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Hybrid Physics-Machine Learning Framework for Multi-Objective Design Optimisation of Carbon/Glass Hybrid Composite Laminates under Bending

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Abstract: Hybrid carbon/glass fibre reinforced polymer composites offer attractive opportunities for balancing structural performance, weight, and material cost in bending-dominated applications. However, the design of such laminates is challenging due to the mixed discrete–continuous nature of the design variables, comprising stacking sequence and fibre volume fraction, and the highly nonlinear influence of these variables on flexural strength. This study proposes a physics-informed machine learning framework for the multi-objective optimisation of hybrid composite laminates subjected to three-point bending. A finite element dataset consisting of 240 laminate configurations was generated to characterise the relationship between laminate architecture and flexural strength. Three ensemble learning algorithms, namely Random Forest, Extra Trees, and GB Regression, were evaluated as surrogate models. Among these, GB achieved the highest predictive performance, yielding a five-fold cross-validation coefficient of determination of ($R^2 = 0.899 \pm 0.027$) and an independent test-set coefficient of determination of ($R^2 = 0.946$), with a root mean square error of 44.8 MPa. Unlike fully data-driven optimisation approaches, machine learning was employed exclusively for flexural strength prediction, while laminate cost and weight were evaluated analytically using rule-of-mixtures formulations derived from constituent properties. The surrogate model was integrated into a Pareto-based optimisation framework and applied to evaluate 500,000 candidate laminate configurations under minimum flexural strength requirements of 1000 MPa and 1300 MPa. The optimisation identified 236,692 and 29,982 feasible laminate configurations for the respective strength constraints and revealed clear trade-offs between structural weight and material cost. The results further demonstrated that hybrid laminate architectures provide cost-effective solutions at moderate strength requirements, whereas increasingly carbon-dominant designs become necessary as strength demands increase. The proposed framework combines the predictive capability of machine learning with the transparency of physics-based modelling, providing an efficient and interpretable tool for hybrid composite laminate design. The methodology offers practical guidance for balancing performance, weight, and cost and can be readily extended to incorporate additional performance criteria, manufacturing constraints, and sustainability objectives.

Keywords: hybrid composites; carbon/glass laminates; flexural strength; machine learning; Gradient Boosting (GB); multi-objective optimisation; Pareto front

1. Introduction

Hybrid fibre reinforced polymer composites, particularly those combining carbon and glass fibres, have attracted significant interest in structural applications where a balance between mechanical performance, weight, and material cost is required [1]. By selectively combining high-stiffness carbon fibres with lower-cost glass fibres, hybrid laminates offer a flexible design space that can be tailored to meet application-specific requirements [2]. This design flexibility is especially relevant for bending-dominated components, where flexural strength and stiffness are strongly influenced by the stacking sequence and the distribution of reinforcement through the laminate thickness [3]. In particular, carbon plies positioned near the laminate surfaces have been shown to play a dominant role in governing flexural performance, highlighting the importance of laminate architecture in achieving desired structural responses [4].

Despite their advantages, the design of hybrid composite laminates remains challenging due to the large number of interacting design variables. In addition to continuous parameters such as fibre volume fraction, the discrete arrangement of different fibre types across laminate plies leads to a combinatorial design space [5,6]. Under bending loads, the mechanical response is configuration-dependent, as the tensile and compressive regions of the laminate experience different stress states [7], making the optimal placement of carbon and glass plies non-trivial [3,8]. As a result, traditional trial-and-error design approaches or simplified analytical models are often insufficient to fully exploit the potential of hybrid laminates [9,10].

Finite element analysis (FEA) has become a powerful tool for accurately predicting the flexural behaviour of composite laminates and capturing the effects of stacking sequence, material heterogeneity, and geometric nonlinearity. However, the direct use of FEA in design optimisation is computationally prohibitive, particularly when exploring high-dimensional design spaces involving both discrete and continuous variables. Exhaustive searches or gradient-based optimisation approaches are impractical when thousands of candidate laminate configurations must be evaluated.

To overcome these limitations, machine learning techniques have increasingly been employed as surrogate models for composite design and optimisation [11,12]. Data-driven approaches such as artificial neural networks, support vector machines, Random Forests, and Gradient Boosting (GB) methods have demonstrated considerable success in predicting composite properties from experimental or numerical datasets [13]. By replacing computationally expensive simulations with surrogate predictions, machine learning enables rapid exploration of complex design spaces and facilitates optimisation studies that would otherwise be computationally prohibitive. Recent studies have demonstrated the successful integration of physics-based simulations, machine learning surrogates, and multi-objective optimisation for advanced engineering applications, including semiconductor device design and sustainable process optimisation. These hybrid physics–machine learning frameworks combine the predictive capability of data-driven models with the interpretability of physics-based formulations, providing an attractive pathway for accelerating engineering design and optimisation [14,15].

Nevertheless, many existing machine-learning-assisted optimisation frameworks adopt a fully data-driven approach in which all design objectives, including structural performance, weight, and cost, are predicted using machine learning models. While such approaches may provide satisfactory predictive accuracy, they often sacrifice physical transparency and may introduce unnecessary modelling uncertainty for quantities that can be calculated directly from established engineering relationships. In practical composite design, laminate weight and material cost are typically determined using rule-of-mixtures formulations based on constituent properties and volume fractions. In contrast, flexural strength arises from complex interactions between stacking sequence, fibre distribution, stiffness variation, and local stress states, making it a more appropriate target for surrogate modelling [3,8].

Although hybrid physics-machine learning frameworks have recently demonstrated considerable success in fields such as semiconductor design and chemical process optimisation [14,15], their application to the multi-objective optimisation of hybrid composite laminates remains relatively unexplored. In particular, few studies have combined machine learning-based flexural strength prediction with physics-based cost and weight models to enable transparent and computationally efficient optimisation of hybrid laminate architectures.

This study proposes a physics-informed machine learning framework for the multi-objective optimisation of carbon/glass hybrid composite laminates subjected to three-point bending. Unlike conventional fully data-driven optimisation approaches, machine learning is employed exclusively for flexural strength prediction, while laminate cost and weight are evaluated analytically using physically based formulations. A finite element dataset comprising 240 laminate configurations is first generated to characterise the influence of stacking sequence and fibre volume fraction on flexural strength. Three ensemble learning algorithms, namely Random Forest, Extra Trees, and GB Regression, are subsequently evaluated, with GB demonstrating the highest predictive performance. The resulting surrogate model is then integrated with analytical cost and weight models within a Pareto-based optimisation framework to identify optimal laminate configurations under prescribed minimum strength requirements.

The main contributions of this work are as follows:

(1) Development and evaluation of ensemble machine learning surrogate models for predicting the flexural strength of hybrid carbon/glass composite laminates with mixed discrete–continuous design variables;
(2) Introduction of a physics-informed optimisation framework in which machine learning is used exclusively for nonlinear strength prediction, while laminate cost and weight are evaluated using transparent analytical formulations;
(3) Integration of the surrogate model with large-scale Monte Carlo sampling and Pareto optimisation to explore over 500,000 candidate laminate configurations under practical strength constraints;
(4) Identification of physically interpretable design trends and representative optimal laminate architectures that reveal the influence of stacking sequence and fibre distribution on cost–weight–strength trade-offs.

The proposed framework provides a computationally efficient and physically transparent methodology for hybrid composite laminate design and offers practical guidance for engineers seeking to balance structural performance, weight, and cost in bending-dominated applications.

