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Artificial Neural Network (ANN) Approach to Predict Tensile Properties of Longitudinally Placed Fiber Reinforced Polymeric Composites including Interphase

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ABSTRACT

Machine Learning has become prevalent nowadays for predicting data on the mechanical properties of various materials and is widely used in various polymeric applications. In the present study, Artificial Neural Network (ANN), a computational tool is used to predict the elastic modulus of a composite of longitudinally placed fiber-reinforced polymeric composite. The novelty in carried work is that the property prediction is carried out considering interphase and its properties. For this, tensile properties data of Longitudinally Placed Bamboo Fiber Reinforced Polyester Composite (LUDBPC), Longitudinally Placed Flax Fiber Reinforced Polyester Composite (LUDFPC) and Longitudinally Placed Jute Fiber Reinforced Polyester Composite (LUDJPC) has been procured to generate ANN models. The Levenberg-Marquardt training algorithm is used to generate the ANN models as it gives more accurate results compared to other ANN algorithms based on interphase properties data. The validation of ANN models was also carried out based on fresh experimental results of BPC/FPC by doing the fabrication with hand layup technique and testing of composites with a Universal Testing Machine (UTM). The present work signifies that the developed ANN models give accurate results with experimental results for the prediction of elastic modulus of composite (E_{cl}) and it can be used for the prediction of longitudinally placed fiber-reinforced composite and E_{cl} of BPC at volume fraction of fiber (v_f):22% is 2248.75 MPa and E_{cl} of FPC at vf:10% is 3210.50 MPa.

1. Introduction

Polymer matrix composites have been boomed as the best upbeat advanced material that can swap conventional materials such as metals and woods [1-3]. Polymer matrix composites have a high strength-to-weight ratio, high corrosion resistance, excellent fatigue resistance, low coefficient to thermal expansion, superior thermal insulation, recyclable and environmentally friendly, relatively low cost, aesthetic color effect, etc. over conventional materials [4-6]. Hence, the polymer composite is selected as a part of the present study.

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Mechanical characterization is an important cycle process for the development and design of composite materials and their components [7]. Tensile properties for various natural fiber and natural fiber-reinforced polymeric composites were examined at different strain rates using experimental investigations [8-9]. Flexural properties of 3D printed wood dust-reinforced PLA composite were investigated experimentally [10]. Wear and friction characteristics of chopped carbon composite were investigated experimentally by varying parameters load, sliding distance, and disc speed [11]. Flexural properties were investigated at different weight fractions of fiber for longitudinally placed and transversely placed natural and synthetic fiber-reinforced polymeric composites [12]. It has been found that data prediction for mechanical and tribological characterization of anisotropic composites by performing numerous experiments is a challenge in the field of composite. Machine learning can be implemented for data prediction in various mechanical engineering applications [13]. Hence, in the present work, the data prediction for tensile properties has been targeted using machine learning concepts because machine learning has become a vital part of engineering and artificial intelligence for data analysis [14]. Machine learning is a set of many algorithms and techniques, which utilize design systems that can learn from data. It is a kind of traditional programming that inputs data and programs to get the output [15].

Artificial Neural Network (ANN) has the potential to minimize the efforts & time and to obtain a more effective system for mechanical-based design, fault identification, and accurate data prediction [16]. Artificial Neural Network is an effective tool for the prediction so it was decided to use it for the mechanical characterization data prediction.

The need for natural fiber-based products has increased instead of synthetic fiber in many applications such as door panels, household furniture, load floors, packaging trays, chassis of lightweight cars, etc. [17-18] and these eco-friendly biocomposites development is the right step to achieve sustainable development goals [19-20]. Natural fiber has lots of benefits over synthetic fibers in terms of properties like low cost, low density, recyclable, biodegradable, no skin irritation, relatively high strength and stiffness, eco-friendly behavior to the environment, easily processed, etc. [21-27]. NF takes over synthetic fiber for cases such as the requirement of low-cost, lightweight, and medium-strength fiber-based applications like cupboards, tables, chairs, sofas, etc., in furniture work [28]. Hence, a natural fiber-reinforced polymeric composite has been chosen for the present study.

