Mechanics of Advanced Composite Structures

Journal homepage: https://macs.semnan.ac.ir/

Semnan University

ISSN: 2423-7043

Research Article

Tensile Strength Prediction of Glass/Epoxy Composite Structures Using Machine Learning and Response Surface Methodology

Milad Shahsavari, Mohammadreza Zamani *, Hosein Parsa

Department of Mechanical Engineering, Malek Ashtar University of Technology, Tehran, Iran

ARTICLE INFO

Article history:

Received: 2023-10-19
Revised: 2024-03-22
Accepted: 2024-05-12

Keywords:

Laminated Composite;
Tensile Strength;
Response Surface Methodology;
Machine Learning;
Stacking Ensemble.

ABSTRACT

Analytical methods for evaluating composite structures face complexities and limitations owing to the anisotropic nature of their material properties. Integrating numerical simulations with artificial intelligence (AI) techniques not only overcomes these limitations but also enhances design flexibility, diversity, speed, and accuracy. Tensile strength is a critical design parameter for such structures, and its precise determination significantly affects the design quality. This study calculates the tensile strength of glass/epoxy laminated composites using two approaches: Machine Learning (ML) and Response Surface Methodology (RSM). RSM is a widely used mathematical modeling technique to establish relationships between independent and dependent variables, while ML—a subset of AI—offers advanced predictive capabilities. Both methods require a Design of Experiments (DoE) and extensive datasets, which were optimized here using Latin Hypercube Sampling (LHS) to reduce sample tests while improving accuracy. Finite Element Analysis (FEA) was employed for dataset generation, validated through experimental tests. The developed models assessed the influence of design parameters (e.g., layer count and orientation) on tensile strength, demonstrating strong alignment with the dataset. This study accelerates the composite design process and enhances the understanding of mechanical behavior.

1. Introduction

Composite structures offer numerous advantages over conventional metallic materials, such as high strength-to-weight ratios, which encourage their utilization in various applications. In the design of composite structures, multiple parameters, including the number of layers, orientation of each layer, and type of matrix and reinforcement materials, play a crucial role, as the mechanical properties of the structure depend on these variables.

Traditional methods for determining mechanical properties include experimental testing, numerical simulations, and analytical models. For instance, Vijayakumar and Palanikumar [1] conducted experimental tests to extract the mechanical properties of composites reinforced with natural fibers. The combined use of numerical simulations and experimental tests is a common approach in mechanical property characterization, as seen in several studies investigating the effect of layup angles on mechanical behavior [2–4]. Given the influence of fiber architecture on composite properties, Muralidhara et al. [5] experimentally examined the tensile and flexural properties of carbon/epoxy composites using T300, T700, and T800 carbon fabrics.

Response Surface Methodology (RSM) has been effectively used in various studies to model and predict the mechanical properties of composites. Ouraghi et al. [6] employed this method to model the dynamic mechanical

* **Corresponding author.**
E-mail address: a_mrzamani@mut.ac.ir

Shahsavari, M. , Zamani, M., Parsa, H. and Eskandari Jam, J. 2025. Title of article. *Mechanics of Advanced Composite Structures*, 12(1), pp. xx-xx

https://doi.org/10.22075/MACS.2024.39315.2050

behavior of hemp/polyester composites, obtaining highly reliable results with minimal error. Saravankumar et al. [7] utilized RSM to enhance the mechanical properties of banana fiber/epoxy composites. Afnaidis et al. [8] applied RSM to optimize the mechanical properties of composites reinforced with date palm fibers.

In subsequent studies, novel approaches such as neural networks and machine learning algorithms have been increasingly adopted to predict the mechanical properties of composites. Khanlua et al. [9], in their study on the effect of poly(methyl methacrylate) (PMMA) fiber diameter on composite strength, compared both neural network and RSM methods. Saha et al. [10] used RSM to analyze and optimize the delamination coefficient of microwave-cured pineapple leaf fiber polymer composites. This study aims to enhance the mechanical properties and performance of natural fiber composites by minimizing delamination problems. Analysis of variance (ANOVA) was used to evaluate the effects of various factors on delamination, and response surface methodology (RSM) was used to optimize the curing conditions. Kumar Singh et al. [11], with the aim of optimizing the mechanical performance of microwave-processed poly-L-lactide (PLLA) / coconut fiber composites, investigated the design and fabrication parameters of the composite, including temperature, time, and weight percentage of coconut fiber. For this purpose, a full factorial design was used for optimization, and the results were analyzed using Design Expert V.10 software. The database for optimization included the results of tensile and flexural tests of the samples under different processing conditions. The results showed that the optimized composite achieved a maximum tensile strength of 18 MPa and a maximum flexural strength of 48 MPa, indicating a significant improvement in the mechanical properties of the composites.

Advances in various scientific fields have led to the development of innovative technologies, such as artificial intelligence (AI), which enables the creation of intelligent models applicable across industries. AI encompasses two major subfields: machine learning (ML) and deep learning (DL) [12]. ML is categorized into supervised, unsupervised, and reinforcement learning [13].

ML has extensive applications in composite structures, including optimization, material property prediction, and structural health monitoring, as highlighted by Okafor et al. [14]. Deep learning has also gained attention in composite design and analysis, where large datasets and deep neural networks are used to predict mechanical properties [15, 16]. Sharma et al. [17] in their study investigated the hardness of PP/CNT and LDPE/CNT composites using machine learning algorithms. Various algorithms such as linear regression, neural networks, support vector regression, k-nearest neighbor, and random forest were used in this study. Finally, the random forest algorithm was selected as the best model, which uses majority voting to improve prediction accuracy. The results show that the LDPE/CNT composite has a higher accuracy than that of PP/CNT, and the random forest model shows the best performance in predicting the hardness of these materials.

