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Using Machine Learning Models for Optimization and Prediction of Mechanical propeties in Lowland- Bamboo, Glass Fiber Hybrid Composites with Al_2O_3 Nanoparticle Reinforcement

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Abstract

This study investigates the flexural properties and hardness of hybrid composites reinforced with lowland bamboo, and glass fibers, incorporating a Auminium Oxide nanoparticles as fillers. Key factors examined include fiber orientation (0°, 45°, and 90°), fiber placement (1, 2, and 3 layers), and Al_2O_3 content (3%, 4%, and 5%). Response Surface Methodology was employed to analyze interactions between these parameters, while Artificial Neural Networks (ANN) and Generative Adversarial Networks (GANs) were utilized for predictive modeling. Experimental results highlighted that the optimal combination for maximizing flexural strength and hardness involved 90° fiber orientation, a fiber sequence and 5% Al_2O_3 content. The study emphasizes the importance of fiber alignment, strategic layer stacking, and nanoparticle reinforcement in enhancing composite properties. The findings not only confirm the mechanical superiority of the optimized hybrid composite but also validate the use of advanced predictive models like GANs and FFNN for material property estimation. This work contributes to developing high-performance hybrid composites with tailored mechanical properties for advanced engineering applications.

1. Introduction

Recently, there has been a growing interest in utilizing natural resource fibers as reinforcement materials for composites due to their lightweight nature, cost-effectiveness, ease of processing, and environmental benefits [1, 2]. Natural fiber composites are key to promoting sustainable development and are well-suited for various applications, including aerospace, sports equipment, and automotive components such as dashboards for sustainableuse [3-5]. Nanoparticles often result in a significant bonding agent between fiber and matrix [6]. To address these challenges, chemical treatments are applied to fibers to reduce moisture absorption, improve chemical composition (such as cellulose, hemicellulose, and lignin), enhance tensile strength and elongation, reduce shrinkage, and increase compatibility between the fiber and matrix. This treatment also chemically alters surface roughness by reducing the hydroxyl groups involved in hydrogen bonding within cellulose molecules, further improving fiber performance in composites [7-9]. The Experimental results demonstrate that concrete reinforced with 0.5% bamboo fibers, 0.5% jute fibers, and 10% silica fume (SF) markedly improved its mechanical qualities. The suggested ANN model shown a significant level of accuracy in predicting the mechanical characteristics of natural-fiber-reinforced concrete [10]. Bamboo fiber-reinforced nanocomposites possess a wide range of applications in the aerospace, auto, athletic equipment, structural, and household appliance sectors [11]. A comparison methodology was established, employing a conventional multi-objective optimization tool, the desirability function,

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alongside a Response Surface Methodology (RSM) model [12].

Hybrid composite validated the uniform distribution of sugarcane bagasse and aluminum oxide particles within the epoxy matrix, which enhances the product's mechanical characteristics [13]. Statistical models were developed utilizing both RSM and ANN, and their prediction efficacy was evaluated through R^2 values. The results indicated that the ANN model surpassed the RSM model in predicting accuracy for this investigation [14]. This study illustrates the efficacy of the ANN-BBD modeling approach in effectively attaining targeted mechanical property values, minimizing production costs, and preserving resources [15]. This methodology, integrating sophisticated machine learning and ensemble techniques, enhances predictive precision for banana composite materials and provides an adaptable structure for diverse materials handling applications [16]. The study investigates the influence of fiber orientation, fiber sequence, and nano-filler on flexural, and hardness properties, as well as the interactions among these variables in composite manufacture.

2. Materials and methods

2.1. Materials

For this study, the used low land bamboo and fiber-reinforced polymer composites are produced through an intricate process that starts with the careful selection of materials. The composite, unidirectional woven natural resource bamboo fiber and glass fiber with a weight of 360 grams per square meter was chosen. The bamboo fibers, and glass fabrics were cut and arranged as specified, and epoxy LY556 mixed with hardener HY951 in a 10:1 weight ratio was applied.

2.2. Methods design of experiments

The RSM is a powerful technique used to analyze and optimize systems affected by multiple factors that influence the desired outcome. It integrates various statistical and mathematical approaches, offering advantages over traditional factorial methods. Table 1 lists the original low and high values for these parameters,

Table 1 Presents Input Factor and Levels.