2. ANN Approach

Chokshi & Gohil (2022) developed mathematical models to predict the elastic modulus of longitudinally placed natural fiber-reinforced polymeric composites including interphase volume fraction from 1% to 20% and varying interphase property variations such as linear variation, hyperbolic variation, parabolic variation, power-law variation and exponential variation as shown in Fig. 1 [29].

Based on this analytical data, inputs, and output were decided to generate ANN models using Alyuda NeuroIntelligence Software as shown in Table 1.

The seven training algorithms: Quick Propagation, Conjugate Gradient Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg-Marquardt, Online Back Propagation, and Batch Back Propagation were accessible to generate ANN models. Using these seven training algorithms, results for the elastic modulus of composite for longitudinally placed Glass/Polyester composites were checked with 49 readings by varying volume fractions of fiber: 0.1619, 0.1618, 0.2013, 0.2729, 0.3389, 0.4108, 0.5729, Interphase:1%, 3%, 6%, 9%, 12%, 15%, 20% and different types of variation: Linear variation, Hyperbolic variation, Parabolic variation, Power law variation, Exponential variation as shown in Table 2 [31]. As per Table 2, the Levenberg-Marquardt training algorithm was chosen for the present work because it gives more accurate results for longitudinally placed composites.

Inputs were selected as Volume fraction of fiber (v_f), Interphase volume fraction (v_i), and Interphase property variations and output was selected as Elastic modulus of Composite (E_{cl}) to generate ANN models. 140 Input and Output values were inserted for each composite: LUDBPC, LUDFPC, and LUDJPC to generate ANN models based on Table 1. Here, bamboo fiber, flax fiber, and jute fiber were selected as per the availability of natural fibers.

ANN approach includes design, training, and testing during the generating of ANN architecture. The design architecture of LUDBPC is shown in Fig. 2. Here, [10-5-1] architecture is selected for training hidden layers, where v_{f1}, v_{f2}, v_{f3}, v_{f4}, v_i, linear variation, hyperbolic variation, parabolic variation, power-law variation, exponential variation, and Ecl are considered as encoded data for preprocessing. Out of 140 records, 96 records were used for the Training set (68.57%), 22 records were used for the Validation set (15.71%) and 22 records were used for the Test set (15.71%). Similar kinds of architectures were observed for the LUDFPC and LUDJPC.

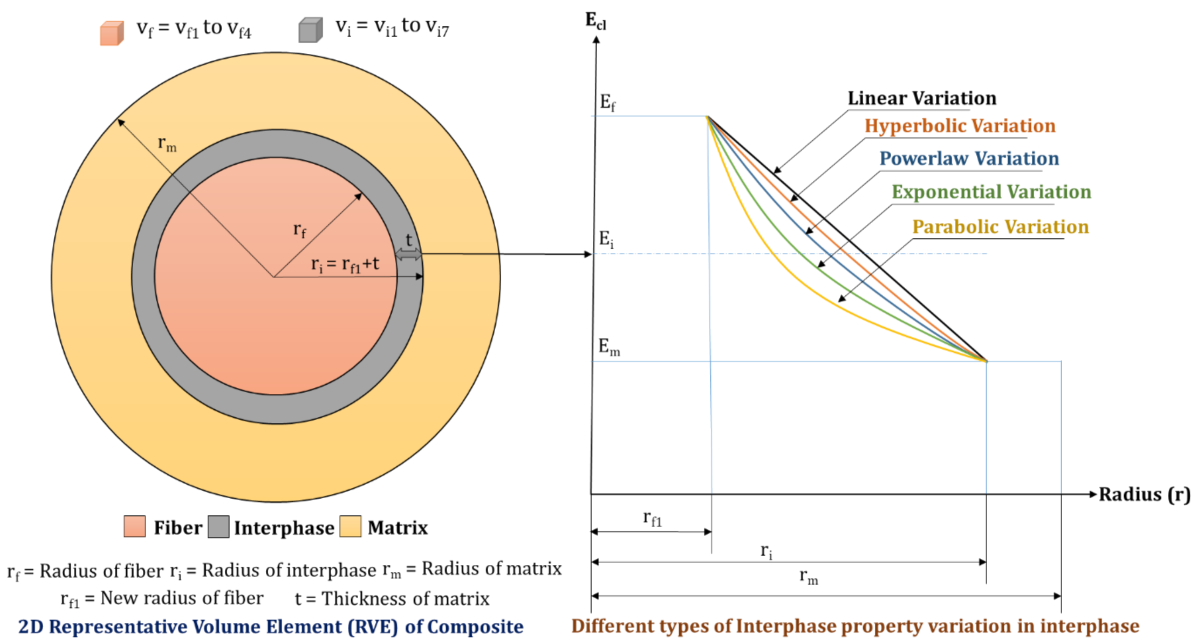

Fig. 1. Geometry to develop mathematical modeling of Composite [29-30]

