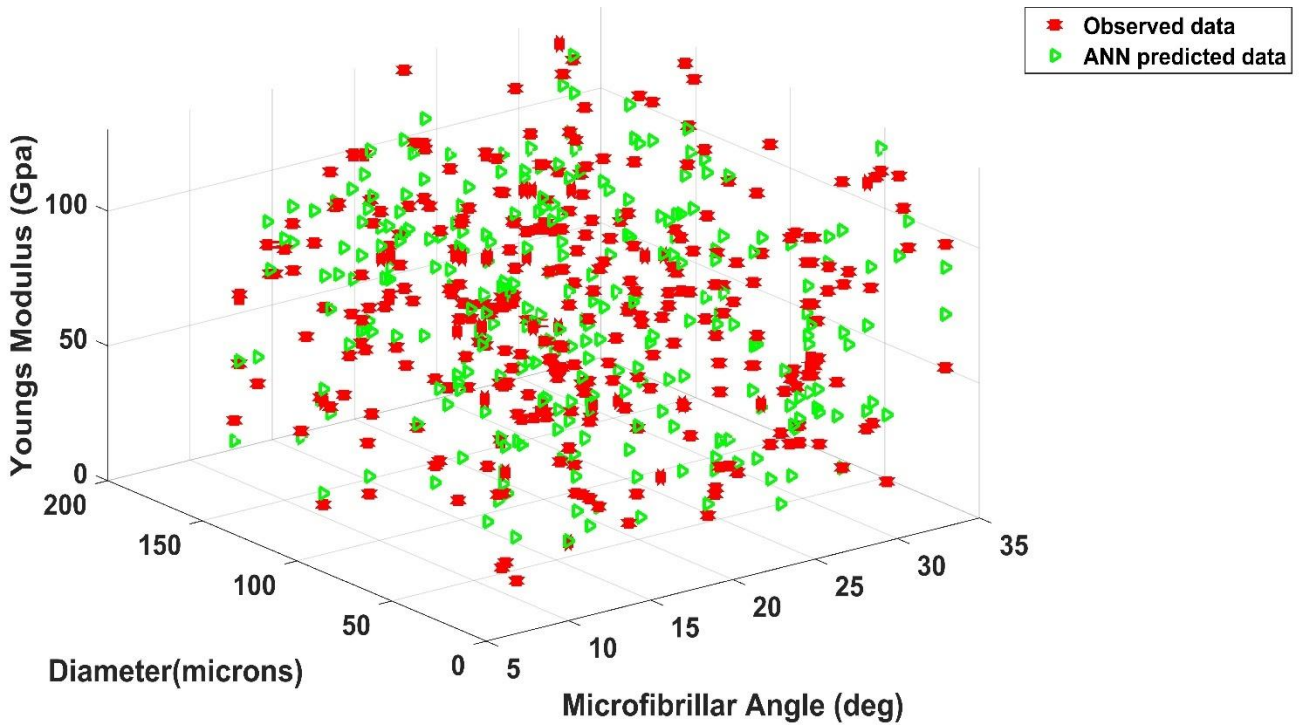


Figure9: A 3D scheme showing the relationship between the two input predictors, Microfibrillar angle and fiber diameter, and the young's modulus output.

