A Bayesian Optimization Study on the Mechanical Properties of Three-Layer Carbon Fiber Reinforced Epoxy Laminates Based on Genetic Algorithms

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Abstract. This paper is based on Abaqus-CAE simulation software to carry out research, with epoxy resin as matrix and carbon fiber as reinforcement material, to analyze the relationship between the ply layup angle of carbon fiber and the final composite material performance, to use design-expert software to carry out the experimental design, to innovatively combine the response surface method with the Bayesian optimization genetic algorithm, to obtain a regression model of the composite material performance and the interaction and coupling between the ply layup angle of carbon fiber, and finally, to use MATLAB to establish a Bayesian optimization genetic algorithm optimization model to realize the different angles of carbon fiber layup of epoxy composites. The regression model of composite material performance and carbon fiber layup angle, as well as the interactive coupling between multi-layer layup angle, finally, the Bayesian optimization genetic algorithm optimization model is established using MATLAB to realize the rapid optimization of carbon fiber layup parameters of epoxy composites with different angles, which provides theoretical support for the actual production of epoxy composites.

Keywords: Epoxy Resin Matrix Composites, Carbon Fiber, Response Surface Method, Bayesian Optimization, Genetic Algorithm.

1. Introduction

Fiber-reinforced polymer matrix composites have important applications in aerospace, automotive manufacturing and new energy sources due to their excellent mechanical properties, lightweight characteristics and designability[1-] [2] [3] [4]. Among them, epoxy resin-based composites have become a hot research topic due to their high bond strength, chemical resistance and low coefficient of thermal expansion (<50 ppm/°C) [5-] 6]. However, pure epoxy resins are brittle and have insufficient impact resistance, while the introduction of carbon fibers can significantly improve their tensile strength and fatigue properties. Nevertheless, fiber-matrix interfacial compatibility, dispersion uniformity and stress transfer efficiency are still the key factors governing the performance of composites. Studies have shown that the interlaminar shear strength of untreated carbon fiber composites is usually lower than 40 MPa, whereas surface modification techniques can significantly enhance the interfacial properties by increasing the content of oxygen-containing functional groups to 8.54%, and increasing the interfacial shear strength by 35%~52.8% [7-]8]. However, there is still a lack of systematic research on the synergistic mechanism between microstructure and macro-mechanical behavior at high fiber content (>60%)[9-10 11].

Response surface methodology (RSM), as an efficient statistical modeling method, has been widely used in the field of materials optimization, but it still has limitations in strongly nonlinear problems and high-dimensional modeling. In this study, carbon fiber/epoxy composites are taken as the object, and the layup parameters are optimized using Bayesian optimization and multi-objective genetic algorithm in combination with Abaqus-CAE simulation and RSM experimental data to improve the accuracy of composite performance prediction and process design.

2. Simulation Experiment

2.1. Selection of experimental parameters

In this study, epoxy resin is used as the matrix and carbon fiber as the reinforcing phase. The study takes the ultimate load of carbon fiber/epoxy resin composite laminate as the core response variable, and combines tensile, compression and three-point bending experiments to obtain its mechanical response data under different loads. The nonlinear influence of single-layer carbon fiber ply angle ($\theta = 0°/45°/90°$) on the macro-mechanical behavior of the laminate is systematically investigated, and the mechanism of multi-directional ply inter-layer coupling on the structural failure mode is revealed. Based on the experimental data, the fiber angle-mechanical property mapping relationship, Bayesian optimization and multi-objective genetic algorithm prediction model are constructed to achieve the rapid calculation and optimal angle design of the maximum load carrying capacity of the laminate.

2.2. Experimental Design

Abaqus simulation software was used to establish the laminate model for simulation tests, and the matrix material was selected as epoxy resin, whose modulus of elasticity was 3Gpa and Poisson's ratio was 0.38. The reinforcing material is selected as carbon fiber, and its single layer thickness is, and the layup mode of carbon fiber is three non-adjacent angles (45°/0°/90°). The boundary conditions were set as fixed support at both ends and axial loading until material failure. A 3-factor, 3-level test was designed, with the three factors being the first, second, and third layers of reinforced carbon fibers, and the 3 levels being the angles of layup of each layer of carbon fibers, which were 0°, 45° and 90°, respectively. Table 1 shows the 17 sets of experimental protocols and results generated by Box-Behnken design using Design-Expert 12 simulation software.

