Sustainable Hemp-Based Composites: Temperature-Dependent Tensile Prediction via Machine Learning and FEM

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Abstract. This study addresses sustainable hemp fiber/epoxy composites with and without fillers—carbon powder (Cp) and groundnut shell powder (GNSP)—as eco-friendly alternatives to synthetic materials for high-temperature applications. According to the experimental results, hemp + GNSP + epoxy had the maximum tensile strength (41.38 MPa), followed by hemp + Cp + epoxy (40.12 MPa) and hemp + epoxy (33.83 MPa). ANSYS simulations (40–80 °C) were conducted using material properties obtained from stress–strain data, and predictive analysis was conducted using machine learning algorithms. According to simulations and experimental studies, the Support Vector Regression (SVR) model outperformed Random Forest and Linear Regression in terms of accuracy. The results also demonstrate that GNSP-reinforced hemp composites showed improved tensile strength retention compared to plain hemp–epoxy and CP-reinforced composites.

Keywords: Tensile strength, Simulation studies, Machine learning models

1 Introduction

Natural fiber-reinforced composites (NFRCs) are environmentally friendly substances that enhance mechanical properties by combining natural plant or animal fibers with a polymer matrix [1–2]. Because of their excellent specific strength, low density, biodegradability, and affordability, they provide an environmentally friendly replacement for synthetic composites. [3–4]. Owing to their lightweight nature and reduced environmental impact, NFRCs are widely used in consumer products, automotive components, construction materials, and packaging industries [5–6]. Among natural fibers, hemp is notable for its strength and stiffness, which are derived from the plant's stem and make it well-suited for reinforcing composite materials. In fact, the mechanical characteristics of hemp fibers are comparable to those of glass

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fibers [7]. The findings of previous studies indicate that the thermal stability of hemp fiber cellulose can be enhanced through high-temperature alkali cooking treatments, effective up to 250 °C [8]. Understanding the behavior of natural composites under aging factors such as moisture, temperature, and environmental exposure is crucial. Research has shown that PHB–hemp fiber composites exhibit reductions in both ultimate strength and elastic modulus, whereas plain PHB polymer films display an increase in elastic modulus but a decrease in ultimate strength and strain when subjected to weathering [9].

Burger's model's mathematical predictions and the composites' experimental creep response agreed well. Atmospheric condition and investigation circumstances at a high temperature of 50 °C had a substantial impact on the creep resistance [10]. Tensile, flexural, and impact tests were performed both before and after exposure to assess how the mechanical characteristics of green composites changed under various accelerated weathering settings.

A study on forecasting the performance of composite materials has addressed various techniques, procedures, and challenges [12]. For example, the tensile strength of nanocomposites has been predicted and optimized using Artificial Neural Networks (ANN) in combination with the Box–Behnken Design (BBD) [13]. Other studies have applied different machine learning techniques to develop constitutive models for both isotropic and anisotropic composites. These models incorporate input data related to composite structures, processing methods, and environmental conditions to effectively predict the mechanical properties of materials [14].

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) algorithms, is emerging as a powerful tool in mechanical and materials engineering due to its ability to predict material properties, design novel materials, and uncover mechanisms beyond conventional intuition [15]. For instance, artificial neural network (ANN) techniques have been employed to optimize performance with banana and coir fibers by selecting appropriate input variables [16]. The role of AI, in combination with non-destructive evaluation (NDE), in advancing industrial systems has also been emphasized in recent reviews [17].

These inputs demonstrate how hemp fibers are being utilized more and more in a range of engineering and industrial applications due to their high strength and specific strength. Using analytical, experimental, and computational methods, it is possible to predict the properties of hemp fiber composites with a high degree of precision. Accelerated research on the impact of environmental factors like moisture and temperature is still necessary, though. The mechanical behavior of natural composites can be predicted and optimized with the help of AI and ML approaches. Researchers can more reliably capture the intricate relationships between fiber, matrix, and environmental influences by combining AI with simulation and experimental study. In this study, hemp fiber reinforced composites in three different configurations—pure polymer, polymer filled with natural groundnut shell powder, and polymer filled with synthetic carbon powder—are investigated using simulations, machine learning models, and experimental studies. In addition to advancing our knowledge of hemp-based composites, this integrated approach shows how AI-driven frameworks may be used to create high-performance, sustainable natural composite materials.

