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ROBUSTNESS OF STACKING SEQUENCES IN LAMINATED COMPOSITE BEAMS UNDER FIBER ANGLE DEVIATIONS

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Abstract
The mechanical response of laminated composite beams is influenced by stacking sequences and fiber orientation angles. Small deviations in fiber angles during manufacturing may significantly alter the stress response and reduce the reliability of nominally optimized designs. This study examines the robustness of ply stacking sequences under fiber angle deviations for three boundary conditions and two stress components. A total of 100,000 stacking sequences, generated at 10° increments, are evaluated using Monte Carlo simulations with 100 random realizations per sequence. The 95th percentile (P95) of the absolute stress is used to identify robust stacking sequences and compare them with nominal optima. The results show that the nominal and robust optima differ in all six scenarios, with the P95 values of nominal optima being 3.23 to 5.11 × 10^4 times higher than those of robust optima. A gradient boosting model is also trained to predict P95 values, achieving R^2 values between 0.88 and 1.00 on the test dataset. These findings highlight the importance of accounting for manufacturing-induced fiber angle deviations in laminated composite beam design.

Keywords: Laminated composite beam, stacking sequence, fiber angle deviation, robust optimization, Monte Carlo simulation, gradient boosting.

1. INTRODUCTION

The fiber orientation angles of individual layers influence the stiffness and stress distribution of laminated composite beams. Therefore, the ply stacking sequence is an important design variable. The stresses associated with a given sequence can be determined analytically or numerically. By varying the fiber angles at specified increments, the considered stacking sequences can be evaluated to identify the configuration that minimizes stress. However, this approach assumes that the plies are manufactured at their prescribed angles. In practice, manufacturing-induced fiber angle deviations may alter the mechanical response of the laminate [1].

Robust design aims to identify configurations that maintain satisfactory performance in the presence of uncertainties. Statistical measures such as the mean, standard deviation, and worst-case response can be used to evaluate design performance under uncertain conditions. Beyer and Sendhoff [2] reviewed methods for robust optimization. António and Hoffbauer [3] proposed a robust design approach for angle-ply composite structures considering uncertainties. Dey et al. [4] investigated the effects of uncertainties on the dynamic response of composite shallow conical shells using a surrogate-based approach.

Machine learning methods have also been applied to predict the mechanical behavior

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of laminated composite structures. Tsiatas et al. [5] evaluated different machine learning algorithms for predicting the response of laminated composite beams. Zhang et al. [6] combined finite element analysis with machine learning to predict the mechanical properties of composite laminates. Liu et al. [7] employed an artificial neural network together with a genetic algorithm for composite design optimization. These studies demonstrate the potential of machine learning for predicting structural responses and supporting design optimization. However, predicting the stress response under manufacturing-induced fiber angle deviations remains an important consideration. In the present study, the machine learning model is developed to predict the 95th percentile (P95) of the absolute stress under such deviations.

This study examines the influence of manufacturing-induced fiber angle deviations on the robustness of stacking sequences in laminated composite beams. Random deviations are introduced into the fiber angles, and each stacking sequence is evaluated using 100 Monte Carlo realizations. The 95th percentile (P95) of the absolute stress is calculated for each sequence, and the sequence with the lowest P95 is identified as the robust optimum. The robust and nominal optima are compared for six combinations of boundary conditions and stress components at three deviation levels. Subsequently, a machine learning model is trained using the resulting dataset to predict P95 values.

2. METHODOLOGY

2.1. Analytical Beam Model

A laminated composite beam consisting of five layers of equal thickness was considered in the study. The beam geometry was defined by a length-to-thickness ratio of $L/h = 100$. A uniformly distributed transverse load of $q = 1000\,N/m$ was applied vertically downward along the beam length. Three boundary conditions were investigated: Clamped-clamped (C-C), clamped-free (C-F), and simply supported-simply supported (S-S). The mechanical response was determined using a three-degree-of-freedom shear deformation beam theory [8], and the corresponding equilibrium equations were solved analytically for each boundary condition.

All layers of the beam were assumed to be made of graphite/epoxy, with the material properties of $E_{11} = 241.5\,GPa$, $E_{22} = E_{33} = 18.89\,GPa$, $G_{12} = G_{13} = 5.18\,GPa$, $G_{23} = 3.45\,GPa$, $\nu_{12} = \nu_{13} = 0.24$ and $\nu_{23} = 0.25$. Normal (σ_x) and shear (τ_{xz}) stresses were evaluated under each boundary condition, resulting in six analysis scenarios. The normal stress was evaluated at $z = -h/2$, with $x = 0$ for C-C and C-F and $x = L/2$ for S-S. The shear stress was evaluated at $z = 0$, with $x = L/4$ for C-C and C-F and $x = 0$ for S-S. For each scenario, the calculated stress is denoted by $g(\boldsymbol{\theta})$, where $\boldsymbol{\theta} = \theta_1, \ldots, \theta_5$ represents the vector of fiber orientation angles of the five layers.