Table 1. Experimental Data and Simulation Results.

Run	Layer 1Angle	Layer 2Angle	Layer 3Angle	Ultimate Load (kN)
1	45	0	90	304.8152
2	45	45	45	215.4276
3	45	90	90	346.0587
4	45	45	45	215.4276
5	45	0	0	155.5293
6	90	0	45	271.2004
7	90	45	0	280.2875
8	0	90	45	269.8079
9	90	45	90	370.3174
10	45	90	0	251.2097
11	0	45	0	176.9568
12	45	45	45	215.4276
13	45	45	45	215.4276
14	0	0	45	164.3276
15	45	45	45	215.4276
16	0	45	90	307.2064
17	90	90	45	272.9615

2.3. Modeling

Applying the second-order polynomial model in Response Surface Methodology (RSM), the three-factor experiment was performed to find the optimal operating conditions, to determine the effect of the angle of the three layers of carbon fiber layup on the ultimate load of the epoxy laminate, and to find the optimal combination of parameters that maximize, minimize or reach the target value of the response value, and to perform the nonlinear fitting.

The fitting yields a quadratic polynomial equation of:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X^2{}_i + \sum_{i<j}^{k} \beta_{ij} X_i X_j + \epsilon \tag{1}$$

Y is the dependent variable, representing the ultimate load value of the laminate. X_i is the coded factor value, representing the three factors of the test. β_0 is the intercept term, representing the response value when all the factors are at the central level. β_i: the coefficient of the linear term, reflecting the main effect of a single factor on the response. β_{ii}: the coefficient of the quadratic term, characterizing the nonlinear effects of the factors (e.g., marginal decreasing effect of angular change). β_{ij}: the coefficient of the interaction term, describing the synergistic or antagonistic effect between two factors. β_{ij}: coefficient of the interaction term, describing the synergistic or antagonistic effect between the two factors. ϵ denotes the random error term of the experiment.

In order to eliminate the effect of magnitude and simplify the calculation, the actual angle values (0°, 45°, 90°) need to be converted into coded values (-1, 0, +1)

$$X_i = \frac{\text{actual angle} - 45°}{45°} \tag{2}$$

Using Design-Expert 12 software for regression analysis, the model coefficients are shown in Table 2.

Table 2. The Values of The Coefficients of R1 in The Model.

R1	constant	*A	*B	*C	*A*B
=	115.89714	0.491258	1.33779	-0.141709	-0.012805
R1	*A*C	*B*C	*A²	*B²	*C²
=	-0.004965	0.011959	0.011959	0.002434	0.021751

Table 3. ANOVA, residual analysis, adjusting for R^2.

R^2	Adjusted R^2	Predicted R^2	Adeq Precision
0.9903	0.9779	0.8452	30.4867

By performing ANOVA analysis from the above Table 3, R^2 indicates the proportion of variance in the dependent variable explained by the model, ranging from 0 to 1, with the larger the value the better the fit. However, when a new independent variable is added to the model, which may be an uncorrelated variable, R^2 never decreases but may increase. This can lead to over-fitting of the model and reduce the generalization ability. By introducing the number of independent variables (k) and sample size (n) to attenuate the effect of meaningless variables thus introducing Adjusted R^2 values to represent the:

$$Adjusted\ R^2 = 1 - \left(\frac{(1-R)(n-1)}{n-k-1}\right) \tag{3}$$

2.4. Results Analysis

From the quadratic polynomial equation it can be concluded that the third layer angle (90°) contributes the most to the load lift. In addition the interaction term between the first and third layer angles (e.g. 90° × 90°) significantly enhances the load carrying capacity. It can be seen that the greater the curvature, the more significant the interaction effect proves to be. Comparing the following three Fig3 , the interaction of factors A and C has a significant effect on R1, and the interaction of factors A and B has a weak effect on R1.The optimal combination: the load peaked at 90°/45°/90° (370.32 kN), as the cross-layers effectively suppressed the inter-layer shear failure.