2. Methods And Methodology:

2.1 Experimental studies:

Tensile tests were conducted on three types of composite specimens:
Hemp fiber reinforced with groundnut shell powder-filled epoxy (Hemp + GNSP + Epoxy)
Hemp fiber reinforced with a pure epoxy polymer matrix (Hemp + Epoxy)
Hemp fiber reinforced with carbon powder-filled epoxy (Hemp + CP + Epoxy)

After being cleansed to get rid of dust and other contaminants, the hemp fibers were alkali treated for four hours with a 5 weight percent NaOH solution. By eliminating surface waxes, lignin, and hemicellulose, this treatment improved fiber–matrix adhesion. Following treatment, the fibers were oven-dried for 24 hours at 60 °C .

The hand lay-up process was used to create the composites. While the filler content (carbon powder or groundnut shell powder) was held at 5%, the fiber weight fraction was kept at 30%. Epoxy resin (LY556) in a 10:1 weight ratio with hardener (HY951) made up the remaining portion. Before being combined with the epoxy, the groundnut shell powder was sieved until the average particle size was less than 100 µm.

The fibers were aligned in a unidirectional manner, and successive layers were impregnated with the resin-filler mixture. A roller was used to ensure uniform distribution of resin and to remove air voids. about 4 mm. In order to prevent stress concentrations during testing, the edges were polished.

After 24 hours of room temperature curing, the laminates were post-cured in an oven set to 80 °C for three hours to fully chemical bond the epoxy. In compliance with ASTM D3039, the cured laminates were cut into tensile test specimens using a diamond-tipped cutter; each specimen had dimensions of 150 mm in gauge length, 25 mm in width, and approximately 4 mm in thickness. The edges were polished to avoid stress concentrations during testing.

Tensile tests were performed at the Prasad V. Potluri Siddhartha Institute of Technology (PVPSIT) facilities in Kanuru, Vijayawada, Andhra Pradesh, India, using a computerized universal testing machine (UTM). At ambient temperature, the trials were conducted with a crosshead speed of 2 mm/min. (Fig.1) The average modulus and tensile strength values were reported after at least five specimens of each kind of composite were analyzed.

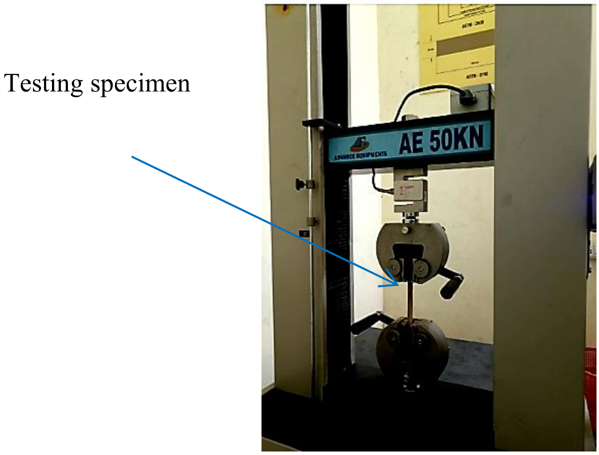
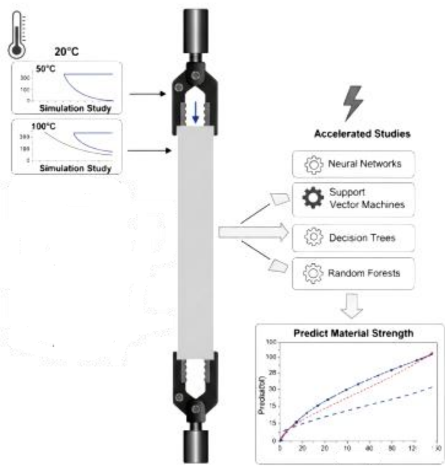


Fig.1. Tensile testing machine setup at room temperature

Experiments on the chosen composites at room temperature are part of the methodology used to forecast the strength of selected composites at various temperatures. Simulation investigations are conducted at various temperatures between 40 °C and 80 °C using these experimental results. Furthermore, ML methods are used to forecast the strength. Lastly, a comparison of the numerical and machine learning outcomes is shown.



