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Prediction of Water Uptake Percentage of Nanoclay-Modified Glass Fiber/Epoxy Composites Using Artificial Neural Network Modelling

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ABSTRACT: This research explores the water uptake behavior of glass fiber/epoxy composites filled with nanoclay and establishes an Artificial Neural Network (ANN) to predict water uptake percentage from experimental parameters. Composite laminates are fabricated with varying glass fiber (40–60 wt.%) and nanoclay (0–4 wt.%) contents. Water absorption is evaluated for 70 days of immersion following ASTM D570-98 standards. The inclusion of nanoclay reduces water uptake by creating a tortuous path for moisture diffusion due to its high aspect ratio and platelet morphology, thereby enhancing the composite's barrier properties. The ANN model is developed with a 3–4–1 feedforward structure and learned through the Levenberg–Marquardt algorithm with soaking time (7 to 70 days), fiber content (40, 50, and 60 wt.%) and nanoclay content (0, 2, and 4 wt.%) as input parameters. The model's output is the water uptake percentage. The model has high prediction efficiency, with a correlation coefficient (R) of 0.998 and a mean squared error of 1.38×10^{-4} . Experimental and predicted values are in excellent agreement, ensuring the reliability of the ANN for the simulation of nonlinear water absorption behavior. The results identify the synergistic capability of nanoclay and fiber concentration to reduce water absorption and prove the feasibility of ANN as a substitute for time-consuming testing in composite durability estimation.

KEYWORDS: Glass fiber epoxy composites; nanoclay; water uptake; ANN

1 Introduction

Fiber reinforced polymer composites (FRPCs) are universally accepted in the automotive industry, marine industry, and civil engineering applications because of their high specific strength, stiffness, corrosion resistance, and light weight [1,2]. Compared to composites reinforced with natural or carbon fibers, glass fiber/epoxy composites provide a more favorable balance between mechanical performance, cost, and environmental durability, making them well-suited for structural applications in the marine and aerospace sectors. Though their short-term performance is satisfactory, long-term performance degrades when subjected to environmental conditions like water, humidity, thermal cycling, and chemical attack. This calls for material modifications and predictive modelling tools to improve performance and predict behavior in service. Water absorption is a critical degradation mechanism in fiber-reinforced polymer composites, leading to plasticization of the matrix, fiber–matrix debonding, and long-term mechanical property deterioration. Even moderate moisture ingress can lead to dimensional instability, reduced load-bearing capacity,



and premature failure in marine, civil infrastructure, and transportation sectors. Therefore, quantifying and predicting water uptake behavior is essential for ensuring structural reliability and longevity [3,4].

Over the past few years, advances in nanotechnology have made it possible to utilize nanofillers to design the properties of polymer composites. Among numerous nanofillers, layered silicate-based nanoclay has emerged as a promising nanofiller capable of improving epoxy matrices' mechanical, thermal, and barrier performances [5–7]. The platelet nature and high aspect ratio of nanoclay help enhance load transfer, decrease moisture permeability, and delay crack propagation [8]. Some studies have shown that adding nanoclay to epoxy/glass fiber composites improves tensile strength, interlaminar shear strength, and hygrothermal aging resistance [9,10]. However, the efficacy of nanoclay reinforcement is influenced significantly by dispersion quality, filler loading, and fiber–matrix interface interaction.

Traditional experimental methods to measure the effect of nanofillers on composite properties are time-consuming, labor-intensive, and material-intensive. In addition, it is challenging for conventional statistical models to predict the nonlinear impact of multiple factors, filler content, environmental exposure, and processing conditions [11,12]. Artificial Neural Networks (ANNs) are powerful tools for modelling complex multivariable systems, especially in material science, where fabrication parameter dependence of performance properties is strongly nonlinear. ANNs are computer models inspired by the brain's operation that can learn complex input-output mappings without direct physical models [13].

ANNs are successfully employed in composite materials to simulate mechanical strength, water absorption, and wear resistance due to fabrication and material characteristics [14,15]. ANNs are distinct from regression models as they can handle nonlinearities and interactions between multiple variables. They are best-suited for systems with complex input–output behavior, such as nanocomposites.

The study by Yıldırım [16] focuses on using an ANN to accurately predict how the weight of glass fiber-reinforced polymer composites filled with SiC nanoparticles changes during artificial aging. The ANN model is developed using MATLAB with a (2-4-1) architecture and is trained using the Levenberg–Marquardt algorithm. It uses nanoparticle weight percentage and aging time as input parameters. The model achieves high prediction accuracy, with a low mean square error of 0.001225 and a strong correlation coefficient ($R = 0.99385$). ANN outperforms traditional models in handling complex, nonlinear data and reduces the need for extensive experimental testing. The study highlights the potential of ANN as an effective tool for simulating material behavior, optimizing composite design, and minimizing both time and cost in materials science.