Name	Units	Low	High
A Fiber orinetation	Degree	0	90
B Fiber sequecnce		1	3
C Al2O3 Filler	%	3	5

3. Results and discussion

3.1. Data-driven evaluation for FS

The Flexural test was followed by analysis using Design Expert 13 software after the formulation of a Central Composite Design. The calculated F-value of 48.83 also shows statistical significance because there is only a 0.01% chance that such an F-value is due to noise. Modeling terms with P-values less than 0.0500 were considered to be of significant importance while terms with P-vales higher than 0.1000 were deemed insignificant. Figure 2 illustrates the correlation between the standard probability distribution and the internal residual Flexural strength. Figure 1(b) revealed the scatter plot of the experimental and residual FS values and all the points were close to zero cross, suggesting a relatively stable variation and therefore no need for data transformation. It is evident from Figure1 (d) that all the data points are approaching the reference line proving that the model is very accurate.

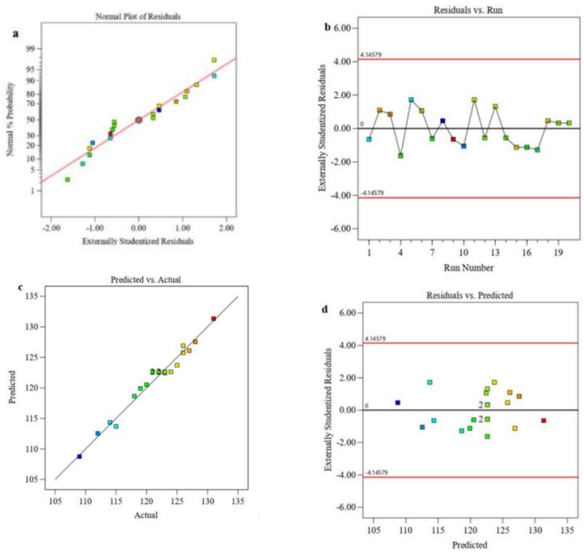

Figure 1 Flexural Response Plot for (a) normal Plot (b) Residual vs Run number (c) Predicted vs Actual (d) Predicted vs Externally studentized Residuals.

The perturbation plot which analyzes the dependency of the FS response on each process variable is presented in Figure 2. Al2O3 content (C) is found to improve the FS when increased, probably due to increased toughness and better adhesion with the epoxy matrix. Likewise, flexural strength rises with an enhancement of the degree of fiber orientation (A) due to its capacity to bear loads. On the other hand, FS is inversely proportional to fiber sequence (B) attributed to a decrease in fiber orientation and interfacial adhesion between the fibers and the polymer matrix.

3.2. Surface response for FS

Figure 2 shows the three-dimensional surface plots and two-dimensional contour maps of FS in terms of different factors. Figures 2(a) and 3(b) show that fiber orientation and fiber sequencing affect FS. For this purpose, Figure 5(a) shows the 3D surface plot and Figure 4(b) shows the 2D contour plot of the FS concerning Al2O3concentration and fiber orientation. Figures 6(a) and 6(b) are the 3D and 2D plots that explain the interactive influence of fiber sequencing and Al2O3 concentration on FS in the hybrid composite [17], who demonstrated that a 90-degree fiber orientation offers superior flexural strength and modulus.

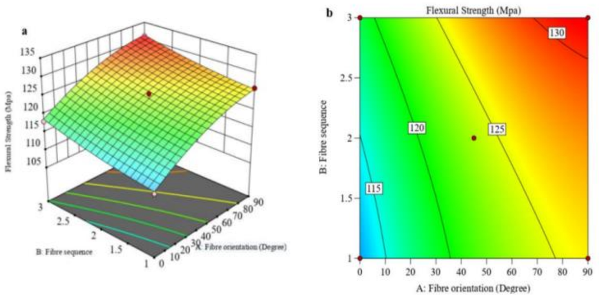

Figure 2. Response of AB Interaction for FS (a) 3D Plot (b) 2D Plot.