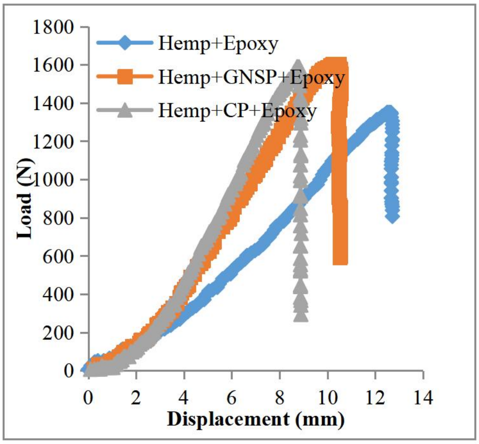


Fig. 2. Methodology for predicting the strength

Fig. 3. Load vs. deflection Hemp composites

Fig. 2 displays the techniques employed in this investigation. The experimental findings were used as input in the simulation experiments as genuine stress–true strain data. Using the same loads and boundary conditions as in the experiments, a coupled thermal–structural analysis was performed in ANSYS to ensure consistency. Fig. 3 illustrates the load-displacement responses of the three different composites: hemp/epoxy, hemp/GNSP + epoxy, and hemp/CP + epoxy.

Figure 3 shows how three different composite specimens—hemp + epoxy, hemp + graphene nanosheet particles (GNSP) + epoxy, and hemp + carbon powder (CP) + epoxy—behave in terms of load versus displacement. The pure hemp + epoxy composite has the lowest load-bearing capacity, with gradual distortion and failure at lower loads and larger displacement. The composite exhibits much higher strength and the highest peak load of the three after GNSP is added, indicating improved stiffness and load-bearing capacity. Compared to pure hemp epoxy, the inclusion of CP boosts strength, although its performance is slightly worse than that of GNSP-reinforced composites.

2.2 Application of Finite Element Method

Finite Element Method (FEM) simulations in ANSYS Workbench were used to predict the tensile response of hemp/epoxy, hemp/GNSP + epoxy, and hemp/CP + epoxy composites. The size and shape of the specimen were modeled using experimental tensile specimens manufactured in compliance with ASTM D3039 requirements (Fig. 4). Fig. 4 displays the material parameters, mechanical load, and thermal load.

The 3D geometry of the composite specimens was constructed using ANSYS Design Modeler, and the meshing was done using ANSYS Mechanical. Using tetrahedral solid elements, a mesh convergence study was performed to determine the final element size of 2 mm for accurate stress distribution. The specimen was subjected to a displacement-controlled force that matched the failure load observed in the experiment at one end, while the other end was entirely constrained. Data from the literature was used to supplement experimental assessment of the material attributes for hemp fiber, epoxy, and fillers (carbon particles and GNSP). To ascertain the composites' effective elastic properties, they were modeled in ANSYS as homogeneous isotropic materials.

Tensile loading was applied incrementally, and the corresponding equivalent von Mises stress contours were obtained for each composite type. The failure loads and associated stress values were extracted and compared with the experimental results. Representative finite element (FE) stress contour plots for the three composite systems are shown in Fig. 5(a–c).

As shown in Table 1, hemp/epoxy composites showing the lowest tensile strength. The greatest improvement (22.3%) was achieved with the addition of groundnut shell powder (GNSP), attributed to enhanced load transfer and crack-bridging effects. Carbon particle-filled composites also showed improved tensile strength (18.58%), although slightly lower than GNSP-filled composites due to comparatively weaker fiber–matrix interactions. Finite element method (FEM) calculations predicted tensile strengths approximately 9% higher than the experimental values in all cases. This over-prediction can be attributed to the numerical model's assumptions of perfect bonding, uniform filler distribution, and the absence of manufacturing defects such as voids or fiber misalignment.

Table 1 summarizes the results, and Fig. 5(a–c) presents the von Mises stress contours for the three composites: hemp + epoxy, hemp + GNSP + epoxy, and hemp + carbon + epoxy. End effects were excluded to ensure that the comparison accurately reflects the uniform stress distribution within the gauge section of the specimens and to eliminate stress concentrations near the grips.

Table.1. Comparison of experimental and simulation results.