Similarly, Capiel et al. [17] design ANN models to predict water absorption in glass fiber-reinforced nanoclay-epoxy composites. Two models are constructed for modified and unmodified bentonite systems. With a three-input (bentonite content, temperature, and immersion time) and one-output (water absorption) architecture with two hidden layers, the networks are trained with the Levenberg–Marquardt algorithm. With over 4600 experimental data points, both models performed exceptionally well regarding predictive capability, with correlation coefficients (R^2) of over 0.96. The two models produce reliable water uptake behavior mapping over time and temperature regimes, enabling the prediction of critical degradation points under service conditions.

In a related study, Saaidia et al. [18] apply ANN to model water absorption in jute and sisal fiber-reinforced epoxy composites with varying lengths of the fibers (5, 10, and 15 mm). The Levenberg–Marquardt algorithm-trained ANN accurately models the saturation kinetic curve of water absorption. The study emphasizes the capability of ANN in optimizing such critical parameters as immersion time and fiber length with reduced reliance on experimental analysis.

Likewise, Makhoul et al. [19] use ANN modelling to simulate water absorption in HDPE/jute fiber biocomposites. The model with input parameters of fiber loading and immersion time, and output as water absorption, has an excellent correlation between simulated and experimental data (R^2 of almost 1).

While prior studies have implemented ANN for predicting mechanical strength [14], wear resistance [15], and even water absorption [16–19], most models have focused on fixed fiber or filler types and used limited input variables. Yıldırım [16] has used a 2-input ANN model to simulate SiC nanoparticle-filled composites, and Capiel et al. [17] have modeled water uptake in nanoclay-epoxy systems without varying the reinforcement. However, composite water absorption is influenced by complex, nonlinear interactions between fiber content, filler dispersion, and soaking time. This study addresses that gap by developing a multi-input ANN model trained on experimentally validated fiber and nanoclay content combinations across immersion durations, thereby capturing synergistic effects that earlier studies have not explored.

This study's novelty lies in developing an ANN-based predictive model for water uptake in a hybrid composite system combining varying glass fiber contents with nanoclay-modified epoxy resin. Unlike earlier models that focused solely on natural fibers, single fillers, or fixed reinforcement levels, this work explores the combined influence of fiber loading and nanoclay concentration across multiple immersion durations. Using a tailored feedforward ANN architecture (3-4-1) with input variables of soaking time, glass fiber wt.%, and nanoclay wt.% allows for accurate modelling of the nonlinear moisture absorption behavior. Furthermore, including intermediate confirmation tests not present in the training set demonstrates the model's strong interpolation capability and generalization strength. This integrated approach offers a cost-effective and accurate alternative to prolonged experimentation, advancing composite design strategies for enhanced hydrothermal durability.

2 Methodology

2.1 Materials and Preparation of Composites

Epoxy resin (L-12) and hardener (K-6) are sourced from Atul Polymers, Gujarat, India, while the bi-directional woven E-glass fabric is obtained from Yuje Enterprises, Bengaluru. The surface-modified nanoclay, containing (25–30 wt.%) trimethyl stearyl ammonium, is purchased from Sigma Aldrich. Selected material properties used in this study are shown in Table 1.

Table 1: Properties of selected material

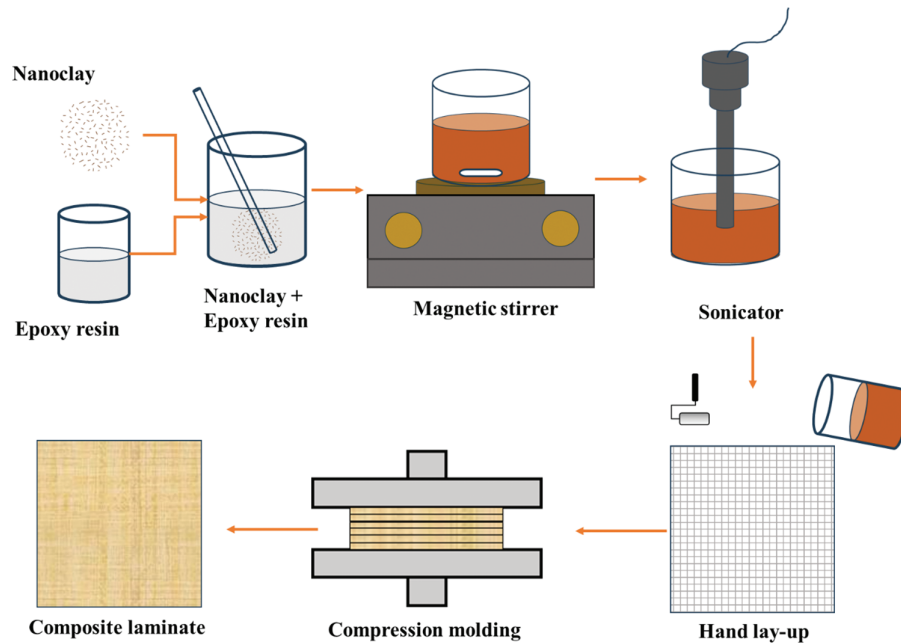
Sl. No.	Material name	Properties
1	Epoxy resin (L-12) and hardener (K-6)	Tensile strength (MPa)—55–70
		Tensile modulus (GPa)—2.5–4
		Flexural strength (MPa)—120–140
		Density (g/cm ³)—1.15
2	Nanoclay (Montmorillonite (MMT))	Appearance (color)—White to off-white
		Appearance (form)—Powder
		Size—<20 μm
		Bulk density—200–500 kg/m ³
		Surface modified contains 15–35 wt.% octadecylamine, 0.5–5 wt.% aminopropyltriethoxysilane.