2.2. Fiber Angle Deviations and Monte Carlo Simulation

Manufacturing-induced fiber angle deviations were modeled by assuming that the actual orientation angle of each layer is $\theta_k + \delta_k$, where θ_k is the nominal fiber angle and δ_k is a random deviation. The deviations were assumed to be independent between layers and normally distributed with zero mean and a standard deviation of σ_θ. Fiber orientation angles ranging from 0° to 90° were considered at 10° increments, resulting in 100000 stacking sequences. For each sequence, 100 Monte Carlo realizations were generated, and the corresponding stresses were calculated using the analytical beam model. The same sets of random deviations were applied to all stacking sequences to ensure consistent comparisons. Three deviation levels, $\sigma_\theta = 1°, 2°, 3°$, were investigated, resulting in a total of 180 million stress calculations across the six analysis scenarios.

Under fiber angle deviations, the stress response of a stacking sequence is represented by a distribution rather than a single deterministic value. The 95th percentile (P95) of the absolute stress was adopted as the robustness criterion. This measure represents a stress threshold below which approximately 95% of the responses are expected to fall under the assumed deviation model. Compared with the mean, P95 places greater emphasis on unfavorable stress responses, while being less sensitive than the sample maximum to individual extreme realizations. The nominal and robust optimal stacking sequences were defined as follows:

$$\boldsymbol{\theta}^*_{nom} = \arg\min_{\boldsymbol{\theta}} |g(\boldsymbol{\theta})| \quad (1)$$

$$\boldsymbol{\theta}^*_{rob} = \arg\min_{\boldsymbol{\theta}} P95_{\delta}(|g(\boldsymbol{\theta} + \boldsymbol{\delta})|) \quad (2)$$

Here, g denotes the stress calculated using the analytical beam model, while $\boldsymbol{\theta}$ and $\boldsymbol{\delta}$ represent the vectors of nominal fiber angles and random angle deviations, respectively. The superscript * denotes the optimal stacking sequence.

The nominal optimum corresponds to the stacking sequence that minimizes the absolute stress without deviations, whereas the robust optimum is the sequence that minimizes the 95th percentile of the absolute stress under random deviations. This distinction allows the sensitivity of nominally optimal designs to manufacturing-induced fiber angle deviations to be assessed. A nominally optimal sequence may be less effective under fiber angle deviations. By comparing the two optima, the potential benefits of incorporating robustness into stacking sequence optimization can be evaluated. The overall workflow of the study is illustrated in Fig. 1.

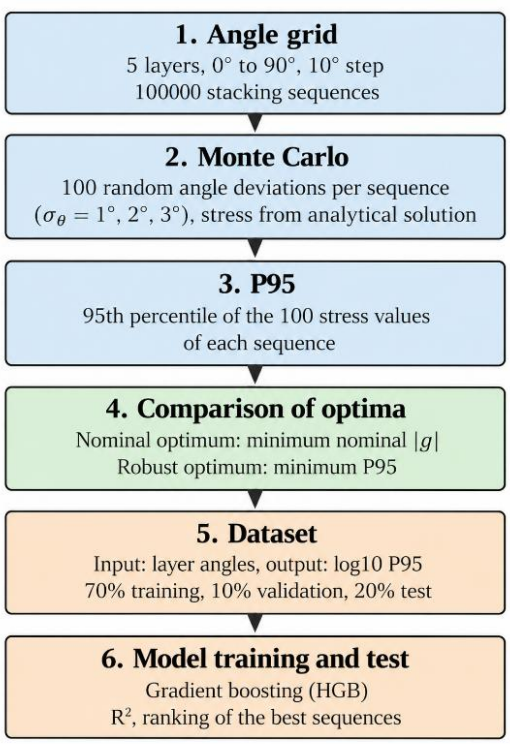


Fig. 1. *Flowchart of the robust optimization and machine learning procedure.*

2.3. Machine Learning Model

As a result of the Monte Carlo simulations, a P95 value was obtained for each stacking sequence defined by five fiber orientation angles, forming the machine learning dataset. The target variable was $\log_{10}(P95)$, calculated for $\sigma_\theta = 2°$. A histogram-based gradient boosting (HGB) regression model was implemented using scikit-learn [10], with a maximum of 600 boosting iterations, a learning rate of 0.05, and a maximum of 63 leaf nodes per tree. Two sets of input features were considered. The HGB angle model used $\sin(\theta_k)$, $\cos(\theta_k)$, $\sin(2\theta_k)$, and $\cos(2\theta_k)$ for each of the five layers, resulting in 20 features. The HGB physics model additionally included seven section stiffness parameters and two parameters derived from the analytical solution, resulting in 29 features. The dataset was randomly divided into training (70%), validation (10%), and test (20%) subsets,

with early stopping applied after 20 consecutive iterations without validation improvement. The procedure was repeated using three random splits, and median results were reported. For comparison, an HGB model was also trained to predict the nominal stress magnitude, $|g|_0$, without fiber angle deviations. Model performance was evaluated on the test dataset using the coefficient of determination (R^2), the number of correctly identified sequences among the 100 best predictions, and the predicted rank of the actual best stacking sequence.

