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Data-Driven Stacking Sequence Optimization of Composite Laminates via Deep Learning Surrogate Models

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Abstract

This study addresses the computational bottleneck and manufacturing constraint integration challenges inherent in conventional genetic algorithm (GA) based stacking sequence optimisation for carbon fibre reinforced polymer (CFRP) laminates, where fitness evaluation traditionally relies on finite element analysis (FEA). A surrogate-assisted optimisation framework integrating one-dimensional convolutional neural networks (1D-CNN) with evolutionary algorithms is proposed to enable efficient stiffness optimisation while ensuring manufacturability. An automated batch processing pipeline combining Python scripting with Abaqus commercial software was developed to generate a high-fidelity dataset comprising 30,185 samples. The trained CNN surrogate achieves millisecond-level prediction of structural compliance with a coefficient of determination (R^2) of 0.9846 on the test set. To handle manufacturing constraints without sacrificing boundary search efficiency, a stepped soft-penalty fitness function was devised, quantifying violations of balance, contiguity, adjacency, and minimum proportion rules as continuous penalty metrics rather than binary hard penalties. Validation on a 40-layer cantilever beam demonstrates that the design feasibility rate reaches 80% within 20 generations, while the optimised solution surpasses the best feasible design in the original database by 6.43% in compliance reduction, with FEA verification errors below 1%. The proposed CNN-GA coupled framework effectively balances computational efficiency with engineering practicality, offering a viable pathway toward intelligent composite design.

Keywords: data-driven, surrogate model, stacking sequence optimisation, genetic algorithm, manufacturing constraints, composite material.

1 Introduction

Composite materials have found widespread applications in aerospace, automotive, and marine industries owing to their exceptional specific stiffness and strength, net-shape manufacturability, and superior resistance to chemical corrosion, fatigue, and impact loading [1, 2]. Carbon fibre reinforced polymer (CFRP) laminates, as representative configurations of fibre-reinforced composites, exhibit significant design flexibility arising from the anisotropic characteristics governed by fibre orientations [3]. Optimising fibre distribution patterns to tailor load transfer paths, structural stiffness, and natural frequencies represents a critical avenue for exploiting the load-bearing efficiency of composite laminates and achieving structural lightweighting [4]。

Genetic algorithms (GA) have emerged as the predominant methodology for stacking sequence optimisation of composite laminates, attributed to their robust performance in handling discrete variables, non-convex search spaces, and multi-objective formulations [5-8]. Nevertheless, conventional GA implementations rely on finite element analysis (FEA) for individual fitness evaluation [9, 10] , where single structural simulations demand substantial computational resources. The requirement for thousands of population evaluations across numerous generations results in prohibitively expensive computational costs, consequently restricting population sizes and evolutionary generations, thereby preventing adequate exploration of the design space and convergence toward global optima [6]. Furthermore, practical manufacturing necessitates adherence to specific process constraints [11, 12] , such as limiting consecutive plies of identical orientation to three layers and enforcing symmetric stacking sequences. Traditional approaches typically employ repair operators or rejection strategies to handle these discrete constraints, introducing additional complexity and computational overhead into the evolutionary process [13-15]. Consequently, resolving the computational bottleneck while ensuring optimisation accuracy and efficiently optimising mechanical performance under manufacturing constraints constitutes a critical challenge requiring immediate attention.

Advances in machine learning technologies offer promising avenues for alleviating the computational burdens [16-18]. Neural network-based predictors serving as surrogate models for FEA enable high-accuracy prediction of structural mechanical responses within milliseconds, directly assuming fitness evaluation responsibilities in genetic algorithms and substantially accelerating iterative processes without compromising evaluation fidelity [19, 20]. Existing investigations predominantly concentrate on surrogate model architecture refinement to enhance prediction accuracy, yet frequently overlook the integration of manufacturing constraints [21]. In practice, manufacturing process rules exhibit distinct logical discriminative characteristics amenable to penalty function formulations (soft constraint mechanisms), where constraint violation severity is quantified as fitness penalty terms. This approach maintains GA robustness while effectively guiding population evolution toward high-performance regions without sacrificing manufacturability.