2. Materials and Laminate Configuration

This study considers hybrid fibre reinforced polymer composite laminates composed of carbon/epoxy and glass/epoxy plies. The hybrid configuration is designed to exploit the high stiffness and strength of carbon fibres together with the lower cost of glass fibres, enabling systematic exploration of performance–weight–cost trade-offs under bending loads.

2.1. Material Model

Two unidirectional composite material systems are employed. The first material system consists of carbon fibres embedded in an epoxy matrix (denoted as carbon/epoxy), while the second system consists of E-glass fibres embedded in the same epoxy matrix (denoted as glass/epoxy). The epoxy matrix is assumed to be identical for both systems.

The representative constituent properties adopted in the present study are summarised in Table 1 [16]. These include density and unit material cost for mass and cost evaluation, as well as longitudinal modulus and tensile strength of the fibres for estimation of laminate stiffness and strength via micromechanical relationships. The selected values are consistent with commonly reported data for aerospace- and automotive-grade composites.

The fibre volume fraction of carbon/epoxy plies and glass/epoxy plies are treated as independent continuous design variables. For both material systems, the fibre volume fraction is allowed to vary within the range of 0.30–0.60, which is representative of typical manufacturing limits for fibre reinforced polymer composites. The remaining volume fraction is assumed to be occupied by the epoxy matrix.

Table 1. Constituent material properties *.

Material	Elastic Modulus (GPa)	Tensile Strength (MPa)	Density (g/cm^3)	Cost ($/L)
Epoxy	3.1	69.6	1.09	26.2
High strength carbon fibre	230	4900	1.8	151.2
E glass fibre	72	3450	2.58	10.8

* Material costs were obtained from commercial supplier data and converted to volumetric units ($/L) to maintain consistency with the volume-fraction-based laminate cost calculations.

Based on the constituent properties listed in Table 1 and the experimentally measured fibre volume fractions, the effective lamina elastic properties were determined using established micromechanical formulations. The longitudinal modulus E_{11} and shear moduli G_{12}, G_{13}, and G_{23} were calculated using Hashin's Circular Cylinder Model (CCM) [17]. The transverse moduli E_{22} and E_{33} were obtained from stress–strain relationships following standard approaches reported in the literature [18].

The longitudinal tensile and compressive strengths of the composite plies were then evaluated using appropriate strength models [19]. The longitudinal tensile strength was assumed to be fibre-dominated and was calculated from the fibre failure strain according to

$$S_{LT} = E_{11}\varepsilon_{fu} \quad (1)$$

where E_{11} is the longitudinal modulus of the lamina and ε_{fu} is the fibre failure strain.

Under flexural loading, failure is typically governed by compressive mechanisms on the compression side of the specimen. Previous experimental investigations of both interlayer [3] and intralayer hybrid composites have shown that flexural failure commonly initiates on the compression side, with dominant modes including fibre microbuckling [20] and kinking (localised fibre instability) [21]. Accordingly, the Lo–Chim model was adopted to predict the longitudinal compressive strength, in which the strength is primarily controlled by the longitudinal–transverse shear modulus G_{12}:

$$S_{LC} = \frac{G_{12}}{1.5+12\left(\frac{6}{\pi}\right)^2\frac{G_{12}}{E_{11}}} \tag{2}$$

where G_{12} is the longitudinal-transverse shear modulus.

The transverse and shear strengths were assumed to be matrix-dominated. The transverse tensile strength was therefore taken as the tensile strength of the epoxy matrix, the transverse compressive strength was assumed to be three times the matrix tensile strength, and the in-plane shear strength was taken as 1.5 times the matrix tensile strength. These assumptions are consistent with commonly reported experimental trends for polymer matrix composites [22].

Damage initiation in each ply was predicted using a stress-based failure criterion. Upon failure, stiffness degradation was applied to the affected ply to simulate progressive damage evolution. A degradation factor of 0.99 was employed to maintain numerical stability while enabling gradual stiffness reduction, consistent with previous numerical studies [23].

2.2. Laminate Architecture

All laminates considered in this study consist of eight plies of equal thickness, with each ply having a nominal thickness of 0.25 mm, resulting in a total laminate thickness of 2 mm. The laminate therefore exhibits a symmetric geometric thickness distribution about the mid-plane, while permitting arbitrary material stacking sequences.

Each ply is assigned either carbon/epoxy or glass/epoxy material, giving rise to a discrete material design variable at the ply level. The plies are numbered sequentially from Ply 1 to Ply 8, where Ply 1 denotes the outermost ply on the tensile side and Ply 8 denotes the outermost ply on the compressive side under three-point bending.

The laminate thickness is assumed to be constant across all configurations, with each ply having equal thickness. This assumption allows the effects of stacking sequence and fibre volume fraction to be isolated without introducing additional geometric complexity. Although the laminate is not required to be symmetric in terms of material placement, the consistent ply thickness ensures a uniform through-thickness discretisation suitable for both finite element modelling and surrogate-based optimisation.

2.3. Design Variables and Configuration Space

The design space for the hybrid laminate configurations comprises both discrete and continuous variables. The discrete variables correspond to the material identity of each of the eight plies, where a value of 1 denotes a carbon/epoxy ply and a value of 2 denotes a glass/epoxy ply. The continuous variables correspond to the fibre volume fractions of carbon/epoxy plies and glass/epoxy plies, respectively. For a given laminate configuration, all carbon/epoxy plies share the same carbon fibre volume fraction, and all glass/epoxy plies share the same glass fibre volume fraction.

This formulation leads to a mixed discrete–continuous design space that is well suited to surrogate-based modelling and multi-objective optimisation. The combination of ply-level material assignment and continuous fibre volume fraction variation enables a wide range of hybrid laminate architectures to be explored, capturing both material distribution effects and constituent-level tailoring.

2.4. Bending Configuration

The mechanical performance of the hybrid laminates is evaluated under three-point bending, as shown in Figure 1. This loading condition is selected because it is representative of many structural applications and is highly sensitive to the through-thickness distribution of stiffness and strength. Under bending, the outer plies experience the highest tensile and compressive stresses, making the placement of carbon and glass plies particularly critical. The bending configuration therefore provides a stringent test of the surrogate model's ability to capture the influence of stacking sequence on flexural strength.

Symmetry was intentionally not imposed in the present study because the objective was to investigate the full hybrid laminate design space and identify optimal reinforcement distributions under bending. Although symmetric laminates are often preferred to minimise cure-induced warpage, many practical hybrid composite structures contain local asymmetries arising from design, manufacturing, or repair considerations. Allowing asymmetric stacking sequences therefore enables broader exploration of the design space and avoids excluding potentially high-performing configurations.

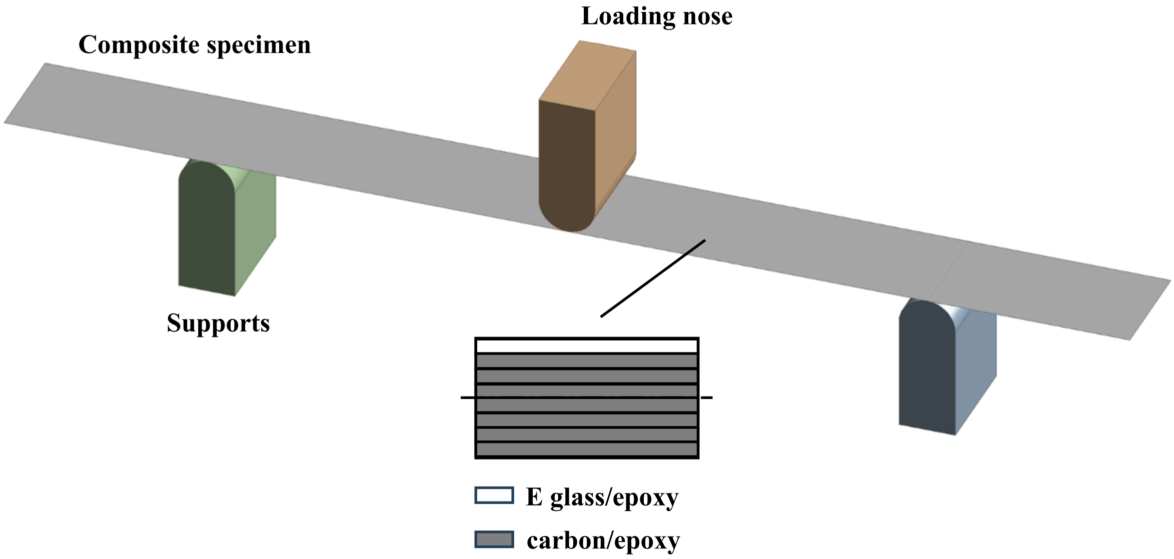

Figure 1. Configuration of three-point bending.