In both RSM and ML, a database is prepared using various experiments. This study utilizes Latin Hypercube Sampling (LHS), a systematic experimental design method that enhances modeling efficiency compared to random sampling techniques such as Monte Carlo. LHS ensures stratified sampling with non-overlapping intervals, improving convergence speed over traditional methods [18–20]. Studies have demonstrated the superior performance of LHS over Simple Random Sampling (SRS) and Full Factorial Design (FFD) [21, 22].

In this study, the tensile strength of glass/epoxy laminated composites was predicted using two methods: machine learning and response surface methodology. In the machine learning approach, "supervised machine learning" was employed. Supervised learning is divided into two categories: regression and classification. According to the objectives of this study, regression was used, which has been extensively applied to predict the mechanical properties of composites [23-25].

For this purpose, after designing experiments using the LHS method for database preparation, the failure force was calculated through numerical simulations for each test case. The numerical model was validated through experimental tests to ensure the reliability of the obtained results. In the composite structure analysis of this study, the parameters of "number of layers" and "layer orientation angle" were considered as analysis variables.

The developed models from both machine learning and RSM can predict the strength by determining the number of layers and their orientation angles, and ultimately, the accuracy of these two models is compared. In this study, the term strength specifically refers to the tensile failure load, defined as the maximum force sustained by the composite specimen under uniaxial tensile loading prior to fracture. The employed method can serve as a novel approach in the design and analysis of composite structures, and its development paves the way for the intelligent design of composite structures.

2. Problem Definition

The composite structure used in this study consisted of a 165 g/m^2 woven glass fabric laminated with epoxy resin. Given the research methodology, creating a high-quality database is crucial. For this purpose, a numerical model validated through experimental tests was employed. The test specimens were fabricated using hand lay-up and vacuum bagging techniques, then subjected to tensile testing.

2.1. Test Specimen Fabrication

In this study, composite specimens were fabricated using a woven glass fiber fabric with an areal weight of 165 g/m^2 and LR225 epoxy resin. The manufacturing process employed the hand lay-up technique combined with a vacuum bag to ensure uniform resin distribution and minimize air entrapment within the composite structure. After placing the layers on a flat mold, a vacuum pressure of approximately 0.8 bar was applied for 8 h. The curing process was then carried out at 80°C for 7 h.

Three different lay-up configurations were considered for the evaluation:

- $[0]_{12}$
- $[\pm 45]_{3S}$
- $[0/45/0/45/0/45]_2$

In all cases, a final panel thickness of 2 mm was targeted. To comply with the dimensional requirements of ASTM D3039 [26], the fabricated panels were cut into precise specimens measuring 250 × 20 mm using a waterjet cutter. For each lay-up configuration, three independent samples were prepared and subjected to tensile testing. The fabrication process was conducted under controlled conditions with high precision to ensure data repeatability and the validity of finite element modeling.

2.2. Tensile Testing

Uniaxial tensile tests were performed using a SANTAM STM-150 machine according to ASTM D3039 to determine the ultimate composite strength. Table 1 presents the obtained mechanical properties, and Figure 1 shows the typical stress-strain curves for the $[0]_{12}$ orientation.

Table 1. Mechanical characteristics from tensile testing

Stacking Sequence	Max Stress (MPa)	Modulus (MPa)	Max Force (N)
$[0]_{12}$	274.5	37464	14330
$[\pm 45]_{3s}$	109.9	12837	5480
$[0/45]_6$	157.08	---	7854.12

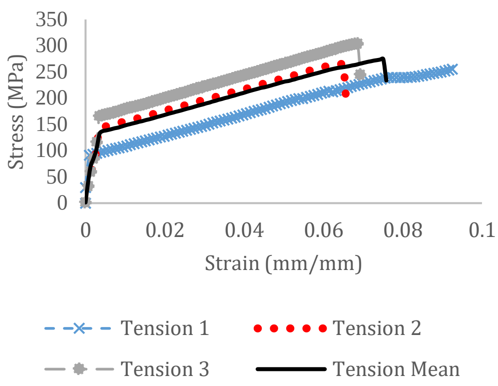

Fig. 1. Tensile test results

According to the results obtained from Table 1, the mechanical properties required for the finite element analysis were obtained, as shown in Table 2. In this table, X_t is the tensile strength in the fiber direction, and S is the shear strength. E is the elastic modulus, and G is the shear modulus.

Table 2. Material properties for FEM

E (GPa)	G (GPa)	X_t (MPa)	S (MPa)
37.464	12.837	274.5	109.9

2.3. Finite Element Simulation

The finite element model was developed in Abaqus using 1,500 S8R shell elements with dimensions matching the experimental specimens, as shown in Fig. 2. The Hashin failure criterion, as presented in Eqs. (1)–(4), was implemented, where damage initiates when any failure index reaches unity [27].

Tensile Fiber Mode
$$\left(\frac{\sigma_1}{X_T}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 \geq 1 \quad (1)$$

Compressive Fiber Mode
$$\left(\frac{\sigma_1}{X_C}\right)^2 \geq 1 \quad (2)$$

Tensile Matrix Mode
$$\left(\frac{\sigma_2}{Y_T}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 \geq 1 \quad (3)$$

Compressive Matrix Mode
$$\frac{\sigma_2}{Y_{TC}}\left[\left(\frac{Y_C}{2S}\right)^2 - 1\right] + \left(\frac{\sigma_2}{2S}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 \geq 1 \quad (4)$$

In equation number one, σ_1 and σ_2 are the applied stress values in the direction of the fibers and perpendicular to the fibers, respectively, and τ_{12} is the shear stress. X_t is the tensile strength in the direction of the fibers, Y_t is the tensile strength in the direction perpendicular to the fibers, and S is the strength of the composite.