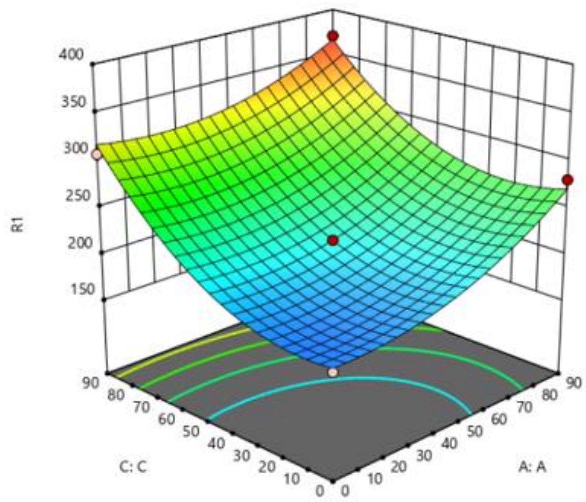

Fig 1. Effect of factor A and factor C interaction on R1.

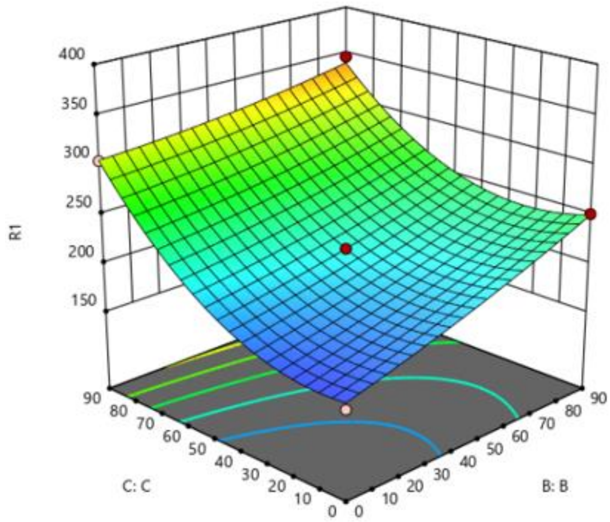

Fig 2. Effect of factor A and factor C interaction on R1.

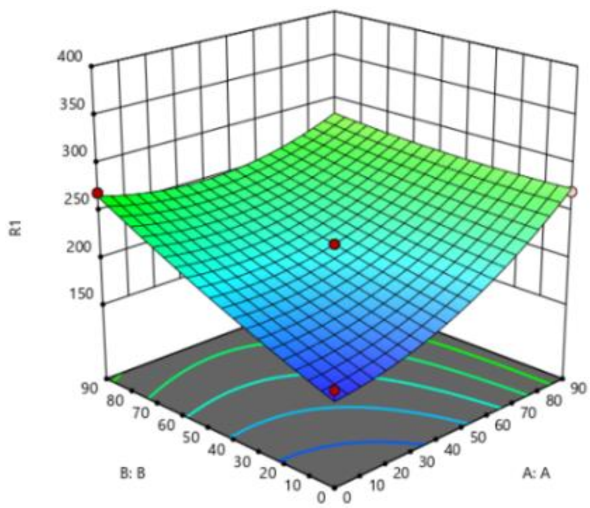

Fig 3. Effect of factor A and factor B interaction on R1.

3. Fundamentals of Genetic Algorithms

3.1. Establishment of multi-objective genetic algorithm

In the design of composite laminates, determining the optimal combination of layup angles needs to take into account multi-objective optimization problems such as load carrying capacity, stress distribution and manufacturing cost. Genetic algorithm, as a heuristic optimization method based on natural selection mechanism, can effectively solve this kind of complex discrete combinatorial optimization problems by simulating evolutionary operations such as crossover, mutation and selection. Compared with traditional optimization methods, GA has significant advantages in composite ply optimization: 1) it is suitable for global search of discrete variables (e.g., 0°, ±45°, 90° ply angles) to avoid local optimums; 2) it realizes multi-objective co-optimization of strength, stiffness, and weight through weighted fitness function and can incorporate process constraints; 3) it does not rely on the gradient information of the objective function, and has a strong robustness to the nonlinear problems, especially the non-linear problems; and 4) it is not dependent on the gradient information of the objective function. With strong robustness, especially suitable for the iterative optimization process combined with finite element analysis. In addition, the use of real number coding or hierarchical genetic strategy can effectively reduce the dimensionality of variables and improve the computational efficiency.