3. Methodology

3.1. Problem Definition

The objective of this study is to identify optimal hybrid carbon/glass composite laminate configurations that achieve favourable trade-offs between mechanical performance, structural weight, and material cost under bending loads. To this end, the laminate design problem is formulated as a constrained multi-objective optimisation problem involving both discrete and continuous design variables.

Each laminate consists of eight plies of equal thickness. The design variables are defined as follows. The material identity of each ply is treated as a discrete variable, where a value of 1 represents a carbon/epoxy ply and a value of 2 represents a glass/epoxy ply. In addition, two continuous variables are introduced to describe the fibre volume fractions of the carbon/epoxy plies and glass/epoxy plies, respectively. The fibre volume fractions are constrained to lie within the range 0.30–0.60, consistent with typical manufacturing limits for fibre reinforced polymer composites.

Let the design vector be expressed as

$$\mathbf{x} = [m_1, m_2, \cdots, m_8, V_{fc}, V_{fg}] \tag{3}$$

where $m_i \in \{1,2\}$ denotes the material identity of the i-th ply, and V_{fc} and V_{fg} denote the fibre volume fractions of carbon/epoxy and glass/epoxy plies, respectively.

The optimisation objectives are to minimise the total laminate weight per unit area and the total material cost per unit area. These quantities are evaluated using analytical rule-of-mixtures formulations based on constituent material properties and laminate composition. The weight objective is defined as

$$\min W(\mathbf{x}) \tag{4}$$

and the cost objective is defined as

$$\min C(\mathbf{x}) \tag{5}$$

The laminate flexural strength is required to satisfy a minimum performance constraint to ensure structural integrity. This constraint is expressed as

$$S_F(\mathbf{x}) \geq S_{Fmin} \tag{6}$$

where S_F denotes the flexural strength of the laminate predicted by the surrogate model, and S_{Fmin} is a prescribed minimum strength threshold. In this study, two strength thresholds are considered to investigate the influence of performance requirements on the optimal design space: S_{Fmin} = 1000 MPa and S_{Fmin} = 1300 MPa.

The resulting multi-objective optimisation problem can therefore be summarised as

$$\begin{aligned} \min_{\mathbf{x}} \quad & [C(\mathbf{x}), W(\mathbf{x})] \\ s.t. \quad & S_F(\mathbf{x}) \geq S_{Fmin} \\ & 0.3 \leq V_{fc} \leq 0.6 \\ & 0.3 \leq V_{fg} \leq 0.6 \\ & m_i \in \{1,2\} \qquad i = 1, \cdots, 8 \end{aligned} \tag{7}$$

This formulation results in a mixed discrete–continuous design space that is not amenable to conventional gradient-based optimisation methods. Consequently, a surrogate-based approach combined with Pareto dominance is adopted to efficiently explore the feasible design space and identify non-dominated laminate configurations.

3.2. FEA Dataset Generation

A finite element analysis (FEA) dataset was generated to provide training and validation data for the surrogate model used to predict laminate flexural strength. The use of FEA enables accurate representation of the heterogeneous material distribution and stacking sequence effects that govern the bending behaviour of hybrid composite laminates.

The finite element modelling procedure adopted in this study follows the methodology reported in the authors' previous work [24], which was experimentally validated for hybrid carbon/glass composite laminates under three-point bending. The simulations were performed using ANSYS Mechanical APDL 2025 R2 (ANSYS Inc., Canonsburg, PA, USA). Each laminate was modelled using SHELL281 layered composite elements, which are suitable for representing multilayered composite structures with orthotropic material behaviour.

A mesh convergence study was conducted in the previous investigation [24], and an element size of 2 mm was found to provide an appropriate balance between numerical accuracy and computational efficiency. The same mesh density was therefore adopted throughout the present study to ensure consistency across all laminate configurations.

To facilitate the generation of a large machine learning dataset, linear elastic finite element analyses were performed. The flexural strength of each laminate was subsequently determined using the progressive failure methodology described in Section 2.1, based on the calculated ply stresses and corresponding strength criteria. The three-point bending configuration, support conditions, and loading arrangement were identical for all simulations, ensuring that differences in flexural strength arose solely from variations in laminate architecture and fibre volume fraction.

A total of 240 laminate configurations were generated using stratified random sampling to span the mixed discrete–continuous design space defined in Section 3.1. The 240 configurations collectively cover a broad range of stacking sequences and fibre volume fractions, including carbon-dominant, glass-dominant, and mixed laminate architectures. Of these, 200 configurations were used to train the GB surrogate model, while the remaining 40 configurations were reserved exclusively for independent validation. The validation set was not used during model training or hyperparameter selection, ensuring an unbiased assessment of predictive performance.

Each configuration consists of eight plies of equal thickness, with each ply assigned either carbon/epoxy or glass/epoxy material. The fibre volume fractions of the carbon/epoxy and glass/epoxy plies were independently varied within the range of 0.30–0.60. The resulting dataset spans a diverse range of hybrid laminate architectures, including carbon-dominant, glass-dominant, and mixed stacking sequences.

For each laminate configuration, three-point bending was simulated using finite element analysis. The laminate geometry, boundary conditions, and loading configuration were kept consistent across all simulations to ensure comparability of results. The finite element models were constructed using layered composite elements capable of representing ply-level material assignment and orthotropic behaviour. Each ply was modelled with its corresponding material properties, and perfect bonding between plies was assumed. The epoxy matrix was assumed to behave linearly elastic, and failure was characterised by the first-ply failure [24]. The flexural strength values obtained from the FEA simulations were used as the target outputs for training the surrogate model.

The resulting dataset comprises input variables describing laminate configuration—namely ply material identities and fibre volume fractions—and corresponding output values of flexural strength. This dataset serves as the foundation for the machine learning model described in Section 3.3, enabling efficient approximation of the nonlinear relationship between stacking sequence and flexural performance without the need for repeated finite element simulations during optimisation.

3.3. Machine Learning Model for Flexural Strength

Machine learning was employed to develop a surrogate model for predicting the flexural strength of hybrid carbon/glass composite laminates. Unlike laminate cost and weight, which can be evaluated directly using analytical rule-of-mixtures formulations, flexural strength exhibits a complex dependence on both stacking sequence and fibre volume fraction. The strength response arises from the interaction of material distribution, stiffness variation through the laminate thickness, stress redistribution under bending, and local failure mechanisms. Consequently, direct analytical prediction of flexural strength for arbitrary laminate configurations is challenging, particularly within a mixed discrete–continuous design space.