S. I no	Type of the material	Tensile strength [MPa] From experiments	% of improvement over pure epoxy mixed composite (Hemp+Epoxy)	Equivalent stress from simulations (without end effects) [MPa]	% of variation with respect to experiments
1.	Hemp+Epoxy	33.832	---	36.922	9.133 %
2.	Hemp+GNSP+Epoxy	41.378	22.3%	45.124	9.053 %
3.	Hemp+Carbon+Epoxy	40.12	18.58%	43.774	9.10%

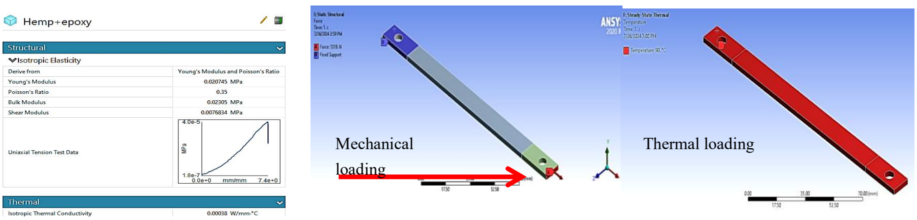


Fig. 4. Material properties, loading, and thermal conditions in FE model

y composite at room temperature

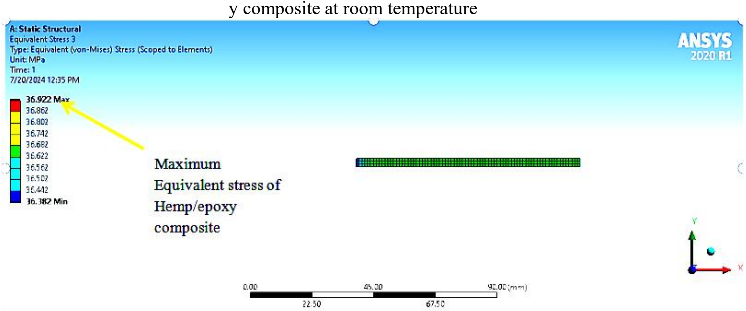


Fig.5.a FE contour of Hemp/epoxy composite at room temperature

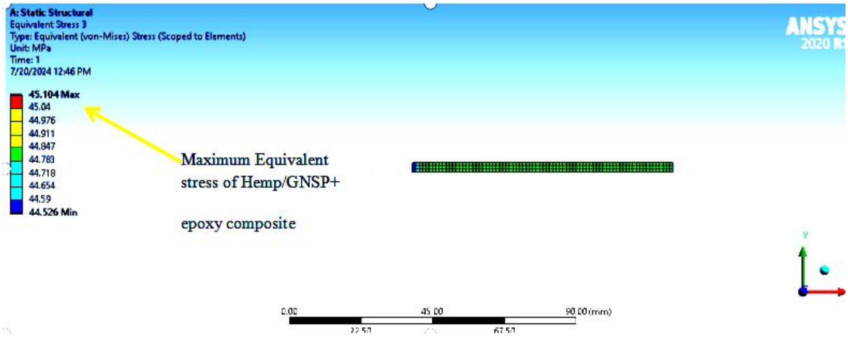


Fig.5.b FE contour of Hemp/GNSP+epoxy composite at room temperature

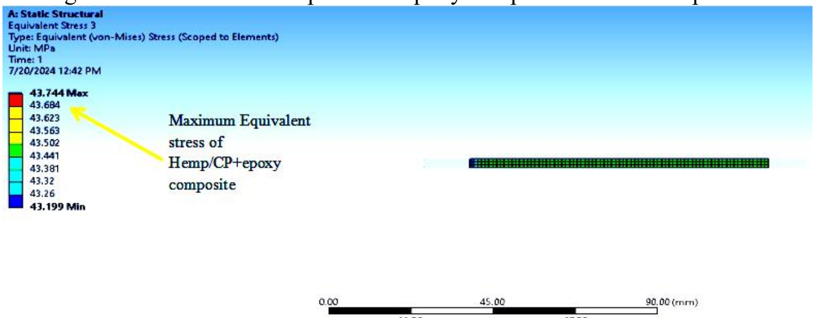


Fig.5.c FEt contour of Hemp/CP+epoxy composite at room temperature

2.3 Application of ML models:

Simulations were conducted throughout a temperature range of 40 °C to 80 °C in order to examine the temperature-dependent mechanical performance of the composites. The FEM models were updated using temperature-dependent experimental input data in the form of true stress–true strain curves after uniform thermal loads were applied. The equivalent stress values for hemp/epoxy, hemp/GNSP + epoxy, and hemp/CP + epoxy composites were extracted to create datasets for each temperature level.