(Continued)

Table 1 (continued)

Sl. No.	Material name	Properties
3	Glass fiber	Tensile strength (MPa)—1720–1950
		Tensile modulus (GPa)—72–76
		Density (g/cm ³)—2.5

Nanoclay is mixed into the epoxy using a magnetic stirrer for 30 min, followed by sonication for 20 min. The resulting nanoclay-epoxy blend is then combined thoroughly with the hardener. Laminates containing varying amounts of glass fiber (40, 50, and 60 wt.%) and nanoclay (0, 2, and 4 wt.%) are fabricated using the hand lay-up method followed by compression molding. A roller is applied over the wet layers to eliminate trapped air and ensure uniform consolidation, starting from the center and moving outward. The compression molding process is performed under 100 bar pressure at 50°C for 24h. Final laminate dimensions are maintained at 300 mm × 300 mm × 3 mm, with a 1% bilateral tolerance in volume. A stopper ensured a consistent laminate thickness of 3 mm. The specific procedures for composite laminate preparation are detailed in Fig. 1. Table 2 presents the weight percentage details of constituents for 50 wt.% glass fiber reinforced composites. The glass fiber weight fraction is precisely controlled using analytical weighing $\pm 0.01\text{g}$. Careful layering during hand lay-up ensures consistent distribution across the laminate surface.

**Figure 1:** Preparation of composite laminates**Table 2:** Weight percentage details of constituents for 50 wt.% glass fibre reinforced composites

	Wt. %	Wt. (g)	Wt. %	Wt. (g)	Wt. %	Wt. (g)
Glass fiber	50	235	50	235	50	235
Epoxy	50	235	48	225.6	46	216.2

(Continued)

Table 2 (continued)

	Wt. %	Wt. (g)	Wt. %	Wt. (g)	Wt. %	Wt. (g)
Nanoclay	0	0	2	9.4	4	18.8
Total	100	470	100	470	100	470

2.2 Water Uptake

Water uptake tests are conducted following ASTM D570-98 standards. Initially, the dry sample weight of each specimen is recorded using a digital weighing machine. The samples are then immersed in tap water at room temperature (25°C) for a duration of 70 days. Five specimens of each type of composite are immersed. The specimens are taken out at weekly intervals, gently wiped with a clean cloth to remove surface moisture, and weighed again. The water uptake (%) is calculated based on the change in mass over the measured time periods. The water uptake percentage is determined by:

$$\% \text{ of water uptake} = \frac{(W_a - W_d) \times 100}{W_d}$$

where, W_a —weight of the specimen after absorption, W_d —Weight of the dry specimen

2.3 Artificial Neural Network (ANN) Modelling

This work develops an ANN-based predictive model to estimate the water uptake percentage of glass fiber/epoxy composites modified with nanoclay under various soaking durations.

2.3.1 Network Design

The ANN architecture is selected based on preliminary trials to balance model simplicity and prediction accuracy. The optimal structure consists of

- Three input nodes, corresponding to soaking time (days), glass fiber content (wt.%), and nanoclay content (wt.%).
- One hidden layer with four neurons, a structure chosen after iterative tuning to avoid underfitting and overfitting. The final ANN architecture (3-4-1) is selected after a manual grid search, trialing different hidden layers (1-3) and neurons (2-6). The (3-4-1) model shows optimal performance in terms of MSE and training stability.
- One output node, representing the predicted water uptake (%).

2.3.2 Transfer Functions and Learning Algorithm

The hidden layer utilizes a *tansig* (hyperbolic tangent sigmoid) function, effectively mapping nonlinear relationships between inputs and outputs in the range of $[-1, +1]$. The output layer employs a *purelin* (linear) function to predict the continuous water uptake percentage value. The training is conducted using the Levenberg–Marquardt (trainlm) algorithm, selected for its superior convergence speed and stability for function-fitting problems with moderate-sized datasets [20].