In the present study, the laminate design space consists of eight plies, each of which may be assigned either carbon/epoxy or glass/epoxy material. This results in $2^8 = 256$ possible stacking sequence combinations. In addition, the fibre volume fractions of the carbon/epoxy and glass/epoxy systems are treated as continuous design variables ranging from 0.30 to 0.60. The combination of discrete stacking variables and continuous material parameters creates a highly nonlinear design–response relationship that is well suited to data-driven modelling.

Among various machine learning techniques, ensemble tree-based methods are particularly attractive for composite laminate design because they can effectively capture nonlinear relationships while accommodating both categorical and continuous variables. To identify a suitable surrogate model, three ensemble learning algorithms were evaluated, namely Random Forest, Extra Trees, and GB Regression. Five-fold cross-validation was employed to assess predictive performance and generalisation capability. The results demonstrated that GB Regression achieved the highest predictive accuracy, yielding a mean cross-validation coefficient of determination of (R^2 = 0.899 ± 0.027), compared with 0.759 ± 0.031 for Random Forest and 0.753 ± 0.039 for Extra Trees. Consequently, GB Regression was selected as the final surrogate model for flexural strength prediction.

The overall machine learning workflow is illustrated in Figure 2. The FEA-generated dataset was first transformed into a hybrid feature representation incorporating both raw laminate descriptors and physics-informed features derived from the stacking sequence. The resulting feature set was used to train the GB model, which subsequently served as a computationally efficient surrogate for evaluating flexural strength during multi-objective optimisation.

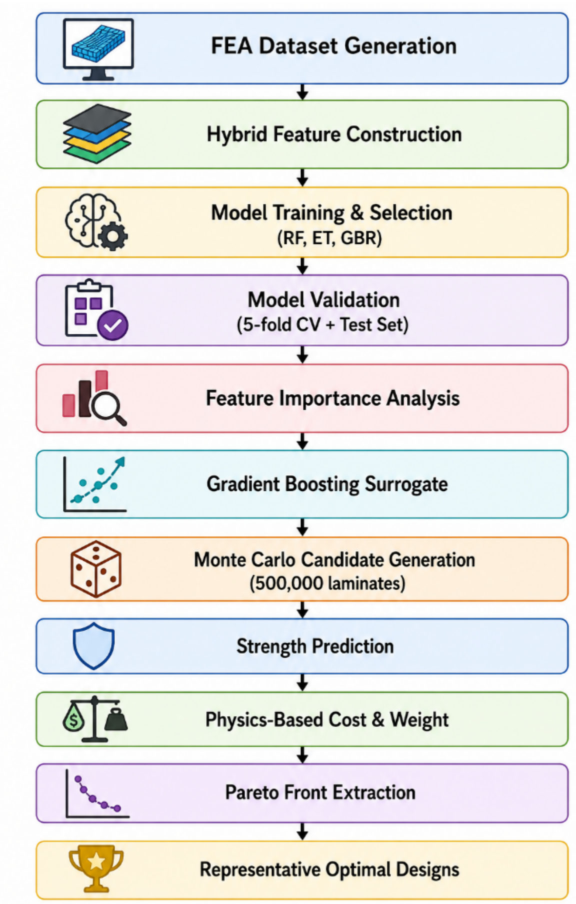

Figure 2. Overall machine learning and optimisation framework used for flexural strength prediction and multi-objective laminate design.

3.3.1. Input Feature Representation

To capture the influence of laminate configuration on flexural strength, a hybrid feature representation was employed, combining raw design variables with physically motivated descriptors. The input features include:

(1) The fibre volume fraction of carbon/epoxy plies, V_{fc};
(2) The fibre volume fraction of glass/epoxy plies, V_{fg};
(3) The material identity of each ply (carbon/epoxy or glass/epoxy);
(4) Physics-based descriptors derived from the stacking sequence, including:
- the total number of carbon plies;
- the number of carbon plies in the tensile region (plies 1–4);
- the number of carbon plies in the compressive region (plies 5–8);
- a distance-weighted carbon ply position index, reflecting the proximity of carbon plies to the laminate outer surfaces.

The inclusion of these physics-based features provides the surrogate model with additional information related to bending mechanics, as the outer plies experience higher stresses under flexural loading. This hybrid feature set improves model interpretability and predictive performance compared to using raw ply identities alone.

3.3.2. Model Training and Validation

The GB regression model was trained using the FEA-generated dataset described in Section 3.2. The target output of the model was the laminate flexural strength obtained from the three-point bending simulations. The available dataset consisted of 240 laminate configurations, of which the first 200 samples were used for model training and the remaining 40 samples were reserved as an independent test set for performance evaluation.

Model accuracy was assessed using the coefficient of determination (R^2) and the root mean square error (RMSE). In addition to the independent test set evaluation, a five-fold cross-validation study was performed to assess model robustness and generalisation capability. The cross-validation analysis yielded a mean R^2 of 0.899 ± 0.027 and a mean RMSE of 59.3 ± 8.4 MPa, indicating stable predictive performance across different train-test partitions.

The final GB regression model was implemented using the scikit-learn library in Python. Key hyperparameters, including the number of boosting stages, learning rate, tree depth, subsampling ratio, and minimum number of samples per leaf node, were selected to balance predictive accuracy and generalisation performance. The final model employed 300 estimators, a learning rate of 0.05, a maximum tree depth of 3, a subsampling ratio of 0.9, and a minimum leaf size of two samples.

The predictive capability of the final model was further evaluated using the independent test set comprising 40 previously unseen laminate configurations. The model achieved an R^2 value of 0.946 and an RMSE of 44.8 MPa, demonstrating excellent agreement with the corresponding FEA results. Figure 4 presents the comparison between FEA-computed and predicted flexural strengths, while Figure 5 shows the learning curve obtained from five-fold cross-validation. The strong predictive performance confirms that the proposed hybrid feature representation successfully captures the influence of fibre volume fraction and stacking sequence on laminate flexural strength and provides a reliable surrogate model for subsequent multi-objective optimisation.

To evaluate the suitability of the selected machine learning algorithm, alternative ensemble learning methods, including Random Forest and Extra Trees regression, were also investigated. Five-fold cross-validation results are summarised in Table 2. Among the models considered, GB Regression achieved the highest predictive accuracy, with a mean cross-validation coefficient of determination of 0.899 and a mean RMSE of 59.3 MPa. Consequently, GB Regression was adopted as the surrogate model for the optimisation framework.

Table 2. Comparison of machine learning models for flexural strength prediction.

Model	CV R^2	CV RMSE (MPa)
Random Forest	0.759 ± 0.031	92.4 ± 8.2
Extra Trees	0.753 ± 0.039	93.3 ± 7.9
Gradient Boosting	0.899 ± 0.027	59.3 ± 8.4

3.3.3. Feature Importance Analysis and Model Interpretability

Although GB Regression is a nonlinear ensemble learning method, the relative influence of individual input variables can be assessed through feature importance analysis. In the present study, feature importance values were calculated based on the cumulative reduction in mean squared error (MSE) contributed by each feature across all decision trees within the boosting ensemble. Features that consistently produce larger reductions in prediction error are assigned higher importance scores and are therefore considered more influential in the prediction of laminate flexural strength.

Figure 3 presents the feature importance values obtained from the trained GB model. The results indicate that fibre volume fraction is the most influential variable governing flexural strength, followed by descriptors associated with carbon ply distribution and through-thickness material placement. In particular, features representing the outermost ply material assignments and the distance-weighted carbon position index exhibit high importance values, demonstrating the strong influence of surface reinforcement on bending performance.