Dataset creation: The true stress–true strain curves derived from trials included roughly 300 data points for each type of composite (Hemp + Epoxy, Hemp + GNSP + Epoxy, and Hemp + CP + Epoxy). Results from FEM simulations, which varied element sizes and temperature levels (from 40 °C to 80 °C in steps of 1°C) to capture intricate mechanical reactions, were added to these data to further enhance them. These factors were combined to provide a complete dataset that had enough size and variety for efficient machine learning training. This method improves the accuracy of model generalization while addressing issues with dataset limits.

Machine learning models considered:
Linear Regression (LR)
Support Vector Regression (SVR)
Random Forest (RF)

While all models performed an adequate task of capturing the experimental trends, Random Forest (RF) performed best overall in terms of accuracy and generalization, especially when it came to managing nonlinear temperature variations. While Linear Regression shown limits in capturing nonlinear behavior, SVR also performed effectively at higher temperatures.The reliance on lengthy experimental trials was greatly decreased by integrating ML models with datasets obtained by FEM. The tensile strength of natural fiber composites at high temperatures can be predicted with this coupled framework in a reliable, cost-effective, and reliable way.

Additionally, it makes material design optimization possible, providing insightful information for the creation of sustainable composites that work reliably under a range of temperature circumstances.

3. Results And Discussions:

For hemp/epoxy composites, the simulation results, Tensile Strength (TS) at temperatures between 30 and 80 °C and the predictions from LR, SVR, and RF are shown in Fig. 6. The Linear Regression model aligns closely with the experimental data, as the strength decreases almost linearly with temperature. SVR attempts to capture non-linear behavior but tends to underestimate the strength at lower temperatures and overestimate it at higher ones. The Random Forest model, due to its piecewise decision-splitting nature, produces a stepwise prediction curve. Although it captures local variations, its lack of smoothness results in only moderate predictive performance.

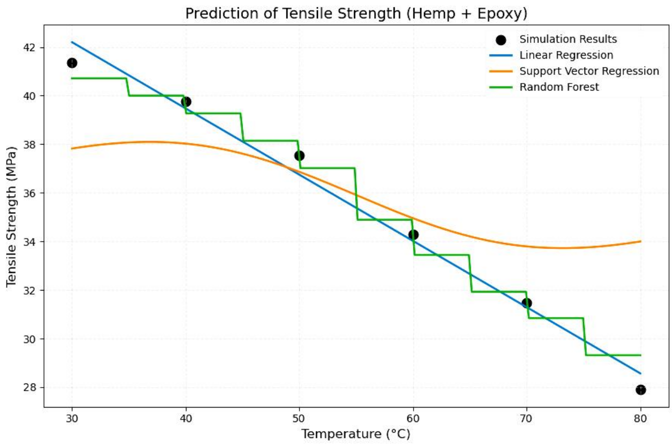


Fig.6. Tensile strength of Hemp/epoxy composite using ML methods

As the temperature increased, the tensile strength of the hemp–GNSP–epoxy composite decreased from 46 MPa at 30 °C to 31 MPa at 80 °C, as shown in Fig. 7. This behavior demonstrates the softening and degradation of the composite with temperature. In predicting this non-linear trend, SVR and Random Forest outperformed Linear Regression. Among them, Random Forest provided the best overall accuracy, closely matching the simulation results across all temperature ranges. The simulation data further revealed that GNSP reinforcement led to greater retention of tensile strength compared to plain hemp–epoxy, resulting in a more gradual strength reduction with temperature. Linear Regression performed relatively well due to the near-linear drop in strength, while SVR maintained high accuracy by capturing minor curvature. Random Forest, although producing a less smooth curve, delivered sufficiently accurate predictions.