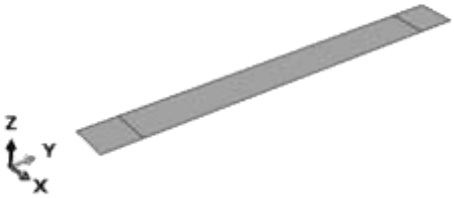

Fig. 2. Tensile test sample modeling

2.1. Model Validation

A database for mathematical modeling was prepared using finite element simulations. Therefore, the accuracy of the simulation results is of utmost importance. Given that in this study, the tensile strength is considered as the structural strength, Table 3 presents the values obtained from the experimental tests and numerical simulations. According to this table, the maximum simulation error was 9.4%, indicating appropriate accuracy in predicting strength. Considering that the simulation approach—whose accuracy depends on element type selection, failure criterion definition, boundary condition application method, loading procedure, and mechanical property determination—has also been used for database preparation, it can be concluded that the data in the database possess the required accuracy and reliability.

Table 3. Tensile Strength comparison

Stacking Sequence	Experimental (N)	FEA (N)	Error (%)
$[0]_{12}$	14330	13336.5	6.9
$[\pm45]_{3s}$	5480	4960.72	9.4
$[0/45]_6$	7854 N	7388.52	5.9

3. Database Preparation

In this study, the composite structure may contain 1 to 12 layers, with each layer having an orientation of either 0° or 45°. Each layer effectively has two input parameters: (1) presence/absence of the layer (binary) and (2) layer orientation. With 12 possible layers, there are 24 total input variables. The experimental design matrix presents particular complexity due to the need to handle inactive layers in the composite structure.

As shown in Figure 3, the input for each layer is configured as follows:

- The primary input takes a value of 0 or 1 (indicating layer absence/presence)
- For active layers (value=1), the orientation angle is specified
- For inactive layers (value=0), the orientation automatically defaults to 0°

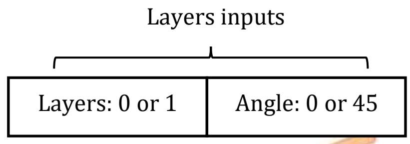

Fig. 3. DOE input parameter configuration

The total number of possible experimental combinations can be calculated using combinatorial principles. Because each of n layers has two possible states (0° or 45°), the total number of combinations is 2^n. For structures with 1-12 layers, the complete experimental space (Equation 5) yields 8,190 possible combinations:

$$N = 2^1 + 2^2 + 2^3 + \cdots + 2^{12} \tag{5}$$

A key advantage of employing machine learning models and the RSM method is the reduction in the number of required experiments, enabling achievement of the desired objectives with appropriate speed and accuracy. As previously explained, this study employed the LHS method to design the experimental matrix. This method was employed to ensure that the selected samples were uniformly and representatively distributed across the multidimensional input space, thus maximizing the information content of the dataset while minimizing the number of required simulations. This approach allowed for effective training of the regression model while keeping the computational effort within practical limits, especially given the high cost associated with each simulation or experiment.

Given the complexity in preparing this matrix, a Python code was utilized, where all necessary conditions for each experiment were specified. The developed code uses the NumPy, Pandas, and pyDOE libraries, with the pyDOE library containing the LHS experimental design method. According to the implemented code, 375 test samples were designed. The choice of 375 samples was guided by a trade-off between the computational cost and model accuracy. As evident from the calculations, the number of test samples was significantly reduced, while the employed method for designing this matrix (LHS) maintained the necessary accuracy to achieve a high-quality model. To evaluate the distribution of various experimental configurations, Figure 4 has been plotted. As demonstrated, the number of designed experimental cases increases progressively with higher layer counts. For database compilation, a dedicated scripting code was developed as follows:

1. Extracts the layup specifications for each experimental run from the design matrix
2. Implements these parameters into the validated numerical model
3. Automatically records the failure force output for each configuration

The DOE is stored in a CSV file, where each row contains the layup specifications for an individual test case. The developed script reads these specifications from the file and implements them into the numerical model, ensuring an accurate representation of the material properties, layer orientations, thicknesses, and stacking sequences within the finite element framework. The simulation workflow, as illustrated in Figure 5, automates the iterative process of applying tensile loading until failure, systematically extracting the maximum failure force for each configuration. This standardized procedure, executed across 375 experimental cases, significantly enhanced the time efficiency and maintained rigorous consistency in dataset generation.

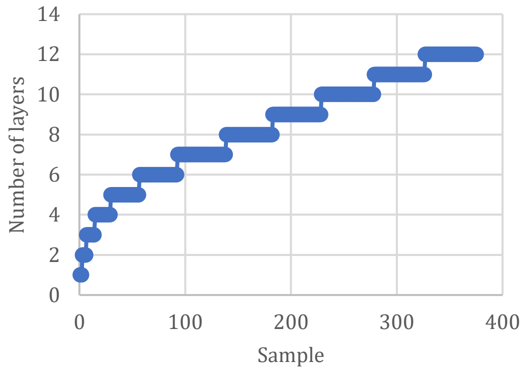

Fig. 4. Statistical distribution of layer counts across sampled configurations

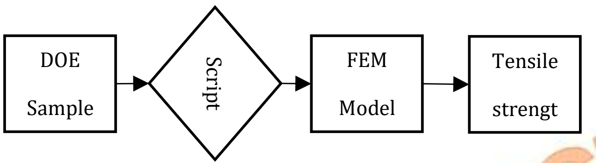

Fig. 5. Schematic of simulation workflow implemented via scripting

4. Modeling Using Response Surface Methodology (RSM)

For the RSM modeling, the prepared test matrix was defined as the input parameter, with the output being the tensile strength for each layup configuration. Following the test matrix definition, the optimal composite layup model was developed to calculate strength based on specified stacking sequences, as represented by the equation in Table 4. The predictive equation derived from the Response Surface Methodology (RSM) models the square root of the tensile strength as a function of the ply angles (Angle1 to Angle12) and their corresponding presence indicators (n1 to n12). The model incorporates both main effects and selected two-way interaction terms between angles and presence variables. The general form is expressed in Equation 6.

$$\sqrt{\text{Failure Force}} = \beta_0 + \sum_{i=1}^{12} (\beta_{i1} \cdot \text{Angle}_i + \beta_{i2} \cdot n_i) + \sum_{j,k} \beta_{jk} \cdot (\text{Interaction Terms}) \tag{6}$$

β_0 is the intercept (constant term), Angle_i denotes the angle of the ith ply (for i=1,...,12), n_i is the indicator variable representing the presence or absence of the ith ply, β_{i1} and β_{i2} are coefficients corresponding to the main effects of the angle and presence variables, respectively, and β_{jk} are coefficients related to the two-way interaction terms between different variables. This comprehensive approach captures both linear and interaction effects of the design variables, contributing to the robustness and high accuracy of the RSM predictions.