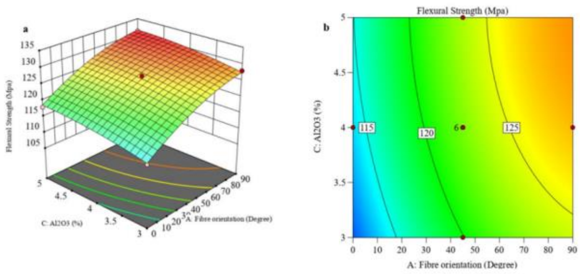

Figure 3. Response of AC Interaction for FS (a) 3D Plot (b) 2D Plot.

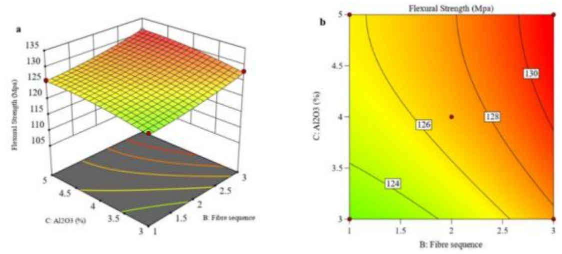

Figure 4 Response of BC Interaction for FS (a) 3D Plot (b) 2D Plot.

3.3. Statistical analysis of H

About the results of multiple regression analysis of the initial data, the use of the second-order polynomial equation was employed. The ANOVA analysis compares the amount of variation between groups (Mean square (MS) effect) to that of within the groups (MS error) and derives an F-ratio and a P-value which comprises parameters such as MS and the sum of squares (SS).

Table 2. ANOVA for H.

Factors	SS	DF	MS	F-value	P-value	
Model	534.86	9	59.43	32.41	< 0.0001	significant
A-Fibre orientation	384.40	1	384.40	209.64	< 0.0001	
B-Fibre sequence	62.50	1	62.50	34.09	0.0002	
C-Al2O3	44.10	1	44.10	24.05	0.0006	
AB	0.0000	1	0.0000	0.0000	1.0000	
AC	0.0000	1	1 0.0000	0.0000	1.0000	
BC	0.5000	1	0.5000	0.2727	0.6129	
A^2	19.11	1	19.11	10.42	0.0090	
B^2	2.05	1	2.05	1.12	0.3151	
C^2	3.55	1	3.55	1.94	0.1942	
Residual	18.34	10	1.83			
Lack of Fit	12.34	5	2.47	2.06	0.2239	not significant

3.4. Surfavr response for H

Figure 5 shows the three and two-dimensional graphs representing hardness depending onvarious factors. Figures 5(a) and 5(b) depict how fiber orientation as well as fiber sequence affect H. Based on these analyses of fiber orientation plotted against the 3D surface, it can be concluded that fiber orientation plays a key role in the enhancement of H with near-optimal values of the parameter. Nonetheless, a slight decrease in H is achieved when both fiber orientation and arrangement change, the maximum H at fibers orientation 90° and sequence. (b) is the 2D contour plot of the Hardness of thetoughened composites, in which the hardness increases to the maxima in 5 wt % Al2O3 and decreases to the minimum value in 3 wt % [19]. In the 3D surface plot and the 2D contour plot obtained in Figure 6 (a) and 10(b), the interaction between Al2O3 concentration and fiber orientation on H is sho6wn. Actual 3D surface and 2D contour plots presented in Figures 10(a) and 10(b) depicted the impact of fiber sequence and Al2O3 concentration on hardness. The 3D plot analysis reveals that a higher Al2O3 concentration of 5% improves the H, which may be attributed to improved distribution of Al2O3 and existence as clusters of nanoparticles in the matrix. Moreover, it rises with an increase of Al2O3 modification and the varied fiber dispositions which are probably attributed to enhanced connectivity between the fibers and the epoxy matrix [20].

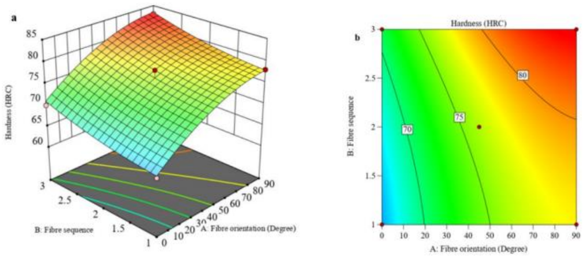

Figure 5. Response of AB Interaction for H (a) 3D Plot (b) 2D Plot.