2.3.3 Training Strategy and Data Management

The available data set is partitioned into 70% for training, 15% for validation, and 15% for testing. Data normalization is applied prior to training to improve convergence, transforming input variables

to a normalized scale suitable for the *tansig* functions. Multiple initializations with random weights are performed to avoid local minima, and the best-performing network (based on minimal validation error) is selected.

2.3.4 Model Evaluation Metrics

The model's learning performance is assisted through Mean Squared Error (MSE), the Regression coefficient (R), gradient, and mu behavior, which is indicative of training stability. The ANN's final architecture and hyperparameters are detailed in Table 3, and the network structure is visualized in Fig. 2.

Table 3: The ANN training parameters

Parameter	Value
Hidden neurons	4
Training algorithm	Levenberg–Marquardt (trainlm)
Learning rate	0.4
Momentum constant	0.9
Performance goal	0.00001
Epoch limit	1000

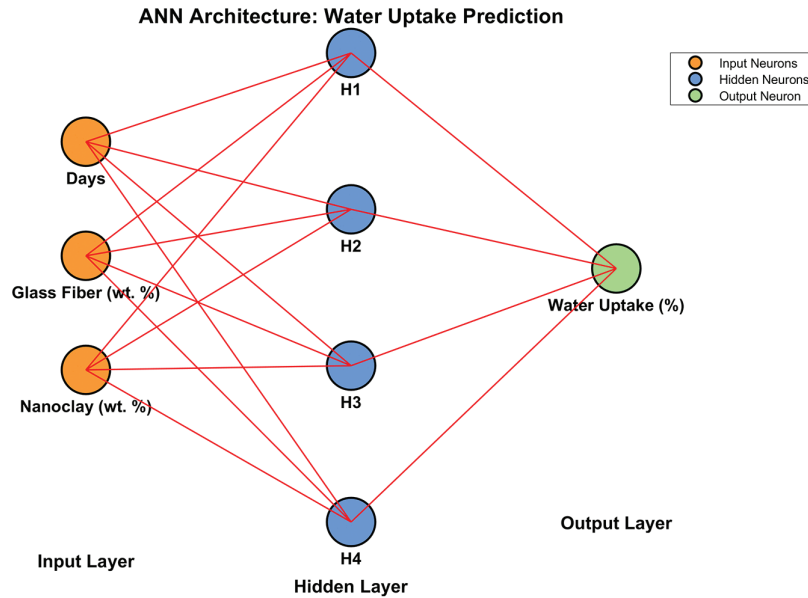


Figure 2: Architecture of the developed ANN model for water uptake prediction

3 Results and Discussion

3.1 Water Uptake (%)

Table 4 illustrates the water uptake behavior of glass fiber reinforced epoxy composites modified with varying nanoclay content over an immersion period of 70 days. Water absorption increases steadily with immersion duration for all composite formulations. The uptake rate is initially high during the early days due to the steep concentration gradient between the dry composite and the surrounding water. This gradually

slows, approaching near-equilibrium by day 70, indicating a saturation behavior characteristic of Fickian diffusion [21]. The saturation of water uptake beyond 63–70 days signifies that most of the accessible voids and hydrophilic regions in the matrix are filled.