This comprehensive approach captures both linear and interaction effects of the design variables, contributing to the robustness and high accuracy of the RSM predictions.

As shown in Figure 6, a Box-Cox transformation with λ=0.5 was implemented in Equation 6 to minimize model error. Figure 7 presents a comparison between the predicted and actual strengths for the data points used in the RSM model fitting. Here, both the actual and predicted values were min-max normalized to a [0–100] scale for visualization. The actual values represent the normalized strength from the dataset, and the predicted values are the corresponding outputs generated by the developed RSM model. The close clustering of data points along the diagonal line confirms the model's strong fitting performance and its capability to accurately capture the underlying relationships within the dataset.

5. Modeling Using Machine Learning Algorithms

Machine learning, a subset of artificial intelligence, is employed for both classification and regression tasks. In this study, supervised learning was used for regression analysis and numerical function estimation to predict the tensile strength of laminated composite structures. Among the various algorithms available for this method, decision tree, random forest, linear regression, XGBoost, and CatBoost were utilized in this study. The XGBoost algorithm was introduced in 2014, and the CatBoost algorithm in 2017, which have high accuracy and processing speed [28, 29].

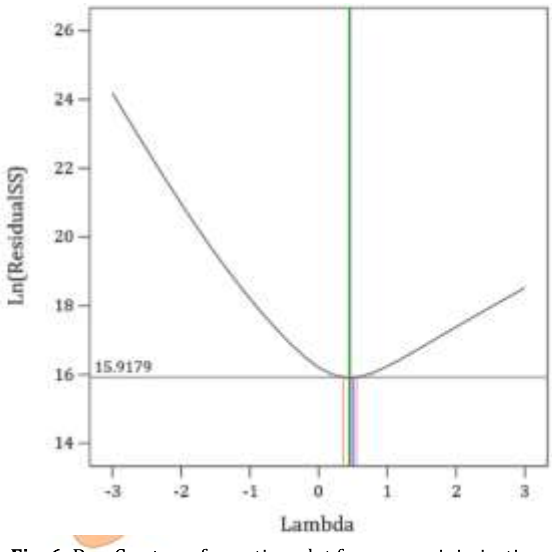

Fig. 6. Box-Cox transformation plot for error minimization

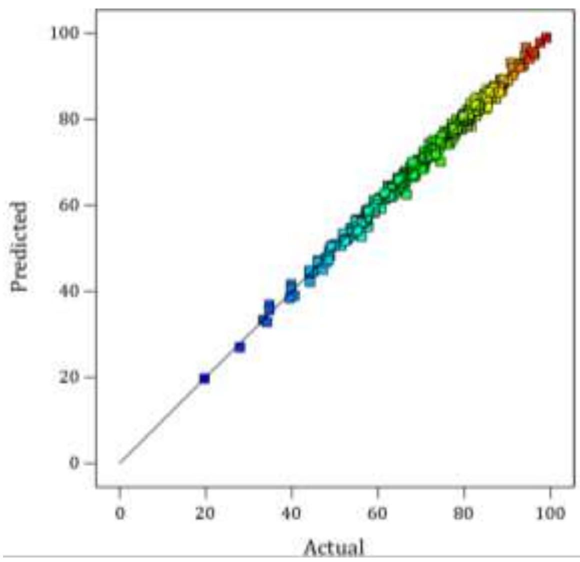

Fig. 7. Actual vs. predicted values using RSM methodology

In addition to evaluating the performance of these individual algorithms, we implemented a stacking ensemble method to enhance the prediction accuracy. In this method, several base models are trained on a dataset, and a secondary model learns to optimally combine the predictions of the base models [30]. This approach is expected to reduce the prediction error in estimating the failure force, with results presented in subsequent sections. In the process of training the models, according to the prepared dataset, which has 375 samples, 90% of the data were used for training and 10% for testing the models, which had 24 input parameters (specifications of 12 composite layers) and one output parameter (composite tensile strength). In the training process, the MAE criterion was used to evaluate the error during model training, the value of which was obtained using Equation 7:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

To develop the stacking model, five algorithms–Decision Tree, Random Forest, Linear Regression, XGBoost, and CatBoost–were initially trained and evaluated using the Mean Absolute Error (MAE) metric. Figure 8 illustrates the variation in error across these models during the training process. Among them, the Decision Tree algorithm showed the highest error, whereas CatBoost a nd Linear Regression demonstrated the lowest. Based on the average MAE performance over multiple iterations, models with substantially higher error values were excluded from the ensemble to improve overall accuracy and prevent a negative impact on the meta-model. Consequently, Decision Tree, Random Forest, and XGBoost were omitted from the final stacking configuration. The final stacking model was constructed using CatBoost and Linear Regression as base learners, with another Linear Regression model serving as the meta-learner to integrate their outputs.

To provide a comprehensive comparison of model performance, Table 5 summarizes the quantitative evaluation metrics for all six regression models examined in this study. These metrics include mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and coefficient of determination (R^2). As shown in the table, the Decision Tree algorithm exhibited the highest prediction error across all metrics, particularly with an MAE of 718.7 and an R^2 of 0.57, indicating relatively poor predictive capability. In contrast, CatBoost and Linear Regression demonstrated the best individual performance, achieving MAE values of 205.1 and 227.2, respectively, along with high R^2 values.