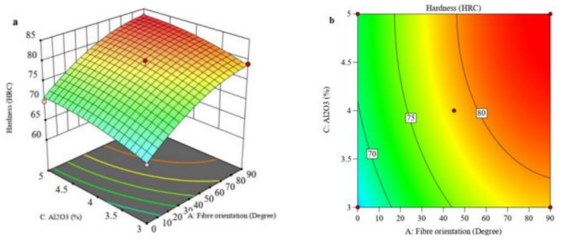

Figure 6. Response of AC Interaction for H (a) 3D Plot (b) 2D Plot.

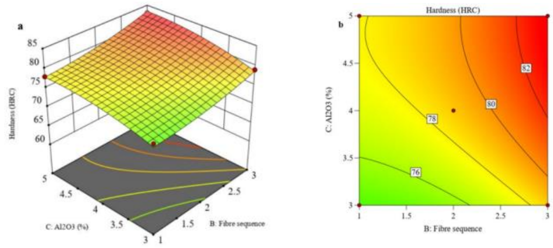

Figure 7 Response of BC Interaction for H (a) 3D Plot (b) 2D Plot.

3.4. Machine learning

ANNs are trained from the data by periodically modifying parameters called connection weights, which then help the network recognize common patterns and make corresponding predictions in fields such as image recognition and optimization. They comprise two competing networks a generator and a discriminator which were found to be significant in improving the general performance of the network [21]. Data closely passes in a straight line from the input layer to the output layer in a perceptron, a type of feed-forward neural network (FFNN), without returning [22]. After generating the model, this is tested on another dataset and their efficiency is measured by using tools such as the MAE, MSE, and a coefficient of determination. Last, we compare and contrast experimental values with predicted values to ensure the reliability of the model and elaborate error analysis reports [23]. Last, the results predicted by the model are compared with experimental values, and a comprehensive report is generated that highlights key observations, the errors, and a comparative analysis between the predicted and experimental values [24]. The GAN is trained for multiple cycles and the game revolves around the generator and discriminator, where both have to play to optimize a definite loss function [25]. Its ability to learn and optimize complex relationships makes it a more suitable choice for handling the intricacies of material behavior compared to RSM [26].

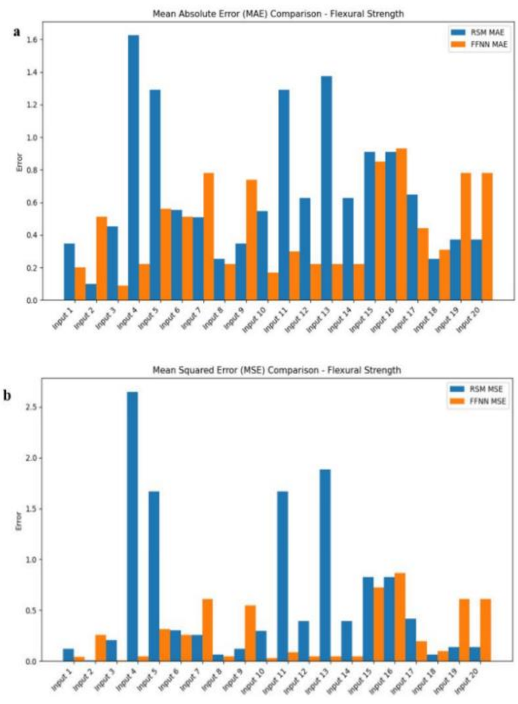

Figure 7 Flexural Strength (a) MAE Plot (b) MSE Plot.