Table 4: Water uptake (%) for different composites

Sl. No.	Days	Glass fiber (wt.%)	Nanoclay (wt.%)	Water uptake (%)	Sl. No.	Days	Glass fiber (wt.%)	Nanoclay (wt.%)	Water uptake (%)	Sl. No.	Days	Glass fiber (wt.%)	Nanoclay (wt.%)	Water uptake (%)
1	7	40	0	0.3	31	7	50	0	0.27	61	7	60	0	0.25
2	14	40	0	0.46	32	14	50	0	0.44	62	14	60	0	0.41
3	21	40	0	0.55	33	21	50	0	0.53	63	21	60	0	0.5
4	28	40	0	0.62	34	28	50	0	0.6	64	28	60	0	0.57
5	35	40	0	0.66	35	35	50	0	0.64	65	35	60	0	0.61
6	42	40	0	0.7	36	42	50	0	0.68	66	42	60	0	0.65
7	49	40	0	0.72	37	49	50	0	0.7	67	49	60	0	0.67
8	56	40	0	0.73	38	56	50	0	0.71	68	56	60	0	0.68
9	63	40	0	0.74	39	63	50	0	0.72	69	63	60	0	0.69
10	70	40	0	0.75	40	70	50	0	0.73	70	70	60	0	0.7
11	7	40	2	0.27	41	7	50	2	0.24	71	7	60	2	0.22
12	14	40	2	0.42	42	14	50	2	0.39	72	14	60	2	0.37
13	21	40	2	0.5	43	21	50	2	0.48	73	21	60	2	0.45
14	28	40	2	0.56	44	28	50	2	0.54	74	28	60	2	0.51
15	35	40	2	0.62	45	35	50	2	0.6	75	35	60	2	0.57
16	42	40	2	0.66	46	42	50	2	0.64	76	42	60	2	0.61
17	49	40	2	0.68	47	49	50	2	0.66	77	49	60	2	0.63
18	56	40	2	0.69	48	56	50	2	0.67	78	56	60	2	0.64
19	63	40	2	0.7	49	63	50	2	0.68	79	63	60	2	0.65
20	70	40	2	0.71	50	70	50	2	0.69	80	70	60	2	0.66
21	7	40	4	0.24	51	7	50	4	0.21	81	7	60	4	0.19
22	14	40	4	0.38	52	14	50	4	0.35	82	14	60	4	0.33
23	21	40	4	0.45	53	21	50	4	0.43	83	21	60	4	0.4
24	28	40	4	0.5	54	28	50	4	0.48	84	28	60	4	0.45
25	35	40	4	0.58	55	35	50	4	0.56	85	35	60	4	0.53
26	42	40	4	0.62	56	42	50	4	0.6	86	42	60	4	0.57
27	49	40	4	0.64	57	49	50	4	0.62	87	49	60	4	0.59
28	56	40	4	0.65	58	56	50	4	0.63	88	56	60	4	0.6
29	63	40	4	0.66	59	63	50	4	0.64	89	63	60	4	0.61
30	70	40	4	0.67	60	70	50	4	0.65	90	70	60	4	0.62

A comparison across glass fiber content at constant nanoclay levels reveals that increasing the glass fiber wt.% results in reduction in water uptake percentage. For instance, composites with 40 wt.% glass fiber and no nanoclay show the highest water uptake at 0.75% after 70 days, whereas those with 60 wt.% glass fiber under the same conditions has a reduced uptake of 0.70%. This reduction is attributed to the hydrophobic nature of glass fibers, which, when present in higher amounts, displace the more hydrophilic epoxy matrix and minimize the overall permeable volume. Additionally, higher fiber loading leads to improved barrier effects due to fiber-matrix interlocking, which hinders the penetration of water molecules [22,23].

Similarly, the incorporation of nanoclay significantly enhances moisture resistance. Increasing the nanoclay loading from 0 to 4 wt.% consistently reduces the water uptake at all time intervals for a fixed glass fiber content. For instance, with 40 wt.% glass fiber, the 70-day water uptake drops from 0.75% (0 wt.% nanoclay) to 0.67% (4 wt.% nanoclay). This improvement is due to the high aspect ratio and platelet-like morphology of nanoclays, which create a tortuous path for water molecules. The dispersion of these particles within the matrix increases the effective diffusion length, thereby reducing the diffusion rate and total water ingress [24,25].

The combined effect of higher glass fiber and nanoclay content is particularly effective. Composites with 60 wt.% glass fiber and 4 wt.% nanoclay exhibit the lowest water uptake percentage across the entire study, with only 0.62% absorption at day 70. This synergy arises from the simultaneous effects of reduced matrix

volume (due to higher fiber content) and enhanced diffusion resistance (due to nanoclay inclusion). These observations demonstrate that integrating both reinforcement strategies improves the hydrothermal stability of fiber-reinforced epoxy composites.

Role of Hand Lay-Up and Compression Molding in Controlling Water Uptake (%)

The fabrication process employed in this study involves hand lay-up followed by compression molding at 100 bar pressure and 50°C for 24h. These processing parameters play a crucial role in determining the composite's void content and interfacial bonding, affecting its water absorption behavior.

Though simple and cost-effective, the hand lay-up technique is susceptible to entrapped air and resin-rich zones if not properly managed. To mitigate this, a roller is used to compress the laminate uniformly and expel trapped air, reducing void formation. The presence of voids can significantly enhance water uptake by providing direct capillary pathways for moisture ingress.

Compression molding under 100 bar pressure enhances consolidation, improving fiber–matrix wetting and minimizing porosity. The moderate curing temperature (50°C) and extended curing time (24 h) ensure thorough cross-linking of the epoxy matrix, promoting better interfacial bonding and reducing the number of unreacted groups that may otherwise attract moisture.

Stronger fiber–matrix adhesion results in fewer interfacial gaps, which are potential moisture ingress sites. Conversely, insufficient pressure or incomplete curing could lead to poor wetting and weak bonding, promoting microcracks and water diffusion. Therefore, the selected processing parameters are critical for mechanical integrity and improving moisture resistance by lowering void content and strengthening the fiber–matrix interface.