Table 1. Data of Input and Output to generate ANN models

Input						Output
The volume fraction of fiber (v_f)				Interphase volume fraction v_i (%)	Interphase property variations	
Composite	LUDBPC	LUDFPC	LUDJPC			
v_{f1}	0.37	0.36	0.30	v_{i1}=1	Linear	Elastic modulus of Composite (E_{cl})
v_{f2}	0.31	0.29	0.27	v_{i2}=3	Hyperbolic	
v_{f3}	0.22	0.25	0.23	v_{i3}=6	Parabolic	
v_{f4}	0.16	0.20	0.21	v_{i4}=9	Power law	
Input : 4×7×5= 140 Values; Output = 140 Values for each composite				v_{i5}=12	Exponential	
				v_{i6}=15		
				v_{i7}=20		

Table 2. Results to select ANN Training Algorithm to build ANN model

Sr. No.	ANN Training Algorithms	Analytical Error (%)	Experimental Error (%)
1	Quick Propagation	3.13	8.82
2	Conjugate Gradient Descent	1.98	8.00
3	Quasi-Newton	2.35	8.71
4	Limited Memory Quasi-Newton	1.57	8.08
5	Levenberg-Marquardt	1.55	7.72
6	Online Back Propagation	6.62	10.23
7	Batch Back Propagation	37.10	35.26

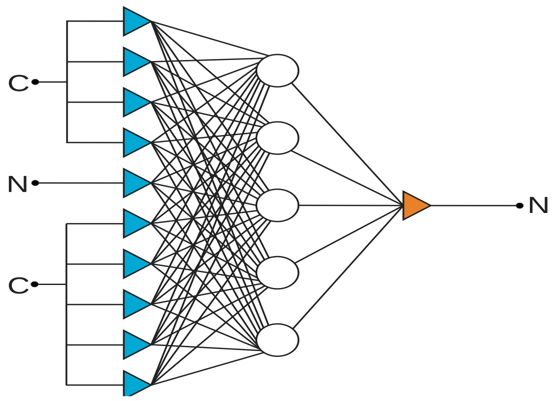

Fig. 2. Design architecture of ANN for LUDBPC [10-5-1]

3. Results and Discussion

The results obtained through the ANN approach for longitudinally placed fiber-reinforced composites are discussed here. ANN results summary actual vs output for all results including training, validation, and testing for LUDBPC is shown in Table 3, where AE is Absolute Error and ARE is Absolute Relative Error. Similar kind of results were obtained for LUDFPC and LUDJPC.

Table 3. Summary of ANN results: Actual vs Output for LUDBPC

LUDBPC	Target/ Actual	Output	AE (%)	ARE (%)
Mean	2228.23	2228.36	2.10	0.00
Std Dev	275.96	275.84	1.78	0.00
Min	1820.32	1827.98	0.07	0.00
Max	2670.89	2666.37	12.59	0.01
Correlation: 0.99 and R^2: 0.99				

From Table 3, it is observed that the results of AE and ARE are found less and the R^2 value is found 0.99 for LUDBPC which is close to 1, which reveals the good accuracy of the regression of the ANN model with actual. Similar observations were found in LUDFPC and LUDJPC.