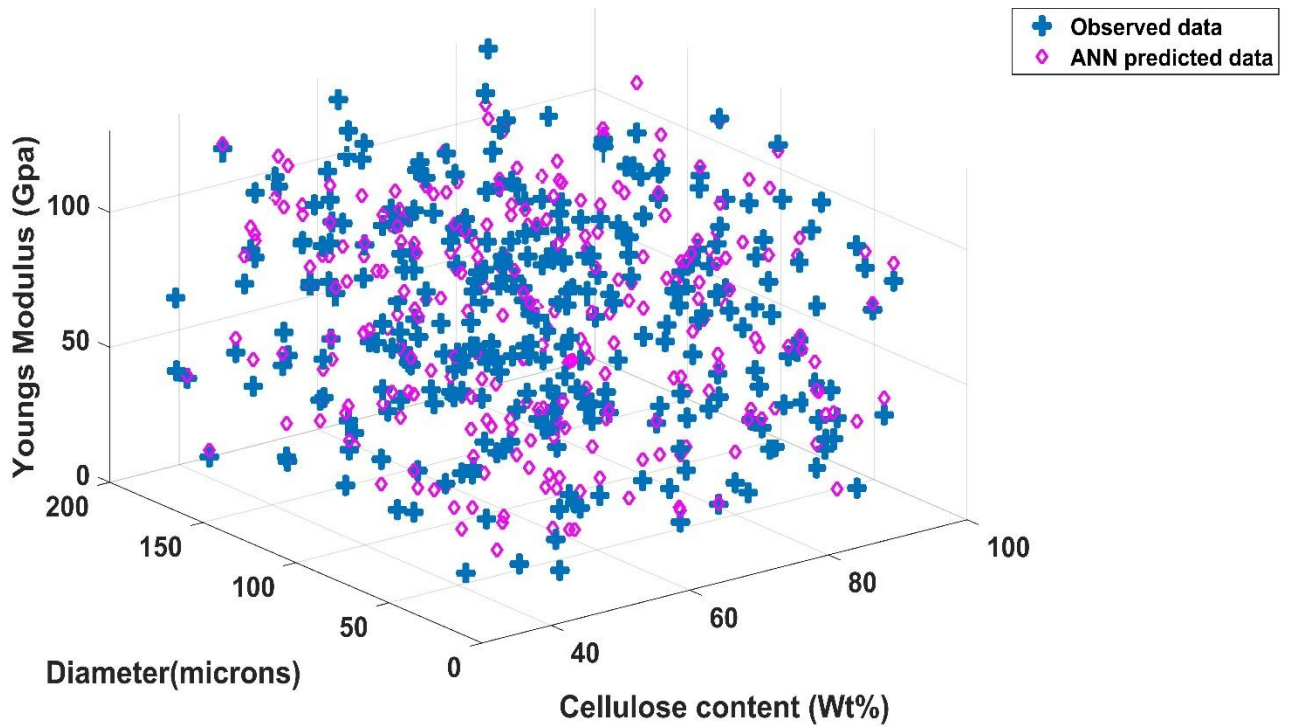


Figure10: A 3D scheme showing the relationship between the two input predictors, fiber diameter and Cellulose content, and the young's modulus output.

The performance of model III was validated with further statistical analysis which observed mean absolute percentage errors (MAPE) of tensile strength and young's modulus on average of 5.28 % and 3.61%, respectively, confirming that increasing hidden layers enhance the accuracy of this predicted model. While on other hand, MAPE is defined as:

$$MAPE = \frac{1}{Q} \sum_{K=1}^Q \frac{|\varepsilon_{p,Q} - \varepsilon_{exp,Q}|}{\Omega_{exp,Q}} \times 100\% \dots \dots \dots (2)$$

Where Q is the samples number, ε_p is the predicted value of mechanical property, and ε_{exp} is the measured value of mechanical property.

Further, to ensure the model III accuracy, a 10-fold cross-validation (K = 10) across all three model architectures is applied. Model III consistently demonstrated high stability across folds with mean R^2 values of 0.92 for UTS and 0.94 for Young's Modulus, confirming strong generalization capabilities without overfitting, as illustrated in table 6. The correlation coefficient is used to validate models by comparing the expected value and the experimental value, as illustrated in figure 11. The closer the correlation coefficient to one, the better the training effect of the model and the better the prediction result.

the correlation coefficient is given by:

$$R^2 = 1 - \frac{\sum_{K=1}^Q (\varepsilon_{exp,Q} - \varepsilon_{p,Q})^2}{\sum_{K=1}^Q (\varepsilon_{exp,Q} - \varepsilon_{m,Q})^2} \dots \dots \dots (3)$$

However, $\varepsilon_{m,Q}$ represents the **arithmetic mean** of all actual experimental values across the dataset.