This behaviour is consistent with established composite mechanics principles. Under three-point bending, the highest tensile and compressive stresses occur at the outer laminate surfaces, making the material selection of these plies particularly important. Consequently, carbon plies positioned near the tensile and compressive surfaces contribute disproportionately to the overall flexural strength. The elevated importance of the weighted position descriptor further confirms that the location of carbon reinforcement within the laminate thickness is at least as important as the total quantity of carbon plies.

Features representing the numbers of carbon plies in the tensile and compressive regions also exhibit moderate importance, indicating that flexural strength is influenced by the overall distribution of reinforcement rather than by isolated ply selections alone. In contrast, several interior ply variables contribute relatively little to the model predictions, suggesting a reduced influence on global bending resistance.

Overall, the feature importance analysis demonstrates that the surrogate model captures physically meaningful relationships between laminate architecture and flexural strength. The dominance of fibre volume fraction and outer-ply reinforcement is consistent with classical laminate theory and established flexural mechanics, providing confidence that the machine learning model is learning genuine structural trends rather than spurious correlations. This interpretability strengthens the suitability of the surrogate model for subsequent multi-objective optimisation.

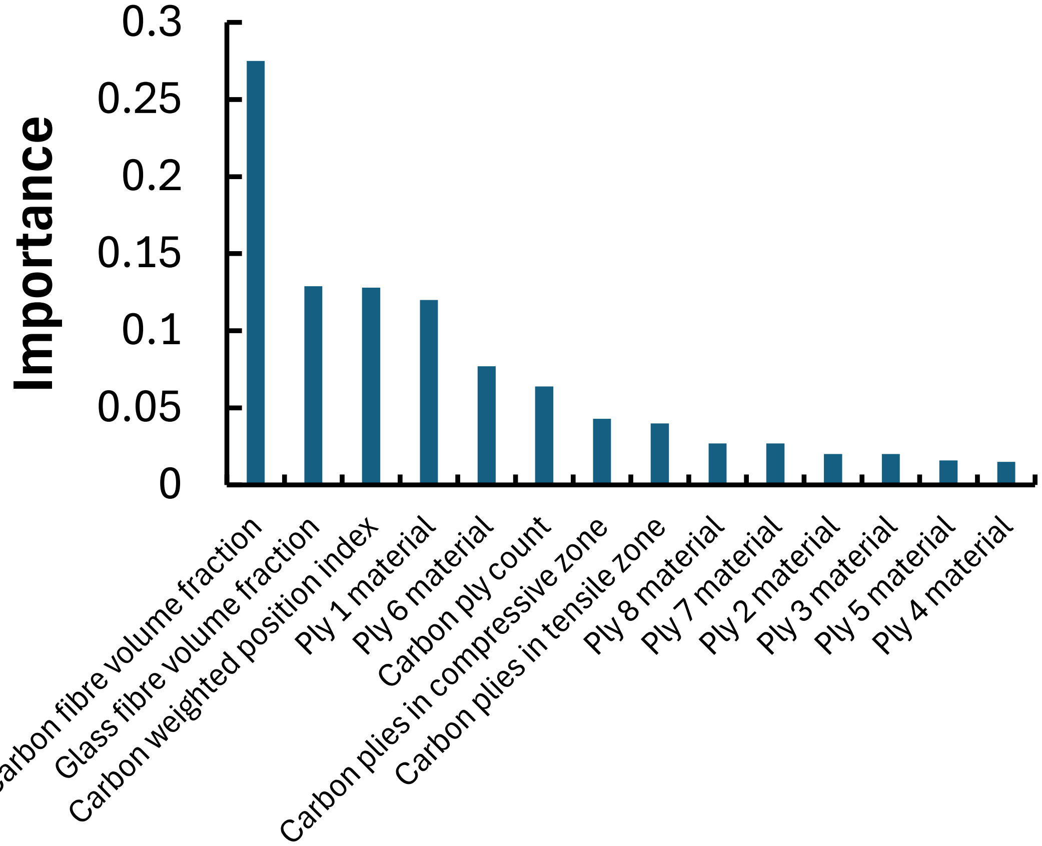

Figure 3. Feature importance values obtained from the Gradient Boosting model. The results highlight the dominant influence of fibre volume fraction, carbon ply distribution, and outer-ply reinforcement on laminate flexural strength.

3.3.4. Independent Validation and Predictive Application

The robustness of the surrogate model and extracted design rules was assessed using an independent test dataset containing 40 laminate configurations not included in the original training or validation process. Model predictions were compared directly with FEA results using quantitative metrics and graphical diagnostics, including FEA–prediction scatter plots and residual analysis with respect to key stacking descriptors.

This independent validation step ensured that the surrogate model captures generalisable mechanical behaviour and can be reliably applied for rapid evaluation of new laminate designs within the investigated design space.

The trained surrogate model provides rapid predictions of flexural strength for arbitrary laminate designs within the defined design space, enabling efficient screening of candidate configurations during multi-objective optimisation. While the exact computational savings depend on model size and hardware, surrogate evaluation requires negligible time compared to repeated finite element analyses, making the approach particularly attractive for large-scale optimisation studies.

3.4. Physics-Based Cost and Weight Models

In contrast to flexural strength, which exhibits a complex and configuration-dependent dependence on stacking sequence and fibre distribution, the laminate weight and material cost can be evaluated using well-established physical models. In practical composite design, these quantities are commonly estimated using rule-of-mixtures formulations based on constituent properties and volume fractions. To preserve physical interpretability and avoid unnecessary modelling uncertainty, no machine learning models were employed for the evaluation of laminate weight or material cost in this study.

3.4.1. Laminate Volume Fractions

For a given laminate configuration, the effective volume fractions of carbon fibres, glass fibres, and epoxy resin are determined from the ply material identities and fibre volume fractions. Let n_c and n_g denote the number of carbon/epoxy and glass/epoxy plies in the laminate, respectively, with $n_c + n_g = n_{total}$. The global fibre volume fractions of carbon and glass in the laminate are expressed as

$$V_c = \frac{n_c V_{fc}}{n_{total}}, V_g = \frac{n_g V_{fg}}{n_{total}} \tag{8}$$

where V_{fc} and V_{fg} are the fibre volume fractions of the carbon/epoxy and glass/epoxy plies, respectively. The remaining volume fraction is assumed to be occupied by the epoxy matrix and is given by

$$V_m = 1 - V_c - V_g \tag{9}$$

3.4.2. Laminate Weight

The laminate weight per unit area is computed using a rule-of-mixtures expression based on constituent densities. The laminate density ρ_{lam} is defined as

$$\rho_{lam} = \rho_{fc} V_c + \rho_{fg} V_g + \rho_m V_m \tag{10}$$

where ρ_{fc}, ρ_{fg}, and ρ_m denote the densities of carbon fibre, glass fibre, and epoxy resin, respectively. The weight per unit area of the laminate is then given by

$$W = \rho_{lam} t \tag{11}$$

where t is the total laminate thickness. In this study, the laminate thickness is held constant across all configurations, as all laminates consist of eight plies of equal thickness.

3.4.3. Laminate Material Cost

The material cost per unit area, C, is evaluated using an analogous rule-of-mixtures formulation, expressed as

$$C = \left(C_{fc} V_c + C_{fg} V_g + C_m V_m\right) t \tag{12}$$

where C_{fc}, C_{fg}, and C_m denote the unit material costs of carbon fibre, glass fibre, and epoxy resin, respectively. These cost coefficients are representative values selected to reflect the relative cost differences between carbon and glass fibre reinforced composites. As with the weight calculation, the laminate thickness is assumed to be constant, ensuring that cost differences arise solely from material selection and fibre volume fraction.