3. RESULTS AND DISCUSSION

3.1. Effect of Angle Deviations

Table 1 presents the nominal and robust optimal stacking sequences for each scenario at $\sigma_\theta = 2°$. The two optimal sequences differ in all six scenarios. Although the nominal optima exhibit low stresses without fiber angle deviations, their stress values increase substantially when small deviations are introduced. For example, in the C-C shear stress (τ_{xz}) scenario, the nominal optimum has a stress magnitude of 1.7×10^{-5} without deviations, whereas the maximum stress magnitude under a single-layer deviation of ±2° reaches 8.1×10^{4}. In contrast, the robust optimum has a higher nominal stress magnitude of 38, but its maximum stress magnitude under the same single-layer deviations is only 188.

Table 1. *Comparison of nominal and robust optimal stacking sequences at* $\sigma_\theta = 2°$.

Scenario	Type	Stacking sequence (°)	$\|g\|_0$ (Pa)	$\|g\|_{2^\circ}$ (Pa)	P95 (Pa)
$\sigma_{x,C-C}$	N	60/20/90/60/40	563	5.3×10^{6}	8.9×10^{6}
	R	80/0/0/0/0	6.1×10^{5}	6.1×10^{5}	6.1×10^{5}
$\sigma_{x,C-F}$	N	90/0/0/80/60	3.2	1.0×10^{7}	1.9×10^{9}
	R	80/90/60/0/0	1.1×10^{4}	3.5×10^{4}	3.7×10^{4}
$\sigma_{x,S-S}$	N	40/40/40/60/60	6.0×10^{4}	1.2×10^{7}	1.2×10^{7}
	R	80/0/0/0/0	9.1×10^{5}	9.1×10^{5}	9.1×10^{5}
$\tau_{xz,C-C}$	N	0/20/40/40/20	1.7×10^{-5}	8.1×10^{4}	2.3×10^{5}
	R	80/80/60/90/0	38	188	279
$\tau_{xz,C-F}$	N	0/10/70/20/70	2	1.0×10^{6}	1.5×10^{6}
	R	0/80/90/70/90	5999	1.1×10^{4}	1.3×10^{4}
$\tau_{xz,S-S}$	N	80/70/60/10/10	338	3.8×10^{5}	1.3×10^{5}
	R	0/0/50/0/10	3.8×10^{4}	3.9×10^{4}	3.9×10^{4}

Note: N = nominal optimum; R = robust optimum; $|g|_0$ = absolute stress without fiber angle deviations; $|g|_{2^\circ}$ = maximum absolute stress under a single-layer deviation of ±2°; P95 = 95th percentile of the absolute stress.

The low nominal stress magnitudes observed in several scenarios are also associated with sensitivity to changes in stress sign. Among the 60 single-layer deviation cases, stress sign changes occurred in 18 cases for the nominal optima and only 2 cases for the robust optima. Furthermore, the P95 values of the nominal optima were 3.23 to 5.11×10^{4} times those of the robust optima, with the lowest ratio observed in the S-S shear stress scenario and the highest in the C-F normal stress scenario. Fig. 2 illustrates the variation in the P95 ratio between the nominal and robust optima with the fiber angle deviation level. The ratio remains greater than 1 at all deviation levels, ranging from 2.07 to 5.11×10^{4}. This consistently higher ratio indicates that the nominal optima are more sensitive to fiber angle deviations than the robust optima. The robust optimal stacking sequence changes with the deviation level in all scenarios except the S-S normal stress scenario. These results indicate that the expected magnitude of manufacturing-induced fiber angle deviations should be considered when selecting robust stacking sequences.