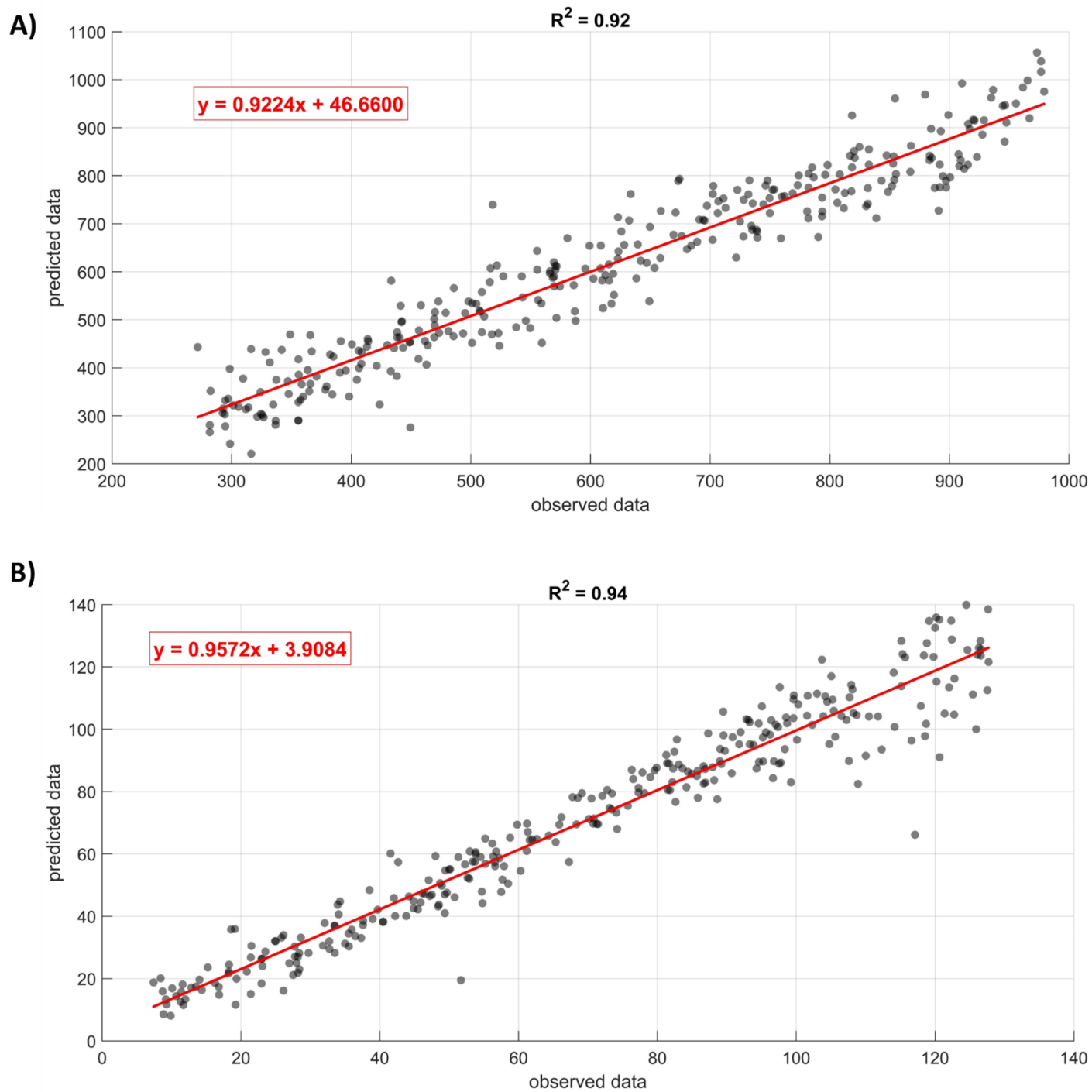


Figure 11: The R-squared values – model III: A) Tensile stress and B) Young's modulus

Table 7: Performance Evaluation of Neural Network Models for Predicting Tensile Stress and Young's Modulus Across Different Architectures

System model	Hidden Layers	Neurons	Tensile stress R^2 (Mean $\pm$ SD)	Tensile stress MAPE (%) (Mean $\pm$ SD)	Young's Modulus R^2 (Mean $\pm$ SD)	Young's Modulus MAPE (%) (Mean $\pm$ SD)
Model I	1	6	0.78 $\pm$ 0.04	14.21 $\pm$ 1.85	0.81 $\pm$ 0.05	11.45 $\pm$ 1.62
Model II	2	6, 12	0.86 $\pm$ 0.03	8.74 $\pm$ 1.12	0.88 $\pm$ 0.03	7.10 $\pm$ 0.95
Model III	3	6, 12, 18	0.92 $\pm$ 0.02	5.28 $\pm$ 0.45	0.94 $\pm$ 0.015	3.61 $\pm$ 0.38

4. Conclusion

This study has successfully created a way to analyze and predict how natural fiber reinforced polymers behave. It uses the methods of Artificial Neural Networks (ANN) to overcome the limitations in conventional linear models for composites research: The ANN structure showed great ability in mapping non-linear interactions between fiber properties—such as microfibrillar angle and cellulose content. Further, the optimized hidden layer structure can minimize the Mean-Square Error (MSE). This enables reliable predictions for tensile strength and Young's modulus in different kinds of natural fibers, providing a high level of agreement between the experimental mechanical characteristics and the derived models. Ultimately, machine learning in bio-composites means natural fiber–reinforced can become competitive with traditional synthetic fibers. This aligns with current needs for solutions that blend peak performance with environmental responsibility. Ultimately, establishing this accurate forward prediction model provides a foundational framework that can support future optimization algorithms for material selection, thereby reducing the reliance on empirical testing in green composite development.

List of abbreviations

Abbreviation	Full Definition
ANN	Artificial Neural Network
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
MAPE	Mean Absolute Percentage Error
UTS	Ultimate Tensile Strength
TS	Tensile Stress / Tensile Strength
YM	Young's Modulus
NFRP	Natural Fiber Reinforced Polymer
MPa	Megapascal
GPa	Gigapascal
Mm	Micrometer (Micron)
SD	Standard Deviation

Availability of data and materials

The dataset used in this study was compiled from previously published literature (see references). Summary data are shown in Tables 1 and 4–7. The full raw dataset is available from the corresponding author on reasonable request

Conflicts of interests

The corresponding author states that there is no conflicts of interest, on behalf of all authors

AI Declaration: The authors confirm that no artificial intelligence (AI) tools or AI-assisted technologies were used in the writing, editing, analysis, or preparation of this manuscript. All content was generated solely by the authors, who take full responsibility for the integrity of the published work.

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