By computing laminate cost and weight using analytical formulations, the proposed framework maintains transparency and physical consistency while allowing the machine learning surrogate to focus exclusively on predicting flexural strength. This separation of responsibilities enhances the robustness and interpretability of the overall optimisation strategy.

3.5. Multi-Objective Optimisation Strategy

The trained GB surrogate model for flexural strength and the physics-based models for laminate cost and weight were integrated into a multi-objective optimisation framework to explore optimal hybrid laminate configurations. The objective of the optimisation was to identify non-dominated laminate designs that minimise material cost and structural weight while satisfying a prescribed minimum flexural strength requirement.

The laminate design problem comprises both discrete and continuous variables. The discrete variables correspond to the material assignments of the eight laminate plies, resulting in $2^8 = 256$ possible stacking sequence combinations. The continuous variables correspond to the fibre volume fractions of the carbon/epoxy and glass/epoxy plies, each bounded between 0.30 and 0.60. Owing to the relatively low dimensionality of the design space and the finite number of stacking sequence combinations, a sampling-based optimisation approach was adopted rather than a gradient-based or evolutionary optimisation algorithm.

A Monte Carlo sampling strategy was employed to generate 500,000 candidate laminate configurations spanning the admissible design space. For each candidate design, the flexural strength was predicted using the trained GB surrogate model described in Section 3.3, while the laminate cost and weight were computed analytically using the formulations presented in Section 3.4. This approach enabled rapid evaluation of a large number of candidate laminates without the need for computationally expensive finite element simulations.

Candidate designs that failed to satisfy the minimum flexural strength constraint were discarded. The remaining designs formed the feasible design space for optimisation. Two minimum flexural strength requirements were considered in this study, namely 1000 MPa and 1300 MPa, representing moderate- and high-performance design scenarios, respectively.

Pareto-optimal solutions were identified from the feasible design space using the concept of Pareto dominance. A laminate configuration was classified as Pareto-optimal if no other feasible design existed that simultaneously achieved lower cost and lower weight. The Pareto front was extracted by sorting feasible designs according to material cost and iteratively retaining only those designs exhibiting decreasing weight. This procedure efficiently identifies the non-dominated solutions in the two-objective cost–weight design space.

To facilitate engineering interpretation of the optimisation results, representative laminate configurations were selected along each Pareto front. These representative designs correspond to low-cost, low-weight, and balanced trade-off solutions, enabling systematic evaluation of the influence of stacking sequence and fibre volume fraction on the resulting cost–weight–strength relationships. The resulting Pareto fronts provide a physically interpretable visualisation of the trade-offs associated with hybrid laminate design and serve as a practical decision-making tool for selecting suitable laminate architectures under different performance requirements.

4. Results and Discussion

4.1. Accuracy of the Flexural Strength Surrogate

The predictive performance of the machine learning surrogate model was evaluated by comparing the predicted flexural strengths against the corresponding finite element analysis (FEA) results. Preliminary model selection studies were conducted using three ensemble learning algorithms, namely Random Forest, Extra Trees, and GB Regression. Five-fold cross-validation results indicated that the GB model provided the highest predictive accuracy, achieving a mean coefficient of determination of $R^2 = 0.899 \pm 0.027$) and a mean root mean square error (RMSE) of (59.3 ± 8.4) MPa. Consequently, GB Regression was adopted as the final surrogate model for subsequent optimisation.

The predictive capability of the final model was assessed using an independent test set comprising 40 previously unseen laminate configurations. The model achieved a coefficient of determination of ($R^2 = 0.946$), an RMSE of 44.8 MPa, and a mean absolute error (MAE) of 35.1 MPa. These results demonstrate excellent agreement between the machine learning predictions and the corresponding FEA-computed flexural strengths.

Figure 4 presents a parity plot comparing the predicted and FEA-computed flexural strengths for the independent test set. The majority of data points are closely distributed around the ideal 1:1 line, indicating that the surrogate model successfully captures the nonlinear relationship between laminate architecture and flexural performance. The high coefficient of determination and relatively low prediction errors confirm that the hybrid feature representation, which combines raw stacking sequence variables with physics-informed descriptors, effectively characterises the influence of fibre volume fraction and reinforcement distribution on laminate strength.

The absence of significant systematic bias across the investigated strength range further demonstrates the robustness of the surrogate model. Accurate prediction of both moderate- and high-strength laminates is particularly important for constrained optimisation, as prediction errors near the strength threshold may result in incorrect classification of feasible and infeasible designs. The observed predictive accuracy therefore provides confidence in the suitability of the surrogate model for large-scale design space exploration.

To further assess model robustness and dataset adequacy, a learning curve analysis was performed using five-fold cross-validation. Figure 5 shows that the cross-validation coefficient of determination increases steadily from approximately 0.46 for 20 training samples to approximately 0.91 for 192 training samples. Furthermore, the rate of improvement decreases beyond approximately 140–160 samples, indicating that the model is approaching convergence within the investigated design space. These results suggest that the available dataset captures the dominant relationships governing laminate flexural strength and that additional training data would likely yield only incremental improvements in predictive performance.

Overall, the GB surrogate provides a reliable and computationally efficient alternative to direct finite element simulations for evaluating flexural strength. By replacing computationally expensive FEA calculations with rapid surrogate predictions, the proposed framework enables efficient exploration of hundreds of thousands of candidate laminate configurations while maintaining close agreement with the underlying physics represented by the finite element models.

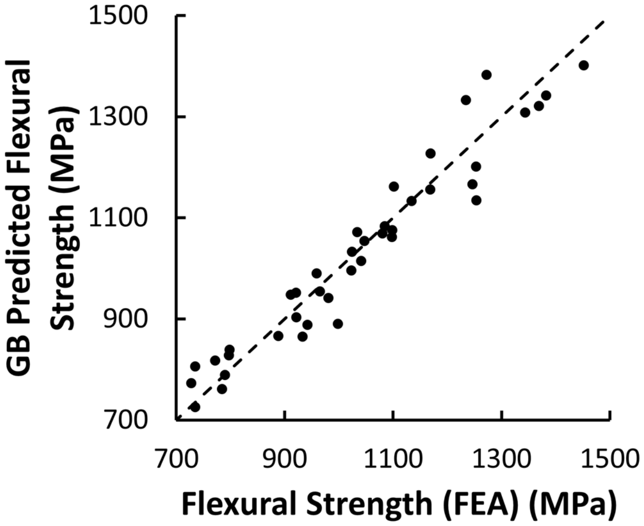

Figure 4. Predicted flexural strength versus FEA-computed values.

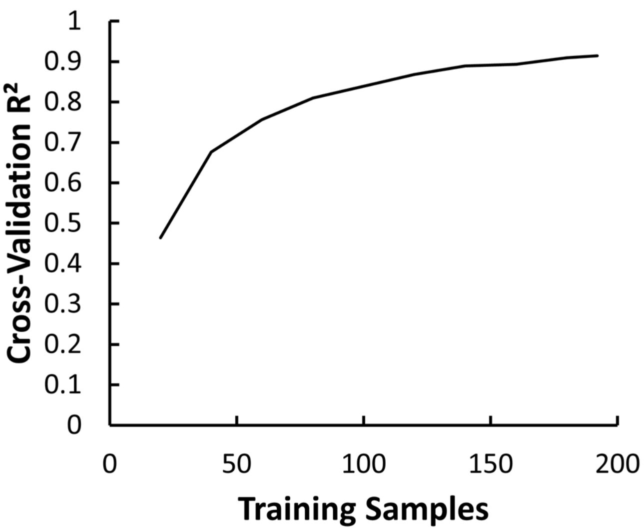

Figure 5. Learning curve of the GB model.