The stacking model, which combined CatBoost and Linear Regression as base learners and used a Linear Regression model as the meta-learner, outperformed all individual models. It achieved the lowest MAE (198.3), lowest RMSE (255.4), and highest R^2 (0.980), indicating a strong generalization ability and improved predictive accuracy.

Table 4. RSM-derived function coefficients for failure force prediction

(**Tensile Strength**)^0.5 =

Constant	+33.33316	Angle1 * Angle2	-0.000273	Angle3 * n5	+0.016968
n1	0	Angle1 * n4	+0.051269	Angle3 * Angle6	+0.000291
Angle1	-0.302847	Angle1 * Angle5	+0.000389	Angle3 * Angle7	+0.000410
n2	+11.71364	Angle1 * Angle6	+0.000726	Angle3 * Angle9	+0.000398
Angle2	-0.207393	Angle1 * n7	-0.016693	Angle3 * Angle10	+0.000334
n3	+10.02133	Angle1 * Angle7	+0.000771	Angle4 * Angle6	+0.000552
Angle3	-0.175117	Angle1 * Angle8	+0.000631	Angle4 * n7	+0.011367
n4	+7.51135	Angle12	-0.115356	Angle4 * Angle8	+0.000274
Angle4	-0.134368	Angle1 * n2	+0.121065	Angle4 * n10	+0.010884
n5	+7.60019	Angle1 * n9	-0.029326	Angle4 * Angle10	+0.000420
Angle5	-0.118832	Angle1 * Angle9	+0.001480	Angle4 * Angle12	+0.001102
n6	+8.25700	Angle1 * n10	-0.021053	Angle5 * Angle7	+0.000175
Angle6	-0.156244	Angle1 * Angle10	+0.001342	Angle5 * Angle8	+0.000377
n7	+7.05916	Angle1 * n11	-0.025674	Angle5 * Angle9	+0.000758
Angle7	-0.154731	Angle1 * Angle11	+0.001125	Angle6 * Angle7	+0.000255
n8	+6.46082	Angle1 * n12	-0.050011	Angle6 * n9	+0.023533
Angle8	-0.133246	Angle1 * Angle12	+0.001713	Angle6 * Angle9	-0.000333
n9	+6.51586	Angle2 * n3	+0.083108	Angle6 * Angle11	+0.000646
Angle9	-0.155891	Angle2 * Angle6	+0.000371	Angle6 * Angle12	+0.001034
n10	+5.30846	Angle2 * Angle7	+0.000638	Angle7 * n10	+0.019140
Angle10	-0.151429	Angle2 * Angle8	+0.000569	Angle8 * Angle9	+0.000287
n11	+5.58250	Angle2 * n9	-0.019233	Angle8 * n11	+0.016566
n6	+8.25700	Angle2 * Angle9	+0.000864	Angle9 * Angle12	-0.001129
Angle11	-0.124245	Angle2 * Angle10	+0.000723	Angle10 * n12	+0.052267
n12	+6.75236	Angle2 * Angle11	+0.000452	Angle10 * Angle12	-0.000929
Angle12	-0.115356	Angle2 * n12	-0.030186	Angle11 * Angle12	-0.000882
Angle1 * n2	+0.121065	Angle3 * n4	+0.039529		

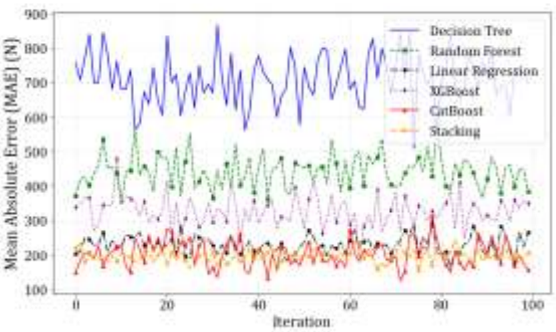

Fig. 8. Training error progression (MAE) for different machine learning models

Figure 9 presents a comparative evaluation of error category predictions between the stacking ensemble model and the best-performing single model, providing valuable insights into classification reliability and error mitigation.

Table 5. Performance metrics of the regression models

Model	MAE	MSE	RSME	R^2
DT	718.7	814110.2	902.2	0.576
RF	442.1	330943.7	575.2	0.851
LR	227.2	84753.2	291.1	0.977
XGB	324.3	195795.8	442.4	0.934
CTB	205.1	81504.6	285.4	0.971
STC	198.3	65257.4	255.4	0.980

Key observations from this analysis are as follows:

- High Agreement in Low-Error Predictions: The confusion matrix illustrates perfect concordance (100% agreement) for predictions with less than 5% error, confirming that all four instances predicted by the single model were accurately replicated by the stacking ensemble. This demonstrates the robustness of both frameworks in achieving high-accuracy classifications.
- Improved Performance in High-Error Cases: For predictions exceeding 20% error, the stacking ensemble exhibited significant corrective capability, successfully reclassifying 50% of misclassified cases (6 out of 12 instances) into lower error categories—four cases into the 5–10% error range and two cases into the 10–20% error range. This error mitigation underscores the ensemble model's stability advantage.

- Statistical Validation of Performance Gains: Quantitative metrics further substantiate the improvements observed in classification accuracy. Cohen's κ coefficient of 0.82 indicates substantial agreement between the models. Additionally, McNemar's test confirms statistically significant enhancements ($p < 0.05$) in 29.4% of classification cases (10 out of 34). Notably, the stacking approach leads to a mean absolute error reduction of 12.7% for high-error (>20%) predictions.

- Identification of Three Behavioral Zones: The matrix defines three distinct classification behavior regions:

a- Consensus Zone (<10% error): 83% agreement between models.

b- Transition Zone (10–20% error): 25% reclassification improvement achieved by stacking.

c- Correction Zone (>20% error): 50% error reduction via stacking.