The analytical results were generated through the mathematical model and ANN model for interphase volume fraction 5% and 10% of fiber volume fraction for longitudinally placed unidirectional composites i.e., LUDBPC, LUDFPC, and LUDJPC, which were not used to generate the ANN models to check the developed ANN model perfectness. The obtained results of LUDBPC were compared as shown in Table 4 and measure error and average bias error using equation 1. Similar kind of results were observed for LUDFPC and LUDJPC.

$$\mathrm{Error}(\%) = \left| \frac{E_{cl}^{ANN} - E_{cl}^{Analytical}}{E_{cl}^{ANN}} \times 100 \right| \tag{1}$$

Table 4. Comparison of ANN results with Analytical results for LUDBPC (Sample result table)

Sr. No.	v_f	v_i (%)	Types of variation	ANN E_{cl} (MPa)	Analytical E_{cl} (MPa)	Error (%)
1	0.37	5	Linear	2634.40	2644.09	0.37
2	0.31	5	Linear	2420.80	2432.20	0.47
3	0.22	5	Linear	2107.23	2114.38	0.34
4	0.16	5	Linear	1895.05	1902.49	0.39
5	0.37	5	Hyperbolic	2634.38	2643.80	0.36
6	0.31	5	Hyperbolic	2417.63	2431.96	0.59
7	0.22	5	Hyperbolic	2104.92	2114.21	0.44
8	0.16	5	Hyperbolic	1893.30	1902.37	0.48
9	0.37	5	Parabolic	2627.85	2632.94	0.19
10	0.31	5	Parabolic	2418.03	2422.84	0.20
11	0.22	5	Parabolic	2103.42	2107.74	0.21
12	0.16	5	Parabolic	1890.57	1897.66	0.37
13	0.37	5	Power law	2629.53	2636.83	0.28
14	0.31	5	Power law	2418.49	2426.13	0.31
15	0.22	5	Power law	2104.45	2110.06	0.27
16	0.16	5	Power law	1891.39	1899.36	0.42
17	0.37	5	Exponential	2631.91	2636.97	0.19
18	0.31	5	Exponential	2419.89	2426.24	0.26
19	0.22	5	Exponential	2104.83	2110.15	0.25
20	0.16	5	Exponential	1892.92	1899.42	0.34
21	0.37	10	Linear	2579.61	2588.55	0.35
22	0.31	10	Linear	2382.30	2385.67	0.14
23	0.22	10	Linear	2078.60	2081.35	0.13
24	0.16	10	Linear	1876.73	1878.48	0.09
25	0.37	10	Hyperbolic	2577.62	2587.63	0.39
26	0.31	10	Hyperbolic	2378.22	2384.90	0.28
27	0.22	10	Hyperbolic	2075.41	2080.81	0.26
28	0.16	10	Hyperbolic	1879.34	1878.08	0.07
29	0.37	10	Parabolic	2566.17	2576.32	0.39
30	0.31	10	Parabolic	2369.07	2375.42	0.27
31	0.22	10	Parabolic	2069.64	2074.09	0.21
32	0.16	10	Parabolic	1872.99	1873.19	0.01
33	0.37	10	Power law	2570.02	2582.93	0.50
34	0.31	10	Power law	2373.14	2380.97	0.33
35	0.22	10	Power law	2072.27	2078.02	0.28
36	0.16	10	Power law	1874.73	1876.05	0.07
37	0.37	10	Exponential	2572.46	2583.40	0.42
38	0.31	10	Exponential	2376.11	2381.36	0.22
39	0.22	10	Exponential	2073.98	2078.29	0.21
40	0.16	10	Exponential	1874.71	1876.25	0.08
					Average Bias Error (%):	0.29

The summary of average bias errors is shown in Table 5. The analytical results were generated using mathematical models as shown in equation 2, which can effectively predict E_{cl} by considering the v_i for longitudinally placed composite. These developed mathematical models have good accuracy with experimental data, and other researchers' data and are best compared to other researchers' models [26].

$$E_{cl} = (E_f v_{fn}) + (E_i v_i) + (E_m v_m)$$
$$\text{Where, } v_i = x \times v_f \text{ and } x = 0.01 \text{ to } 0.20 \quad (2)$$

Table 5. Summary of average bias errors

Sr. No.	Composites	Average Bias Errors (%)
1	LUDBPC	0.29
2	LUDFPC	0.83
3	LUDJPC	0.50

From Table 5, it is observed that the average bias errors are found 0.29% for LUDBPC, 0.83% for LUDFPC, and 0.50% for LUDJPC, which are very low and below 10%. It shows that the ANN model is in agreement with analytical results developed through mathematical models for longitudinally placed fiber-reinforced composites. Moreno et al. (2013) reported that mean absolute percentage error <10 is highly accurate forecasting for Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) models, which also reveals that presented ANN results have good accuracy in all types of composites [32].