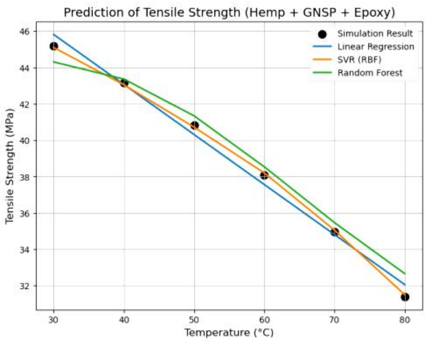


Fig.7. TS h of Hemp/GNSP+epoxy composite

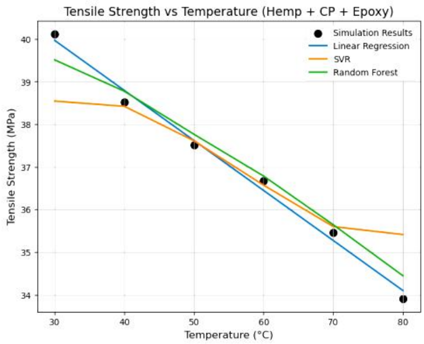


Fig.8. TS of Hemp/CP+epoxy composite

Fig. 8 shows the effect of temperature (30–80 °C) on the tensile strength of hemp + CP + epoxy composites. Both experimental and computational results indicate a gradual decrease in strength, from about 40 MPa at 30 °C to 34 MPa at 80 °C. Linear Regression (blue), based on a purely linear assumption, captures the overall downward trend but underestimates strength at higher temperatures. [18]. SVR (orange) provides a closer approximation at mid-range temperatures, though it deviates at the extremes—underestimating at low temperatures and overestimating at high ones. Random Forest (green) effectively tracks the trend but produces slight oscillations due to its stepwise prediction nature. Across all composites, SVR consistently delivers the most accurate forecasts, particularly at higher temperatures where non-linearity becomes more pronounced.[19]. Random Forest also performs well but introduces step-like artifacts, while Linear Regression, although too simplistic for precise predictions, works reasonably well when the strength–temperature relationship is nearly linear, as in hemp + GNSP + epoxy.

For each machine learning model, 95% confidence intervals and statistical validation metrics—including the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) were calculated to ensure robustness and reliability. RF model achieved the best performance, with $R^2 = 0.982 \pm 0.01$, RMSE = 3.8 ± 0.5 MPa, and MAE = 2.1 ± 0.4 MPa, demonstrating excellent agreement with both experimental and FEM data. Support Vector Regression (SVR) provided dependable predictions across the dataset but with slightly lower accuracy (R^2 = 0.955 ± 0.02, RMSE = 5.6 ± 0.6 MPa, MAE = 3.2 ± 0.5 MPa). Linear Regression performed the least effectively, with R^2 = 0.918 ± 0.03, RMSE = 7.4 ± 0.7 MPa, and MAE = 4.1 ± 0.6 MPa, as it was unable to capture nonlinearities in stress–strain behavior. These findings clearly establish RF as the most reliable model for predicting the mechanical properties of natural composites, followed by SVR, while Linear Regression is less effective for nonlinear material behavior.

Grid search with cross-validation was used for hyperparameter tweaking for both SVR and Random Forest in order to guarantee a fair comparison of the models. SVR's ability to capture nonlinear behavior was greatly enhanced by optimizing the kernel type, gamma values, and penalty parameter (C).These differences show that model performance is not only due to inherent algorithmic structure but also strongly influenced by the choice and optimization of hyperparameters. For Random Forest, the minimum samples per split were adjusted to balance accuracy and smoothness of predictions; however, RF maintained its inherent stepwise nature, while SVR displayed smoother fits at the expense of slight deviations at temperature extremes. Linear Regression, lacking tunable hyperparameters beyond polynomial extension, served as a useful baseline but failed to model nonlinearities.

4. Conclusions:

As the temperature increases from 30°C to 80°C, the tensile strength of all composites diminishes. The plain hemp–epoxy composite exhibits the steepest reduction (~46 MPa → ~31 MPa), indicating weaker thermal stability.

The addition of graphene nanosheet particles (GNSP) significantly improves reinforcement efficiency and heat resistance, retaining tensile strength more effectively at elevated temperatures. carbon powder (CP) also enhances performance, though to a lesser degree than GNSP.

Among the ML models evaluated:

Linear Regression fails to capture nonlinear stress–temperature behavior, leading to poor accuracy.

Random Forest (RF) captures broad nonlinear trends but produces step-like predictions.

Support Vector Regression (SVR) demonstrates the most reliable predictions, especially in the mid-to-high temperature range, closely matching experimental results.

The integration of FEM + ML, validated by experiments, provides a robust predictive framework for high-temperature applications of sustainable composites. By considering temperature and moisture influences simultaneously, this study advances beyond existing NFRC approaches, offering eco-friendly alternatives to synthetic composites with practical implications for design and industrial adoption.

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