This analysis substantiates that the stacking ensemble architecture not only preserves the predictive accuracy of individual models but actively compensates for their limitations in high-error regimes. The demonstrated error-correcting capability is particularly valuable for composite material applications where overestimation of failure resistance could lead to catastrophic design failures.

6. Results

In this research, both RSM and machine learning methods were used to predict the tensile strength of laminated composite structures. During the training process of the machine learning model, 10% of the data was excluded from training and used for testing the model. These test data were then input into the RSM model (shown in Table 4), and its output is plotted in Figure 10. In this figure, the RSM output is compared with actual values, demonstrating that the developed model shows good agreement with reality.

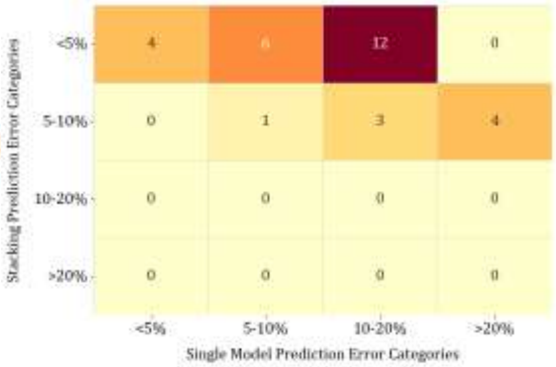

Fig. 9. Confusion matrix of strength error classification

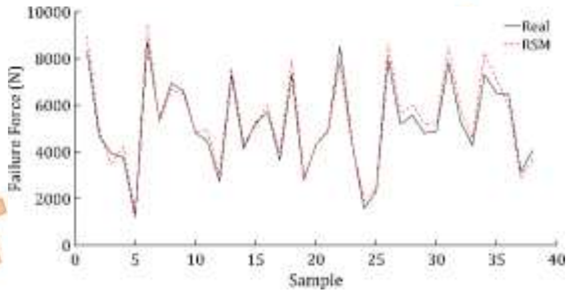

Fig. 10. Comparison of RSM predictions versus actual data

To better understand the machine learning approach, the three algorithms with the highest accuracy were compared along with the RSM model results. Figure 11 shows the tensile strength prediction errors in different samples for these methods and clearly shows that the combined accumulation method provides higher accuracy. As a result, the accumulation-based model was selected as the final machine learning approach.

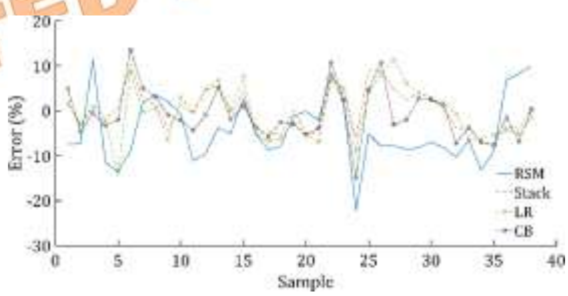

Fig. 11. Error percentages of selected ML algorithms & RSM

The reported accuracy for both ML and RSM models (as shown in Figure 11) was achieved using the LHS-designed database. To evaluate the advantages of the LHS approach compared to conventional random sampling, an alternative database consisting of 375 randomly generated layout configurations was constructed. Both ML and RSM models were retrained on this random dataset, and the prediction performance was evaluated accordingly. The comparative results are shown in Figures 12 and 13, which show that the models trained on the LHS-designed database outperform the models trained on the random sampling data. The improved performance can be attributed to the space-filling nature of LHS, which ensures a more uniform and stratified coverage of the input design space. This helps capture nonlinear relationships more effectively and reduces the risk of clustering and underrepresented regions in the dataset—issues commonly associated with purely random sampling.

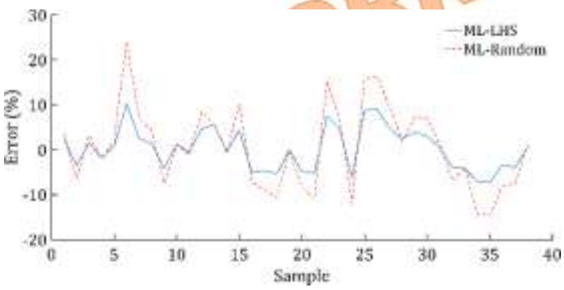

Fig. 12. ML performance: LHS vs random sampling

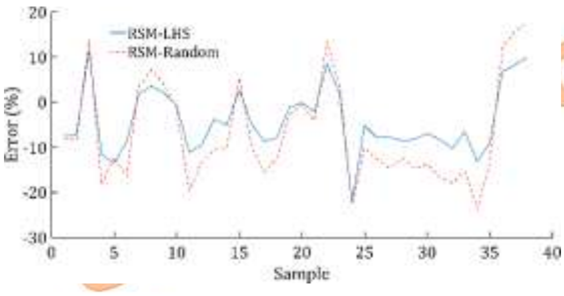

Fig. 13. RSM performance: LHS vs random sampling

To further clarify the advantage of LHS sampling, the graph in Figure 14 is plotted. As shown in the bar graph, the average prediction error in the LHS-based sampling strategy is significantly lower compared to the random sampling method. This result reinforces the conclusion that LHS sampling leads to superior predictive modeling performance and confirms its suitability for complex multivariate problems, such as composite failure prediction.

7. Conclusions

The primary objective of this study was to develop a model capable of rapidly and accurately predicting the failure strength of laminated composites. To achieve this goal, both RSM and machine learning approaches were employed, necessitating the creation of a high-quality database. The implementation of Latin Hypercube Sampling (LHS) proved particularly valuable, significantly enhancing model accuracy while reducing the required number of tests. Given that in the methods used, the model will be formed using a database, the quality of the dataset is of great importance so that the method used can achieve acceptable results with a smaller number of experiments. The use of this technique is a key strength of this research that may serve as a model for future studies.