4. Validation

For the validation of ANN models for longitudinally placed fiber-reinforced composites with experimental work, it was decided to use fresh experimental results for bamboo/polyester composites (BPC) and flax/polyester composites (FPC). For this, fabrication and tensile testing of longitudinally placed BPC and longitudinally placed FPC were carried out using the hand layup method and UTM as shown in Fig. 3 and Fig. 4.

Fig. 3. Fabricated plates of longitudinally placed BPC and FPC

Fig. 4. Tensile testing of the composite specimen on UTM

The tensile testing was carried out as per ASTM D3039/3039M-08 [33]. The experimental results through the fabrication and testing of composites are shown in Table 6 and the Stress-Strain graph for BPC and FPC are depicted in Fig. 5 and Fig. 6 respectively.

Table 6. Experimental results for the validation of ANN

Sr. No.	Composites	v_f	E_{cl} (MPa)
1	BPC	0.22	2248.75
2	FPC	0.10	3210.50

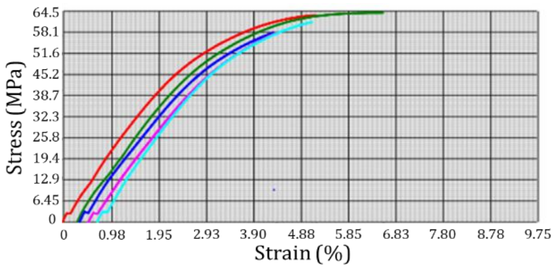

Fig. 5. Stress-Strain graph for BPC

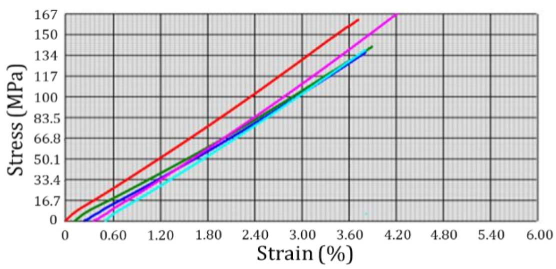

Fig. 6. Stress-Strain graph for FPC

The calculated elastic modulus composite through the ANN approach is compared with an experimental elastic modulus of composite to measure the error and average bias errors as shown in Table 7 and Table 8, where error is found using equation 3.

$$\text{ror}(\%) = \left| \frac{E_{cl}^{ANN} - E_{cl}^{Experimental}}{E_{cl}^{ANN}} \times 100 \right| \quad (3)$$

From Table 7 and Table 8, it is observed that the average bias error is 9.65% for BPC and 2.55% for FPC, which reveals the good accuracy of regression of ANN results with experimental results. Hence, it can be said that the ANN approach is validated through experimental work for longitudinally placed fiber-reinforced composites.

Table 7. Comparison of ANN results with experimental results for BPC

Sr. No.	Composites	v_f	v_i (%)	Types of variation	ANN E_{cl} (MPa)	Experimental E_{cl}(MPa)	Error (%)
1	BPC	0.22	15	Linear	2038.96	2248.75	9.33
2	BPC	0.22	20	Linear	2022.79	2248.75	10.05
3	BPC	0.22	15	Hyperbolic	2040.50	2248.75	9.26
4	BPC	0.22	20	Hyperbolic	2023.70	2248.75	10.01
5	BPC	0.22	15	Parabolic	2040.82	2248.75	9.25
6	BPC	0.22	20	Parabolic	2029.75	2248.75	9.74
7	BPC	0.22	15	Power law	2034.30	2248.75	9.54
8	BPC	0.22	20	Power law	2021.40	2248.75	10.11
9	BPC	0.22	15	Exponential	2038.62	2248.75	9.34
10	BPC	0.22	20	Exponential	2026.40	2248.75	9.89
						Average Bias Error (%):	9.65