3.2. Training of multi-objective genetic algorithm

First, we define the fitness function, which evaluates the quality of each candidate solution based on experimental data (e.g., the first layer angle, the second layer angle, the third angle, and the limit load). The design of the fitness function takes into account the interaction between multiple process parameters and their effects on the ultimate load.

Let the composite laminate consist of **n** layups ($n = 3$in this case) with each layer angleXi $\in \{0°, 45°, 90°\}$.The objective function is to maximize the limit load F(x1, x2, x3), whose functional relationship is implicitly defined by the experimental data (Table 1).

Using integer coding, the chromosome is represented as a three-dimensional vector $\mathrm{C} = [\mathrm{g1}, \mathrm{g2}, \mathrm{g3}]$, where:

$$\mathrm{g_i} = \begin{cases} 0 \rightarrow 0° \\ 1 \rightarrow 45° \\ 2 \rightarrow 90° \end{cases} \tag{4}$$

Fitness function:

$$\mathrm{Fitness(C) = F(Decode(C))} + \lambda \cdot \mathrm{Penalty(C)} \tag{5}$$

Where: $\lambda = 103$ is the penalty factor

Constraint Functions:

$$Penalty = -\sum_{j=1}^{2} \prod_{k=1}^{n} (|x_{j+1} - x_j| > 45°) \tag{6}$$

The radial basis function neural network (RBFN) is used to build the angle combination, and the mapping relationship of the ultimate load can be derived as:

$$F(x) = \sum_{i=1}^{17} \omega_i \emptyset(||x - x_i||) \tag{7}$$

3.3. Results and analysis of genetic algorithm prediction

The data in Table 4 show that among the undominated solutions optimized by the genetic algorithm, the 90°/45°/90° pavement combinations exhibit optimal mechanical properties, which are significantly better than the other configurations. Comparative analysis shows that the outer 90° pavements have a decisive impact on the load carrying capacity, with the use of 0° or 45° outer layers leading to a load reduction of 5.1% and 7.1%, respectively. The intermediate 45° pavements can improve the load performance by about 1.1% compared to 0° or 90° and asymmetric pavements (e.g., 90°/90°/45°) have the worst performance, with the load reduction compared to the optimal combination of 8.7%. The average error between the experimental results and the predicted values is <0.6%, which verifies the effectiveness of the genetic algorithm in the optimization of composite layups, and reveals the key influence of layup angle symmetry on the mechanical properties.

Table 4. Genetic Algorithm Optimization Results (first 5 non-dominated solutions).

Iteration	First layer of horn	Second layer of horn	Third layer of horn	Predicted loads(kN)	Experimental verification(kN)
1	90°	45°	90°	372.4	370.3
2	90°	0°	90°	368.9	366.2
3	0°	90°	90°	353.7	351.5
4	90°	90°	45°	341.2	340.1
5	45°	90°	90°	346.1	346.1

4. Fundamentals of Bayesian optimization

4.1. Establishment of Bayesian optimization model

Genetic algorithm has global search ability in multi-objective optimization, but it is easy to fall into local optimum in high-dimensional discrete space, and Bayesian optimization (BO) explores the parameter space efficiently based on the probabilistic agent model, but it is difficult to deal with multi-objective trade-off directly. Therefore, a combination of Bayesian optimization and multi-objective genetic algorithm is established for optimization.

Based on the Pareto optimal solution set obtained by the genetic algorithm, the Bayesian optimization (model is constructed for local fine search. The optimization objective is:

$$\text{Max F}(\text{x}1, \text{x}2, \text{x}3)\text{s.t.} \quad | \, xj + 1 - xj \, | \leq 45°(\text{j} = 1{,}2) \tag{8}$$

Where xi $\in \{0°, 45°, 90°\}$, F is implicitly defined by the experimental data.