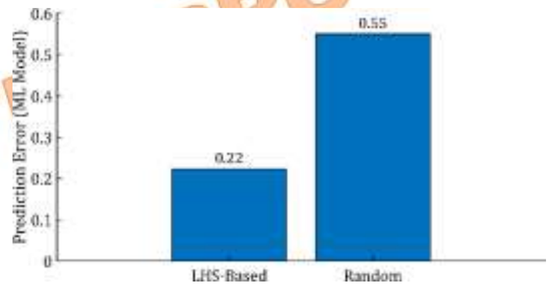

Fig. 14. Comparison of ML Model Errors for LHS vs. Random Sampling

Given the obtained database - whose variable input characteristics and occasional absence of certain layers in different tests constituted one of the most significant challenges of this research - both RSM and machine learning models were developed using multiple different algorithms. For the machine learning approach, in addition to employing various algorithms, the stacking method was utilized. This intelligent approach creates a new model by leveraging trained base models.

The obtained results demonstrated that using this method can improve the accuracy of outcomes. Notably, this technique has been relatively underutilized in previous research on mechanical property characterization of composite structures. The findings clearly showed that this method enhances the prediction accuracy of mechanical properties - particularly failure strength, which was the focus of this study.

Ultimately, the error comparison between the two methods (RSM and the stacking-trained machine learning model) revealed that the machine learning model achieves better accuracy than RSM. These findings, with careful validation, could support future research and development efforts in various industrial fields, including aerospace engineering.

One limitation of this study lies in the restricted range of ply orientation angles within the dataset. Specifically, only 0° and ±45° orientations were employed. This choice was based on two practical considerations. First, the fabric used in this study was a bidirectional woven type, which exhibits nearly symmetric mechanical behavior along the 0° and 90° directions due to its balanced architecture [31].

Second, the selected angles reflect typical industrial practices and are consistent with many previous experimental and numerical studies, where uncommon angles such as 15° or 30° are rarely utilized [27, 32]. While this design improves the practical relevance of the model for real-world applications, it may limit the generalizability of the predictions to laminate configurations involving nonstandard angles. Future research should consider incorporating a broader range of ply orientations to better assess the model's robustness and accuracy across diverse layup scenarios.

To better understand the significance of the present study, a comparison with previous works has been conducted. The results obtained from the proposed models, particularly the stacking-based ensemble and RSM, demonstrate promising predictive accuracy in estimating the failure load of glass/epoxy laminated composites. Compared to earlier studies such as those by Dalfi et al. [2] and Kumar et al. [4], which primarily relied on classical finite element and experimental methods without integration of data-driven techniques, our approach exhibits enhanced prediction performance through the use of machine learning and advanced sampling strategies.

The application of Latin Hypercube Sampling (LHS) distinguishes this work from conventional sampling methods commonly used in similar studies, such as uniform or random sampling [22]. The systematic distribution of sample points across the design space via LHS has contributed to increased model robustness and generalizability.

Moreover, unlike prior research that employed individual machine learning algorithms such as artificial neural networks (e.g., [23], [24]), the implementation of a stacking ensemble method in this study yields superior performance by combining multiple base learners. This aligns with recent trends in materials science toward ensemble modeling techniques [25], [30].

Although this study does not explicitly model manufacturing-induced imperfections such as voids or fiber waviness, the numerical simulation was calibrated using experimentally determined failure loads. By adjusting FEM model parameters, the model indirectly accounts for minor defect effects observed in the tested specimens. Nevertheless, for improved accuracy and generalizability, future work should incorporate uncertainty modeling or defect representation more explicitly.

Furthermore, integration of the Response Surface Methodology (RSM) with mechanical modeling approaches, as adopted in studies like [6], [7], is also incorporated here. However, our work improves upon previous efforts by validating RSM outputs through cross-verification with finite element analysis results and experimental data, thereby enhancing prediction accuracy and model reliability.

In summary, this study demonstrates the feasibility of using both machine learning and response surface methodology separately for the analysis of composite materials. The results of the two approaches were compared, indicating that the stacking-based machine learning model provides superior prediction accuracy. Additionally, the use of Latin Hypercube Sampling (LHS) and ensemble modeling techniques contributes to the improved accuracy and robustness of the machine learning predictions.

References

[1] Vijayakumar, S. and Palanikumar, K., 2019. Mechanical property evaluation of hybrid reinforced epoxy composite. *Materials Today: Proceedings*, 16, pp. 430–438.

[2] Dalfi, H., Al-Obaidi, A., Tariq, A., Razzaq, A. and Rafiee, R., 2023. Optimization of the mechanical performance and damage failure characteristics of laminated composites based on fiber orientation. *Frontiers of Structural and Civil Engineering*, 17(9), pp. 1357–1369.

[3] Nagaraja, K.C., Rajanna, S., Prakash, G.S., Praveennath, G. and Alipour, M., 2020. Studying the effect of different carbon and glass fabric stacking sequence on mechanical properties of epoxy hybrid composite laminates. *Composites Communications*, 21, p. 100425.

[4] Kumar, N., Kumar, S., Tyagi, A., Kumar, D. and Shekhar, C., 2020. Finite element and micromechanical analysis of glass/epoxy laminated composite with different orientations. *Materials Today: Proceedings*, 28, pp. 1899–1903.

[5] Muralidhara, B., Kumaresh, S.P. and Suresha, B., 2020. The effect of fiber architecture on the mechanical properties of carbon/epoxy composites. *Materials Today: Proceedings*, 22, pp. 1755–1764.

[6] Ornaghi, H.L., Roberta, R.M.N., Francisco, M.M. and Sabu, T., 2021. Modeling of dynamic mechanical curves of kenaf/polyester composites using surface response methodology. *Applied Polymer*, pp. 78–87.