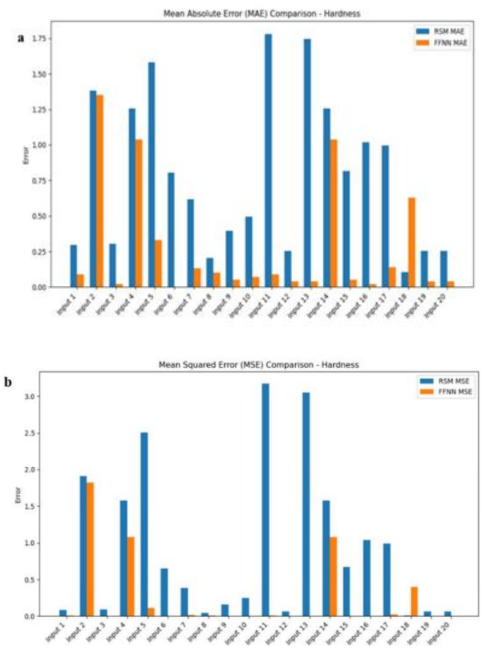

Figure 8 Hardness (a) MAE Plot (b) MSE Plot.

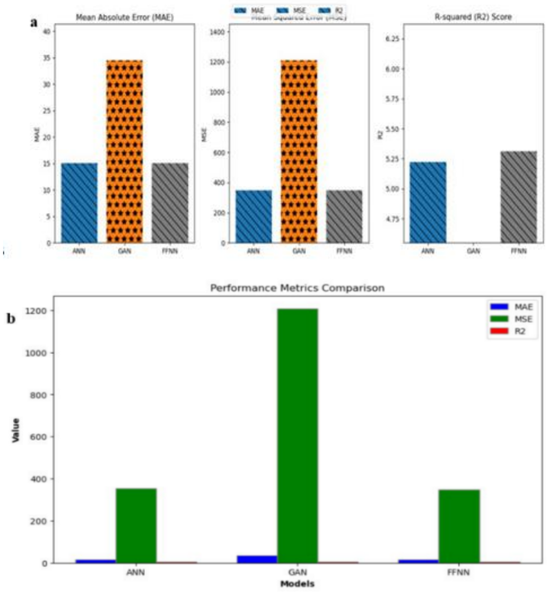

Figure 9 (a) Comparison of MSE, MAE, and R2 against ANN, GAN, and FFNN (b) 458 Performance Metrics.

Among the models, FFNN gives the lowest MAE (15.05) and MSE (347.65) and highest R^2 (5.31 demonstrating a better fit for the actual data and thereby giving better predictive accuracy [27]. Figure 9 (b) illustrates that the FFNN is the most reliable model among all the models evaluated, indicating that it can manage the comprehensiveness and variability of data [28]. Which is shown in Figure 9 (b) demonstrating that the FFNN can manage the comprehensiveness and variability of data depicting it as the most trustworthy model among all the compared models [29]. Flexural strength measurements range from 100 to 135 MPa. These prediction models are validated by the relative consistency between actual and anticipated values in the majority of samples [30]. RSM offers relatively stable and accurate predictions, while ANN is an appropriate approach for capturing more complex patterns; therefore, both can be considered valuable tools for the estimation of flexural strength in that ANN is better performed. The two techniques demonstrate the yield of accurate hardness prediction, the superiority of ANN in recognising complex and composite patterns, and the consistency of RSM in producing positive outcomes, proving that while both techniques are helpful, ANN is superior at predicting composite materials.

4. Conclusion

This work studied the flexural characteristics and hardness of hybrid composites containing bamboo fibers, kenaf, and glass fiber, as well as Al_2O_3 nanoparticle reinforcement. Using RSM, ANN, FFNN, and GAN the work successfully investigated the interactions between fiber orientation, fiber arrangement and Al_2O_3 content to predict their impact on composite properties. The experimental observations determined that 90° fiber angle, the best stacking sequence and 5% Al_2O_3 nanoparticles gave the highest results in flexural strength and hardness. An improvement of 18% in flexural strength and 32% in hardness was observed in the experimental results. This study demonstrated that FFNN outperformed RSM, GAN, and ANN for predicting material properties, indicating the applicability of FFNN for modeling high-order interactions in composites.The utilization of ANN and FFNN enables a forecast of composite performance, which is an excellent advance for expanding the efficiency of material design and minimizing expenditure on experimental iterations. This work highlights the need to have computational methods in close cooperation with experimental models to improve the possibility of sustainable development composites for sustainable use application within the structural and engineering disciplines.

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