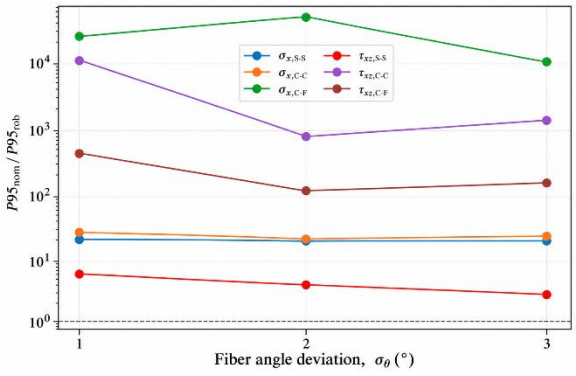


Fig. 2. *Ratio of P95 values for nominal and robust optima as a function of fiber angle deviation level.*

3.2. Prediction Results

Table 2 presents the prediction performance of the HGB models on the test dataset. For the P95 target, the HGB physics model achieved R^2 values ranging from 0.88 to 1.00, whereas the HGB angle model, based solely on fiber orientation angles, achieved values ranging from 0.74 to 1.00. For nominal stress prediction, the HGB physics model achieved R^2 values ranging from 0.67 to 1.00.

Table 2. *Prediction performance of the HGB models on the test dataset.*

Scenario	R^2 (P95 angle)	R^2 (P95, physics)	R^2 ($\lvert g\rvert_0$, physics)	Top 100 (P95)	Rank (P95)	Rank ($\lvert g\rvert_0$)
$\sigma_{x,C-C}$	0.94	0.96	0.74	84	1	2136
$\sigma_{x,C-F}$	0.94	0.96	0.75	82	2	1286
$\sigma_{x,S-S}$	1.00	1.00	1.00	98	1	839
$\tau_{xz,C-C}$	0.74	0.88	0.76	82	2	375
$\tau_{xz,C-F}$	0.87	0.95	0.67	82	40	2259
$\tau_{xz,S-S}$	0.95	0.96	0.67	83	1	337

Note: Angle = HGB angle model; physics = HGB physics model; $\lvert g\rvert_0$ = absolute stress without fiber angle deviations, Top 100 = number of the true best 100 stacking sequences appearing among the model's 100 best predictions; Rank (P95) = predicted rank of the actual best stacking sequence based on P95; Rank ($\lvert g\rvert_0$) = predicted rank of the actual best stacking sequence based on nominal stress. All values are medians over three random splits.

For the P95 target, the model correctly identifies 82 to 98 of the 100 best stacking sequences, depending on the scenario, and ranks the actual best sequence among the top two in five of the six scenarios. In contrast, for the nominal stress target, the actual best sequence ranks between 337 and 2259 in the model predictions. When the fiber orientation angle of a single layer is changed by 10°, the correlation between the corresponding stress values ranges from 0.099 to 0.98 for nominal stress and from 0.63 to 0.99 for P95. Since P95 represents the 95th percentile of the absolute stress over multiple fiber angle deviations, it exhibits smoother variations between neighboring stacking sequences. This behavior is consistent with the higher prediction accuracy achieved for P95 compared with nominal stress, as illustrated in Fig. 3.

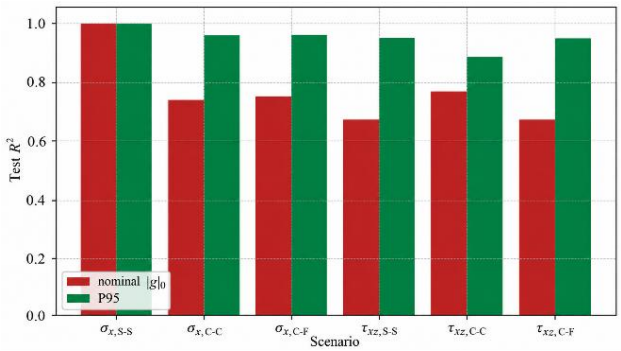


Fig. 3. *Comparison of test R^2 values for nominal stress and P95 predictions across the six scenarios.*

4. CONCLUSIONS

In this study, the effects of manufacturing-induced fiber angle deviations on the stress response of five-layer laminated composite beams were investigated. A total of 100000 stacking sequences were evaluated using Monte Carlo simulations, and the 95th percentile (P95) of the absolute stress was used as the robustness criterion. In all six scenarios, the nominal and robust optimal stacking sequences differed. At a fiber angle deviation level of 2°, the P95 values of the nominal optima were 3.23 to 5.11×10^4 times those of the robust optima, demonstrating the importance of accounting for manufacturing deviations in stacking sequence selection.

The histogram-based gradient boosting model predicted P95 with test R^2 values ranging from 0.88 to 1.00 and ranked the actual best stacking sequence among the top two in five of the six scenarios. These results suggest that machine learning can support the identification of robust stacking sequences when extensive Monte Carlo evaluations are computationally demanding. The present study was limited to 100 Monte Carlo samples per stacking sequence and assumed independent fiber angle deviations between layers. Future work will consider a finer fiber angle increment of 5°, larger Monte Carlo sample sizes, and deviation distributions derived from experimental manufacturing data.

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