Table 8. Comparison of ANN results with experimental results for FPC

Sr. No.	Composites	v_f	v_i (%)	Types of variation	ANN E_{cl} (MPa)	Experimental E_{cl} (MPa)	Error (%)
1	FPC	0.10	15	Linear	3134.64	3210.50	2.36
2	FPC	0.10	20	Linear	3126.76	3210.50	2.61
3	FPC	0.10	15	Hyperbolic	3131.21	3210.50	2.47
4	FPC	0.10	20	Hyperbolic	3125.99	3210.50	2.63
5	FPC	0.10	15	Parabolic	3130.07	3210.50	2.51
6	FPC	0.10	20	Parabolic	3124.84	3210.50	2.67
7	FPC	0.10	15	Power law	3130.95	3210.50	2.48
8	FPC	0.10	20	Power law	3125.57	3210.50	2.65
9	FPC	0.10	15	Exponential	3131.41	3210.50	2.46
10	FPC	0.10	20	Exponential	3125.56	3210.50	2.65
						Average Bias Error (%):	2.55

Table 9. Experimental Data of Bolcu et al. (2004) for Validation

Sr. No.	Composite	Composite Code	E_f	E_m	v_f	E_{cl} (MPa)	Reference
1	Flax/Epoxy Composites (FEC)	FEC-1	28000	4500	0.40	12920	[34]
2		FEC-2	28000	4500	0.50	15450	
3		FEC-3	28000	4500	0.60	17770	

Table 10. Comparison of Bolcu et al. (2004) experimental data with ANN results

Sr. No.	Composite Code	v_f	v_i (%)	Types of variation	ANN E_{cl} (MPa)	Experimental E_{cl} (MPa)	Error (%)
1	FEC-2	0.5	15	Linear	15374.62	15450	0.49
2		0.5	15	Hyperbolic	15242.72	15450	1.34
3		0.5	12	Parabolic	16611.78	15450	7.52
4		0.5	15	Powerlaw	14568.18	15450	5.71
5		0.5	12	Exponential	16545.23	15450	7.09
						Average Bias Error (%):	4.43

For the validation of ANN models for longitudinally placed fiber-reinforced composites with existing literature, it was decided to use the results of Bolcu et al. (2004) for Flax/Epoxy Composites (FEC) as shown in Table 9 [34]. ANN model was created using the experimental data of FEC-1 & FEC-3 and validated using experimental data of FEC-2 for random five inputs as shown in Table 10. From Table 10, it is observed that the average bias error is 4.43% for FEC-2, which reveals the good accuracy of regression of ANN results with experimental results of Bolcu et al. (2004). Hence, it can be said that the ANN approach is also validated through existing literature for longitudinally placed fiber-reinforced composites. Therefore, the ANN approach may be used to predict the longitudinal elastic modulus of the composite.

5. Conclusions

Ecl of BPC at 22% vf is reported as 2248.75 MPa and Ecl of FPC at 10% vf is reported as 3210.50 MPa as per experimental findings.

The predicted results for the longitudinal elastic modulus of composites through the ANN approach are in good agreement with results developed through proposed mathematical models, justifying that the ANN approach can be used to predict the longitudinal elastic modulus of composites. Similarly, the validations of ANN results for longitudinally placed fiber-reinforced composite with experimental results are also in good agreement, reconfirming the same fact that the ANN approach can be used to predict the longitudinal elastic modulus of composites.

The developed ANN approach can be used for the tensile property prediction of longitudinally placed fiber-reinforced composite.

A good amount of data is essential to generate an accurate ANN model.

This ANN approach can also be used in the prediction of transversely placed fiber-reinforced composite.

This ANN approach can also be used in the prediction of other mechanical properties: flexural properties, compressive properties, impact properties, tribological properties, etc.

Nomenclature

LUDBPC	Longitudinally Placed Bamboo Fiber Reinforced Polyester Composite
LUDFPC	Longitudinally Placed Flax Fiber Reinforced Polyester Composite
LUDJPC	Longitudinally Placed Jute Fiber Reinforced Polyester Composite
ANN	Artificial Neural Network
UTM	Universal Testing Machine
v_f	The volume fraction of fiber
v_i	Interphase volume fraction
E_{cl}	Elastic modulus of Composite
E_f	Elastic modulus of fiber
E_i	Elastic modulus of interphase
E_m	Elastic modulus of the matrix
AE	Absolute Error
ARE	Absolute Relative Error
BPC	Bamboo/Polyester composite
FEC	Flax/Epoxy Composites

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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