3.2 Artificial Neural Network

The experimental dataset used for training, validation, and testing of the ANN model is derived from the water uptake measurements presented in Table 4, which are obtained from immersion tests on composites with varying soaking time, glass fiber, and nanoclay contents conducted as per ASTM D570-98.

The chosen ANN architecture reflects a balance between model complexity and prediction robustness, avoiding overfitting while capturing nonlinear dependencies between the input variables and moisture absorption behavior. The method exhibits fast convergence within 18 epochs, with the best validation performance achieved early, suggesting effective learning.

The training performance curve in Fig. 3 reveals a steep decline in Mean Squared Error (MSE) within the first 10 epochs, after which it asymptotically approaches a minimal error plateau. The optimal validation performance is reached at epoch 10, beyond which the validation error starts to increase, indicating the onset of overfitting prevention through early stopping mechanisms. The minimum MSE achieved is approximately 1.38×10^{-4} , with the best model captured before validation failure increments. The alignment between the training, validation, and testing curves suggests that the network generalizes well without overfitting.

The training state plot in Fig. 4 provides insight into the internal optimization dynamics of the ANN model. The gradient decreases smoothly to 7.18×10^{-5} , reflecting steady learning progress toward convergence. The mu, damping parameter, decreases rapidly in the early epochs, stabilizing at 10^{-5} , indicative of the model transitioning from global to fine-tuning adjustments. Validation failures remain zero until epoch 16 after which minor increments are observed, signaling that the model retained a strong generalization ability over a significant portion of the training cycle.

Each experimental data point represents the mean of five replicate tests. Standard deviation across replicates is consistently below $\pm 0.02\%$, indicating high repeatability. For clarity, error bars are omitted from figures, but this statistical consistency supports the model's validity.

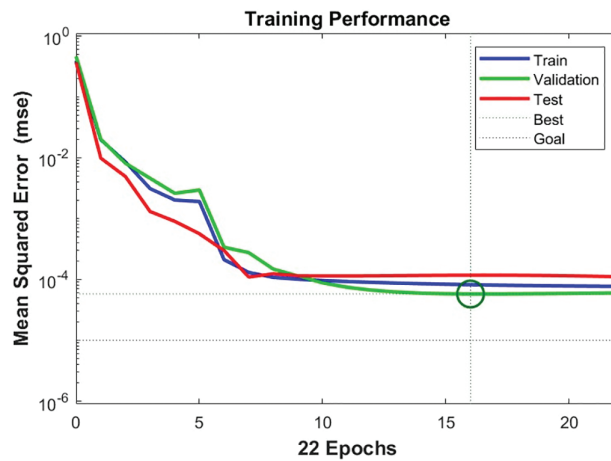


Figure 3: Training performance of ANN

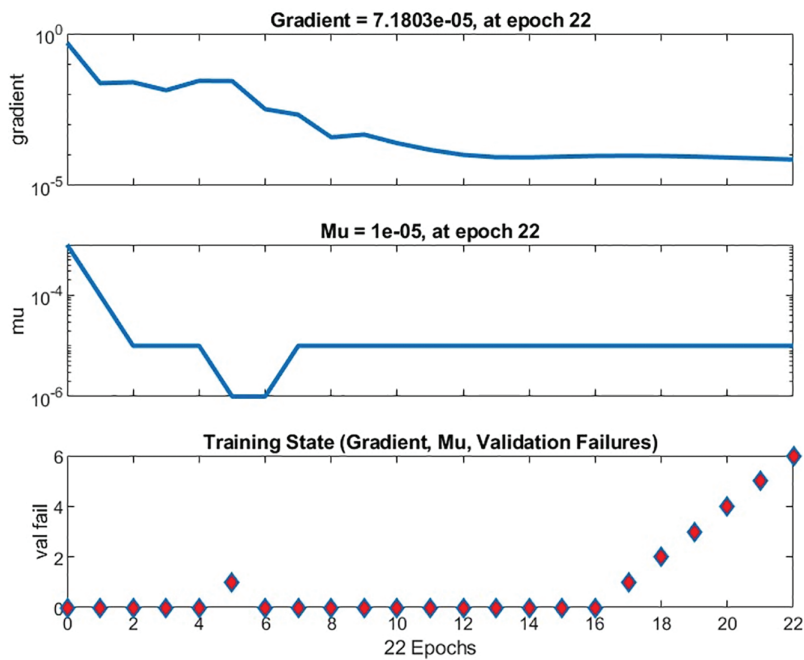


Figure 4: Training state plot—evolution of the gradient, Mu, and validation failure

The regression plot in Fig. 5 demonstrates an exceptionally high correlation between the network's predictions and the experimental targets. The coefficient of determination exceeds 0.99, validating that the ANN can effectively capture and reproduce the physical relationship between moisture absorption and the composite's formulation and exposure time.