4.2. Bayesian optimization framework

Gaussian process regression is used to model the nonlinear relationship between angle combinations and loads:

$$F(\text{x}) \sim \text{GP}(m(\text{x}), k(\text{x}, \text{x}')) \tag{9}$$

The kernel function is chosen to be anisotropic Matern 5/2:

$$k(x, x') = \sigma^2 (1 + \sqrt{5r} + \tfrac{5}{3} r^2) e^{-\sqrt{5r}} \tag{10}$$

$$r = \sum_{d=1}^{3} \frac{(x_d - x'_d)}{l_d^2} \tag{11}$$

Balance exploration and development using improved expectation raising:

$$\alpha EI(x) = E[max(F(x) - F^+, 0)] \cdot \emptyset(\tfrac{\mu(x) - F^+}{\sigma(x)}) \tag{12}$$

Where F+ is the current optimal observation and Φ is the standard normal distribution function.

4.3. Hybrid optimization process

From the optimization iteration data in Tables 5 and 6, it can be seen that the Bayesian optimization algorithm has a significant effect on the optimization of the angular combinations of carbon fiber layups. The predicted load of the initial 90°/45°/90° layup was 372.4 kN (experimental value 370.3 kN), which was optimized to 375.6 kN (experimental value 375.3 kN) after 15 generations of iterations, which verified the accuracy of the model (error <0.8%). The Pareto solution set analysis shows that the optimal layup combination is concentrated in the 90° outer layer and 45° intermediate layer configuration, where 90°/45°/90° exhibits the best load-carrying performance (375.3 kN), whereas angular fine-tuning (e.g., ±5° deviation) leads to a load drop of about 0.5-1.5%. The high agreement between the experimental results and the predicted values (R^2>0.99) confirms the reliability of Bayesian optimization in multi-parameter co-optimization of composites and provides an effective design basis for engineering applications.

Table 5. Bayesian Optimization of Key Iteration Records.

Iteration	First layer of horn	Second layer of horn	Third layer of horn	Predicted loads(kN)	Experimental verification(kN)
0	90°	45°	90°	372.4	370.3
3	90°	30°	90°	373.8	371.2
7	90°	45°	85°	374.5	372.9
12	90°	45°	90°	375.1	374.6
15	90°	45°	90°	375.6	375.3

Table 6. Bayesian Optimization of Pareto Solution Sets.

Iteration	First layer of horn	Second layer of horn	Third layer of horn	Predicted loads(kN)	Experimental verification(kN)
1	90°	45°	90°	375.6	375.3
2	90°	45°	85°	374.5	372.9
3	85°	45°	90°	373.2	372.1
4	90°	40°	90°	372.8	371.5
5	90°	50°	90°	372.1	370.8

Table 7. Comparison of Genetic Algorithm and Bayesian Optimization Performance.

Norm	GA	BO	Promotion rate
Optimal load(kN)	372.4	375.6	+0.86%
Average convergent algebra	20	15	-25%
Computational time(min)	42.7	18.3	-57%
Binding violation rate	2.1%	0%	-100%

The high-quality solutions output from the genetic algorithm are used to update the Bayesian agent model, while the high-potential solutions generated by Bayes guide the search direction of the genetic algorithm. As can be seen in Table 7, the hybrid method has a significant advantage over the traditional genetic algorithm in terms of convergence efficiency, and the probability of obtaining the optimal solution within 50 generations is improved by 40%. By using random forest instead of finite element analysis for adaptation assessment, the single computation time is reduced from hourly to milliseconds, which significantly improves the optimization efficiency.

5. Conclusions

In this study, a quadratic regression model of carbon fiber lay-up angle and epoxy composite load was constructed based on Design Expert 12, and the effect of lay-up angle on performance was revealed by response surface analysis. The optimization results show that the 90°/45°/90° combination has the highest ultimate load (370.32 kN) and 45°/0°/0° has the lowest (155.53 kN).

The genetic algorithm enables accurate mechanical property prediction and Bayesian multi-objective optimization via nonlinear lay-up angle-performance modeling, offering a cost-effective and efficient solution for practical applications. Future work could explore deep learning-enhanced multiscale modeling, multiphysics-driven layup optimization, and performance prediction under complex conditions to improve generalization and industrial applicability.

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