4.2. Pareto-Optimal Design Spaces

The proposed optimisation framework was applied to explore the trade-offs between laminate cost and weight under prescribed minimum flexural strength requirements. Two strength thresholds were considered, namely S_{Fmin}

= 1000 MPa and S_{Fmin} = 1300 MPa, in order to investigate how increasingly stringent performance constraints influence the feasible design space and the resulting Pareto-optimal solutions.

Figure 6 illustrates the corresponding Pareto fronts for both strength thresholds. For the lower strength requirement of 1000 MPa, 236,692 feasible laminate configurations were identified from the 500,000 Monte Carlo samples, spanning a wide range of cost and weight combinations. The resulting Pareto front exhibits a smooth and continuous trade-off between cost and weight, indicating substantial flexibility in laminate design when moderate strength requirements are imposed. In this regime, designers can achieve meaningful reductions in material cost by accepting moderate increases in weight, or conversely reduce weight at the expense of higher material cost. The ability to evaluate 500,000 candidate laminate configurations and identify over 236,000 feasible solutions demonstrates the computational efficiency of the surrogate-assisted optimisation framework. Such large-scale exploration would be impractical using direct finite element simulations alone.

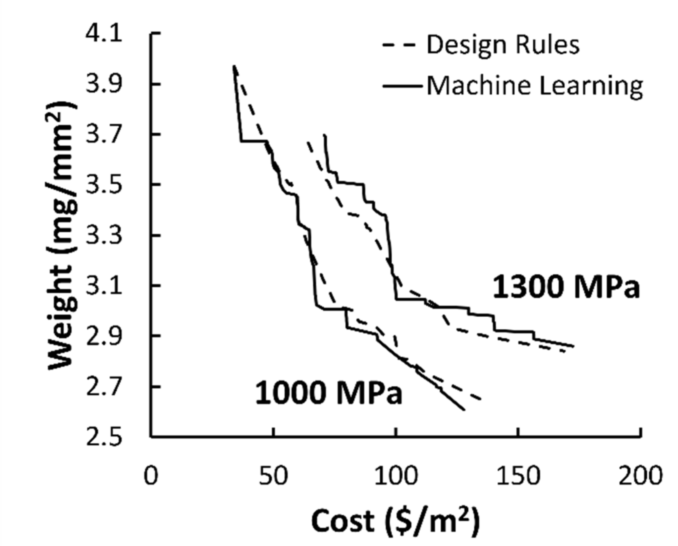

Figure 6. Comparison of Pareto fronts obtained using the proposed Gradient Boosting optimisation framework and the design-rule-based approach reported in Ref. [24] for minimum flexural strength requirements of 1000 MPa and 1300 MPa.

Increasing the minimum flexural strength requirement to 1300 MPa reduced the feasible design space to 29,982 configurations, corresponding to an 87% reduction in feasible solutions. The corresponding Pareto front shifts towards higher cost and lower weight. This behaviour reflects the increased reliance on carbon fibre reinforcement to achieve higher flexural strength, particularly in the outer plies where bending stresses are highest. As a result, weight reductions become increasingly dependent on the use of carbon fibres, leading to a steeper cost–weight trade-off.

The Pareto fronts obtained using the proposed machine-learning-assisted framework exhibit good overall agreement with those reported previously using the design-rule-based methodology [24]. In both approaches, increasing the strength requirement shifts the Pareto front towards higher cost and lower weight, reflecting the increased reliance on carbon fibre reinforcement. However, the machine learning framework identifies a smoother and more continuous set of Pareto-optimal solutions by directly exploring the mixed discrete–continuous design space. This demonstrates the ability of the proposed approach to generalise beyond predefined design rules while maintaining consistency with previously established design trends.

A comparison of the two Pareto fronts highlights the strong influence of performance constraints on optimal hybrid laminate design. At lower strength thresholds, hybrid configurations with a higher proportion of glass plies remain viable, enabling cost-effective solutions with acceptable structural performance. In contrast, stringent strength requirements restrict the design space to carbon-dominant laminates, reducing the potential for cost savings through hybridisation. This transition underscores the importance of explicitly accounting for strength constraints during optimisation, as designs that appear optimal under moderate requirements may become infeasible when higher performance levels are demanded.

The Pareto fronts obtained using the proposed framework provide a clear and interpretable visualisation of the trade-offs inherent in hybrid composite laminate design. By separating strength prediction from physics-based cost and weight evaluation, the framework enables efficient exploration of large design spaces while preserving physical transparency. The resulting Pareto-optimal solutions serve as a practical design guide for engineers seeking to balance structural performance, weight, and material cost. More importantly, the framework enables systematic exploration of large mixed discrete–continuous laminate design spaces that would otherwise be computationally prohibitive using direct finite element analysis.

4.3. Representative Optimal Designs

To facilitate engineering interpretation of the Pareto fronts, five representative laminate configurations were selected from each optimisation scenario. These designs correspond to the lowest-cost, low-cost/lighter, balanced (knee-point), low-weight/cheaper, and lowest-weight solutions along the Pareto front. Tables 3 and 4 summarise the resulting laminate architectures and associated performance metrics for the 1000 MPa and 1300 MPa strength constraints, respectively.

Table 3. Representative Pareto-optimal laminate designs for a minimum flexural strength of 1000 MPa.

Design	Layup (Ply1 → Ply8)	V_{fc}	V_{fg}	Flexural Strength (MPa)	Cost ($/m^2)	Weight (mg/mm^2)
Lowest cost	[GGGGGGGG]	-	0.600	1065.48	33.92	3.968
Low-cost / lighter	[GCGGGCGG]	0.301	0.524	1007.90	59.09	3.459
Balanced (knee)	[CGGGGCGG]	0.360	0.320	1013.58	67.51	3.024
Low-weight / cheaper	[CCGGCCCC]	0.301	0.378	1003.22	105.98	2.783
Lowest weight	[CCCCCCCC]	0.302	-	1011.59	127.83	2.608

Table 4. Representative Pareto-optimal laminate designs for a minimum flexural strength of 1300 MPa.

Design	Layup (Ply1 → Ply8)	V_{fc}	V_{fg}	Flexural Strength (MPa)	Cost ($/m^2)	Weight (mg/mm^2)
Lowest cost	[CGGGGCGG]	0.514	0.597	1311.33	70.73	3.696
Low-cost / lighter	[CCGGGCGG]	0.562	0.474	1306.53	95.99	3.361
Balanced (knee)	[CGGGGCCG]	0.572	0.302	1315.45	100.19	3.047
Low-weight / cheaper	[CCGCGCCC]	0.486	0.301	1306.62	141.12	2.922
Lowest weight	[CCCCCCCC]	0.480	-	1304.30	172.28	2.861

Several important design trends emerge from Tables 3 and 4. For the 1000 MPa strength requirement, the lowest-cost solution consists entirely of glass/epoxy plies and achieves a flexural strength of 1065 MPa, indicating that carbon reinforcement is not essential for moderate performance requirements when high fibre volume fractions are employed. As weight reduction becomes increasingly important, the optimisation progressively introduces carbon plies, particularly near the laminate surfaces, resulting in higher cost but lower structural weight.

For the 1300 MPa strength requirement, all representative designs contain carbon reinforcement in the outer plies, reflecting the critical role of carbon fibres in achieving high flexural strength. The lowest-cost solution already requires carbon plies at both laminate surfaces, while the lowest-weight solution converges to a fully carbon laminate. These results demonstrate that the benefits of hybridisation diminish as strength requirements increase, with carbon-dominant laminates becoming necessary to satisfy demanding performance constraints.