The multi-state regression plot in Fig. 6 extensively evaluates the ANN's predictive capability across all data splits—training, validation, and testing. All the regression lines are closely aligned with the ideal $Y = T$ line, indicating minimal bias and high precision. The overall R -value of 0.998 substantiates that the model maintains consistency and reliability across the entire data spectrum.

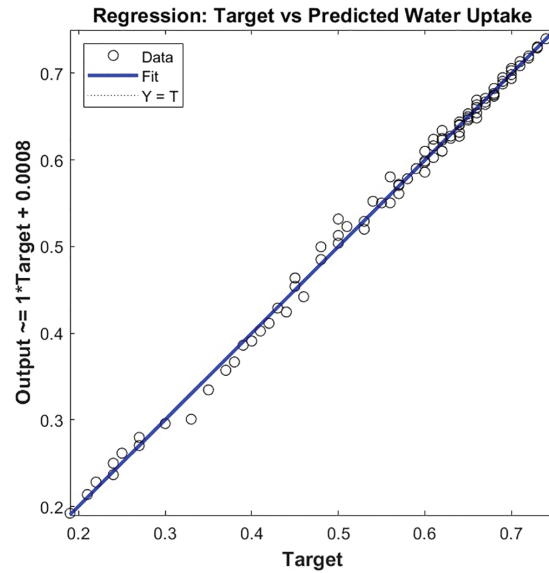


Figure 5: Regression plot for comparing ANN-predicted water uptake values to experimental targets

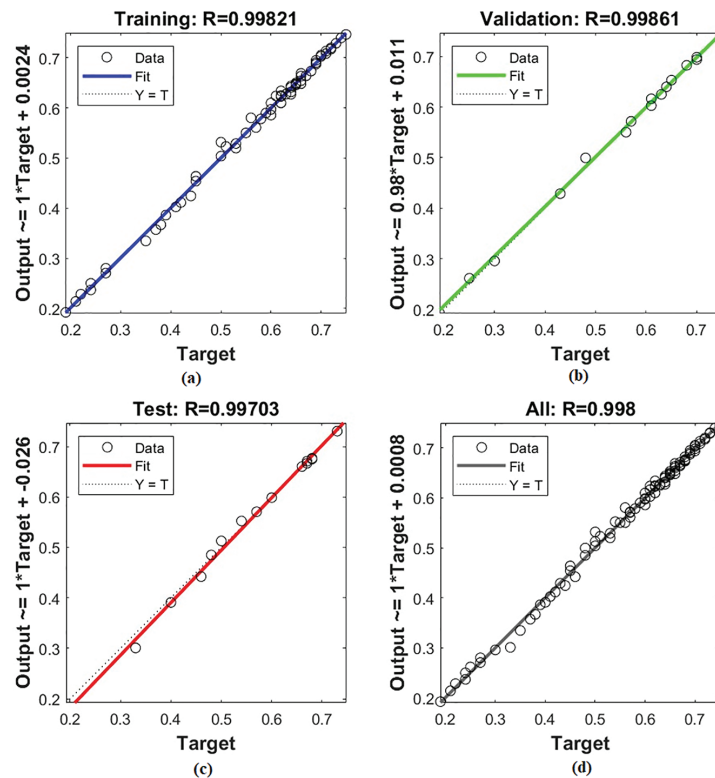


Figure 6: Regression plots for ANN model performance across (a) training, (b) validation, (c) testing, and (d) overall data sets

3.3 Comparison Data

Fig. 7 directly compares the experimental water uptake (%) values and those predicted by the ANN model across all test conditions. The close alignment between both sets of data points validates the robustness and predictive capability of the trained ANN. This figure underscores the model's ability to generalize

across various composite configurations. The minimal deviation between the actual and predicted values reflects a high degree of correlation, which is further supported by regression metrics (with $R \approx 0.998$) discussed earlier in Figs. 5 and 6. Such an agreement confirms the ANN's suitability for modelling nonlinear, multivariate relationships in composite materials and demonstrates its potential as a surrogate for expensive and time-consuming experimental campaigns.