[7] Saravanakumar, S., Sathiyamurthy, P. and Pathmanaban, P., 2024. Integrating machine

learning and response surface methodology for analyzing anisotropic mechanical properties of biocomposites. *Composite Interfaces*, Taylor & Francis, pp. 101–140.

[8] Khanlou, H., Sadollah, A., Chin Ang, B., Hoon Kim, J., Talebian, S. and Ghadimi, A., 2014. Prediction and optimization of electrospinning parameters for polymethyl methacrylate nanofiber fabrication using response surface methodology and artificial neural networks. *Neural Computing and Applications*, pp. 267–777.

[9] Fnides, M., Amroune, S., Belaadi, A., Saada, K., Chai, B.X., Abdullah, M., Alshaikh, I., Ghernaout, D. and Al-Khawlani, A., 2024. Modeling and optimizing the alkaline treatment process to enhance the date palm fibers' tensile mechanical properties using RSM. *Journal of Natural Fibers*, pp. 125–145.

[10] Saha, M., Singh, H., Srivastava, V. and Singh, M.K., 2024. Analysis and optimization of delamination factor for microwave-cured pineapple leaf fiber polymer composite through ANOVA analysis. *Applied Science and Engineering Progress*, 17(4), Article 7531. https://doi.org/10.14416/j.asep.2024.08.010

[11] Singh, M.K., Verma, N. and Zafar, S., 2019. Optimization of process parameters of microwave processed PLLA/coir composites for enhanced mechanical behavior. *Journal of Physics: Conference Series*, 1240(1), p. 012038. doi.org/10.1088/1742-6596/1240/1/012038.

[12] Theobald, O., 2017. *Machine Learning for Absolute Beginners: A Plain English Introduction* (2nd ed.). United States Press, pp. 287–296.

[13] Flach, P., 2012. *Machine Learning: The Art and Science of Algorithms That Make Sense of Data*. Cambridge University Press.

[14] Okafor, C., Iweriolor, S., Ani, O.I., Shahnawaz, A., Mehfuz, S., Onyekachukwu, G., Emmanuel, O., Emeka, S., Echezona, I. and Peter, O., 2023. Advances in machine learning-aided design of reinforced polymer composite and hybrid material systems. *Hybrid Advances*, 2, p. 100026.

[15] Tao, F., Liu, X., Du, H. and Yu, W., 2021. Learning composite constitutive laws via coupling Abaqus and deep neural network. *Composite Structures*, 272, p. 114137.

[16] Huang, J.S., Liew, J.X., Ademiloye, A.S. and Liew, K.M., 2020. Artificial intelligence in materials modeling and design. *Archives of Computational Methods in Engineering*, pp. 200–232.

[17] Sharma, H., Arora, G., Kumar, R., Debnath, S. and Siengchin, S., 2025. Machine learning-based study of hardness in polypropylene/carbon nanotube and low-density polyethylene/carbon nanotube composites. *Discover Materials*, 5(1), Article 176. doi.org/10.1007/s43939-025-00176-z.

[18] Johansson, A.M. and Sandgren, G.E., 2002. Latin hypercube sampling for stochastic finite element analysis. *Journal of Engineering Mechanics*, pp. 121–125.

[19] Singh, V.P., Jain, S.K. and Tiwari, A., 2007. *Risk and Reliability Analysis*. American Society of Civil Engineers.

[20] Kim, H.H. and Moon, Y., 2006. Improvement of overtopping risk evaluations using probabilistic concepts for existing dams. *Springer*, pp. 223–237.

[21] Chung, H., Senior, M., Wong, K.P., Lee, H.W. and Zhang, J.H., 2009. Probabilistic load flow evaluation with hybrid Latin hypercube sampling and Cholesky decomposition. *IEEE Transactions on Power Systems*, 24(2), pp. 120–126.

[22] Cho, Y., Seong, D., Yoo, S. and Kim, J., 2021. Comparison of factorial and Latin hypercube sampling designs for meta-models of building heating and cooling loads. *Energies*, pp. 201–224.

[23] Wang, X., Liu, N., Zhau, J., Li, Z., Meng, Q., Guan, Z. and Du, S., 2023. Highly efficient simulation of composites by determining failure initiation and fracture angle with artificial neural networks. *Composite Structures*, 307, p. 116644.

[24] Qian, Z., Zhang, N., Liu, Y. and Cheng, W., 2019. Prediction of mechanical properties of carbon fiber based on cross-scale FEM and machine learning. *Composite Structures*, 212, pp. 199–206.

[25] Fontes, A. and Shadmehri, F., 2023. Data-driven failure prediction of fiber-reinforced polymer composite materials. *Engineering Applications of Artificial Intelligence*, 120, p. 105834.

[26] ASTM D3039, 2017. Standard test method for tensile properties of polymer matrix composite materials. *Annual Book of ASTM Standards*.

[27] Kaw, A.K., 2006. *Mechanics of Composite Materials*. Taylor & Francis.

[28] Shin, H., Kim, K.J., Park, W.J., Hong, D.H., Yoo, I. and Lee, K.S., 2024. Machine learning models for the noninvasive diagnosis of bladder outlet obstruction and detrusor underactivity in men with lower urinary tract symptoms. *International Neurourology Journal*, pp. 641–647.

[29] Kumari, V., 2023. Credit risk prediction using ensemble machine learning algorithms. In: *Proceedings of the International Conference on Inventive Computation Technologies*, pp. 979–986.

[30] Chagahi, M., Mohammadi, D.M., Moshiri, B. and Piran, J., 2024. Cardiovascular disease detection using a novel stack-based ensemble classifier with aggregation layer, DOWA operator, and feature. *Computers in Biology and Medicine*, pp. 108–115.

[31] Gay, D., Hoa, S.V. and Tsai, S.W., 2003. *Composite Materials: Design and Applications*. CRC Press.

[32] Daniel, I.M. and Ishai, O., 2006. *Engineering Mechanics of Composite Materials*. Oxford University Press.