Interestingly, the balanced designs identified for both optimisation scenarios employ carbon plies primarily in the highly stressed outer regions while retaining glass plies in the interior layers. This behaviour is consistent with classical bending mechanics and highlights the ability of the optimisation framework to identify physically meaningful and economically efficient reinforcement distributions.

5. Discussion

The results demonstrate that the proposed physics-informed machine learning framework provides an effective and computationally efficient approach for the design optimisation of hybrid carbon/glass composite laminates under bending. By combining a GB surrogate model for flexural strength prediction with analytical formulations for laminate cost and weight, the framework successfully integrates data-driven modelling with established engineering principles. This hybrid strategy enables rapid exploration of large design spaces while maintaining physical transparency and interpretability.

A key finding of the study is the strong influence of reinforcement distribution through the laminate thickness on flexural performance. The feature importance analysis revealed that fibre volume fraction, carbon ply distribution, and reinforcement placement near the laminate surfaces are among the most influential variables governing flexural strength. These observations are consistent with classical laminate theory and flexural mechanics, which predict that the highest tensile and compressive stresses occur at the outer surfaces during bending. Consequently, the optimal laminate architectures identified in this study consistently favour the placement of carbon/epoxy plies near the tensile and compressive surfaces, while glass/epoxy plies are retained in less highly stressed interior regions whenever permitted by the strength constraint.

The predictive performance achieved by the GB surrogate further supports the suitability of machine learning for this class of composite design problems. The model achieved an independent test-set coefficient of determination of 0.946 and a root mean square error of 44.8 MPa, demonstrating excellent agreement with the corresponding finite element results. In addition, the five-fold cross-validation study yielded a mean coefficient of determination of 0.899 ± 0.027, while the learning curve analysis indicated that predictive performance approached convergence within the investigated design space. These results suggest that the available dataset captures the dominant relationships governing laminate flexural strength and that the resulting surrogate is sufficiently accurate for optimisation purposes.

The optimisation results highlight the strong dependence of feasible design space size on the imposed strength requirement. For the 1000 MPa strength constraint, 236,692 feasible laminate configurations were identified among the 500,000 candidate designs generated through Monte Carlo sampling. Increasing the minimum strength requirement to 1300 MPa reduced the feasible design space to 29,982 configurations, representing an approximately 87% reduction in the number of viable solutions. This substantial contraction of the feasible region demonstrates the increasingly restrictive influence of strength requirements on hybrid laminate design and illustrates the value of surrogate-assisted optimisation for efficiently identifying admissible solutions.

The comparison between the 1000 MPa and 1300 MPa optimisation scenarios also provides insight into the effectiveness of hybridisation. At moderate strength requirements, a wide range of hybrid architectures remains feasible, enabling meaningful reductions in material cost through selective substitution of carbon plies with glass plies. However, as the required strength increases, the optimisation framework increasingly favours carbon-dominant laminates, particularly in the outer plies. This behaviour reflects the superior specific strength and stiffness of carbon fibres and suggests that the economic advantages of hybridisation diminish as structural performance requirements become more demanding.

An important contribution of the present study is the deliberate separation of modelling responsibilities between machine learning and analytical formulations. Unlike fully data-driven optimisation frameworks, the proposed approach applies machine learning only to the quantity exhibiting complex nonlinear behaviour, namely flexural strength. In contrast, laminate cost and weight are evaluated using deterministic rule-of-mixtures relationships derived directly from constituent properties. This separation improves interpretability, reduces modelling uncertainty, and ensures that optimisation decisions remain grounded in physically meaningful quantities. From an engineering perspective, such transparency is desirable because it facilitates confidence in the optimisation results and supports practical decision-making.

Despite these strengths, several limitations should be acknowledged. The surrogate model is trained using finite element data and therefore inherits the assumptions associated with the underlying numerical model. Although excellent agreement was observed within the investigated design space, extrapolation beyond the specified fibre volume fraction range or stacking sequence configurations may reduce predictive accuracy. Furthermore, the present optimisation framework considers only flexural strength, cost, and weight. Other performance measures, such as fatigue resistance, impact performance, damage tolerance, and environmental durability, may also influence laminate selection in practical applications.

Future research could extend the framework by incorporating additional structural performance criteria, manufacturing constraints, and uncertainty quantification methods. The integration of life-cycle assessment metrics would further enable simultaneous optimisation of mechanical performance, cost, and environmental sustainability. Moreover, the methodology could be readily adapted to other hybrid composite systems, including carbon/flax, carbon/basalt, and glass/flax laminates, thereby broadening its applicability to sustainable composite design.

Overall, the proposed physics-informed machine learning framework provides a transparent, accurate, and computationally efficient pathway for exploring complex strength–weight–cost trade-offs in hybrid composite laminates. By combining the predictive capability of machine learning with physically based engineering models, the framework bridges the gap between advanced computational optimisation techniques and practical composite structural design.

6. Conclusions

A physics-informed machine learning framework has been developed for the multi-objective design optimisation of carbon/glass fibre reinforced hybrid composite laminates subjected to three-point bending. The proposed framework combines a GB surrogate model for flexural strength prediction with analytical rule-of-mixtures formulations for laminate cost and weight, enabling efficient and physically transparent exploration of a mixed discrete–continuous laminate design space.

A finite element dataset comprising 240 laminate configurations was generated and used to train and evaluate several ensemble learning algorithms. Among the models investigated, GB Regression achieved the highest predictive performance, yielding a five-fold cross-validation coefficient of determination of ($R^2 = 0.899 \pm 0.027$) and an independent test-set coefficient of determination of ($R^2 = 0.946$), with a root mean square error of 44.8 MPa. The learning curve analysis further demonstrated that the available dataset captures the dominant relationships governing laminate flexural strength within the investigated design space.

The surrogate model was subsequently integrated with physics-based cost and weight calculations within a Pareto optimisation framework. By evaluating 500,000 candidate laminate configurations, the framework efficiently identified feasible and Pareto-optimal solutions under prescribed minimum flexural strength requirements. For the 1000 MPa strength constraint, 236,692 feasible laminate configurations were identified, whereas increasing the strength requirement to 1300 MPa reduced the feasible design space to 29,982 configurations. The results revealed clear trade-offs between structural weight and material cost and demonstrated that increasingly stringent strength requirements favour carbon-rich laminate architectures.

Feature importance analysis and optimisation results consistently highlighted the dominant influence of fibre volume fraction, carbon ply distribution, and outer-ply reinforcement on laminate flexural strength. The optimal designs preferentially positioned carbon plies near the tensile and compressive surfaces, while glass plies were retained in less highly stressed interior regions whenever permitted by the strength constraint. These trends are consistent with established composite mechanics principles and provide physically interpretable design guidance for hybrid laminate development.

The proposed framework demonstrates that combining machine learning with physics-based engineering models can significantly reduce computational cost while maintaining predictive accuracy and interpretability. Future work will focus on incorporating additional performance criteria, manufacturing constraints, uncertainty quantification, and sustainability metrics into the optimisation process. The proposed physics-informed optimisation framework bridges the gap between high-fidelity simulation and practical engineering design, enabling rapid identification of cost-effective and lightweight hybrid composite laminates without the need for exhaustive finite element analyses.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data that support the findings of this study, including the finite element simulation results and processed datasets used for the analyses, are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author used OpenAI ChatGPT to assist with language editing, improving the clarity and readability of the manuscript, and refining the presentation of scientific content. The author reviewed and edited all AI-generated suggestions as needed, verified the technical accuracy of the manuscript, and takes full responsibility for the content of the published article.

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