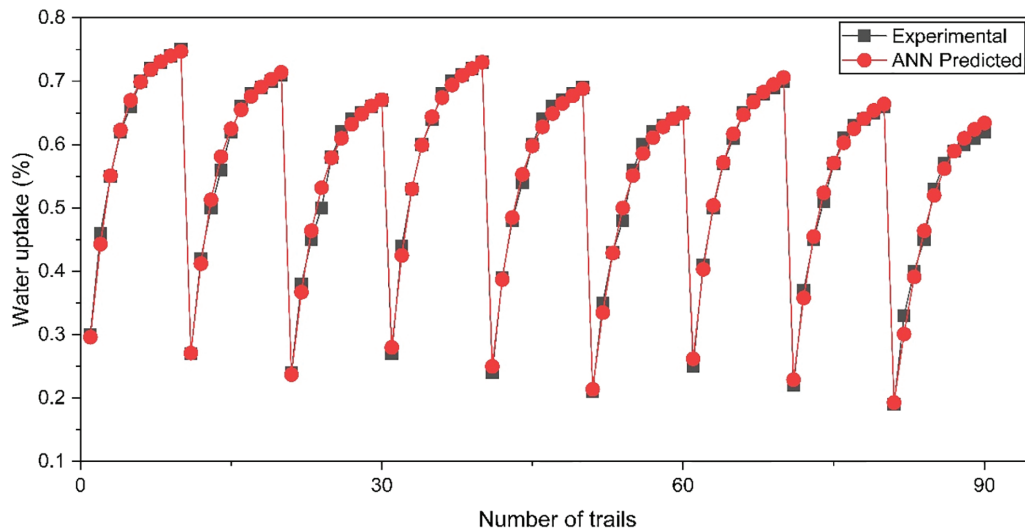


Figure 7: Comparison of experimental findings and ANN output

3.4 Confirmation Tests

Table 5 presents the results of independent confirmation tests conducted at selected intermediate immersion durations (10, 25 and 45 days) that are not part of the ANN training dataset. The experimental water uptake values are directly compared with ANN-predicted outputs for composites with varying glass fiber (40–60 wt.%) and nanoclay content (0–4 wt.%). The observed differences between experimental and predicted values are minimal, generally within $\pm 0.015\%$, demonstrating excellent predictive performance.

Table 5: Confirmation tests for different days

Days	Glass fiber (wt.%)	Nanoclay (wt.%)	Water uptake (%)	ANN predicted	Absolute error (%)
25	40	0	0.59	0.594	0.004
25	40	2	0.53	0.552	0.022
25	40	4	0.48	0.504	0.024
45	50	0	0.69	0.681	0.009
45	50	2	0.65	0.636	0.014
45	50	4	0.61	0.597	0.013
10	60	0	0.32	0.324	0.004
10	60	2	0.28	0.285	0.005
10	60	4	0.25	0.24	0.010

For instance, the water uptake for a composite with 40 wt.% glass fiber and 0 wt.% nanoclay after 25 days is measured as 0.59%, while the ANN predicted 0.594%. Similarly, for a 60 wt.% glass fiber and 4 wt.%

nanoclay sample at 10 days, the measured uptake is 0.25%, closely matching the predicted value of 0.24%. These results affirm the ANN robustness and ability to interpolate accurately within the tested parameter space. Such validation further strengthens the model's applicability in reducing experimental workloads and expediting moisture-related performance assessment in nanoclay-modified composite systems.

4 Conclusion

This study focuses on developing an ANN model to predict water uptake behavior in nanoclay-modified glass fiber/epoxy composites subjected to prolonged immersion. Composite laminates are fabricated with varying glass fiber (40–60 wt.%) and nanoclay (0–4 wt.%) contents, and their water absorption behavior is experimentally evaluated over 70 days.

The developed ANN model accurately predicts water uptake in nanoclay-modified glass fiber/epoxy composites with an R^2 of 0.998 and minimal prediction error ($\pm 0.015\%$). Incorporating 4 wt.% nanoclay led to a ~11% reduction in water uptake at 10 days compared to composites without nanoclay. Similarly, increasing glass fiber from 40 to 60 wt.% reduces water absorption by ~7%. The ANN model reliably captures these nonlinear effects, offering a cost-effective alternative to long-duration testing and enabling faster material optimization in moisture-sensitive composite applications.

These findings offer practical value for industrial composite design by enabling significant reductions in prototype testing and development time. The validated ANN model provides a fast, cost-effective tool for predicting moisture uptake across various formulations, allowing early-stage screening and optimization without extensive experimental trials. This approach supports accelerated design cycles and efficient material selection for moisture-critical applications.

The current ANN model is trained solely in water immersion data at room temperature $\sim 25^\circ\text{C}$ using tap water and nanoclay contents of 0, 2 and 4 wt.%. Therefore, predictions are limited to these conditions and may not be accurate for different temperatures, immersion media, or nanoparticle types and concentrations. To improve its applicability, future work should include additional inputs like immersion temperature, pH, and filler type, enabling the model to predict water uptake under varied conditions for real-world durability assessments.

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Availability of Data and Materials: The authors confirm that the data supporting the findings of this study are available within the article.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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