To address these research gaps, this study proposes a CNN-surrogate-assisted genetic algorithm methodology for laminate optimisation design, aiming to achieve macroscopic structural stiffness optimisation while ensuring manufacturability. By constructing high-precision neural network predictors to replace finite element analysis, rapid mapping between stacking sequences and mechanical properties is established, enabling efficient population fitness evaluation. Manufacturing constraints are programmatically assessed through dedicated functions, and a stepped soft-penalty mechanism is integrated into the fitness function to guide the genetic algorithm in searching for performance-optimal solutions while respecting process rules. This paper establishes a comprehensive workflow encompassing finite element database construction, neural network predictor training, penalty-constraint-embedded genetic algorithm optimisation, and simulation verification. The remainder of this paper is organised as follows: Section 2 defines the target mechanical responses and manufacturing design constraints for laminates, and elaborates on the training data construction procedure; Section 3 details the neural network predictor architecture and genetic algorithm training strategy, validates the prediction accuracy and computational efficiency, and expounds the design of the manufacturing constraint penalty mechanism; Section 4 presents validation cases using typical laminate structures, comparing optimisation results with finite element simulation data to verify the effectiveness in computational efficiency and optimisation quality; Section 5 concludes with the core contributions and future research directions.

2 Problem Definition and Data Construction

This section delineates the optimisation objectives and constraints encompassed herein and expounds upon the database construction methodology.

2.1 Mechanical Performance Indicators

Addressing performance requirements for deformation control in composite structures, this study selects structural compliance as the characteristic parameter for macroscopic mechanical response quantification, enabling intuitive revelation of how stacking sequence design governs structural stiffness. It is noteworthy that the forward solution accuracy of compliance using existing FEA methods has been thoroughly validated; selecting this response as the performance metric provides reliable support for constructing high-quality datasets.

According to the Classical Laminated Plate Theory (CLT), the constitutive equations for laminates are defined, with the element stiffness matrix expressed by Equation (1):

$$\mathbf{K}_i = \iint \begin{bmatrix} \mathbf{B}_p \\ \mathbf{B}_b \end{bmatrix}_i^{\mathrm{T}} \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B} & \mathbf{D} \end{bmatrix}_i \begin{bmatrix} \mathbf{B}_p \\ \mathbf{B}_b \end{bmatrix}_i dxdy \tag{1}$$

where **A**, **B**, and **D** represent the extensional stiffness matrix, bending stiffness matrix, and coupling stiffness matrix of the laminate, respectively. The mid-plane strains and curvatures at arbitrary locations within the element are related to nodal displacements through the element strain-displacement matrices $\mathbf{B}_p$ and $\mathbf{B}_b$, which are computed from element shape functions and their spatial derivatives.

The physical essence of compliance represents the deformation magnitude generated in a structure under unit external loading, directly reflecting the structure's capacity to resist deformation induced by external loads. Under the premises of linear elastic constitutive relations and small deformation assumptions, structural compliance exhibits a strictly reciprocal relationship with stiffness, enabling direct quantification of global deformation behaviour without reliance on local stress-strain details. This characteristic renders compliance suitable for engineering stiffness assessment of complex structures such as composite laminates. Based on the aforementioned theory and finite element methodology, individual element stiffness matrices are assembled into the global structural stiffness matrix **K**, with the structural compliance expressed as:

$$C = \sum_{i=1}^{N} C_i = \frac{1}{2}\mathbf{u}^{\mathrm{T}}\mathbf{K}\mathbf{u} \tag{2}$$

where **u** denotes the global nodal displacement vector.

2.2 Manufacturing Constraint Definitions

Given the characteristics of composite laminates, including numerous design variables and complex failure mechanisms, mature empirical design guidelines have been established within the industry to direct stacking sequence formulation and enhance laminate manufacturability. This study incorporates six specific manufacturing constraints during the stacking sequence design process:

- **Discrete angle constraint:** Ply orientations are restricted to discrete values of 0°, ±45°, and 90°.
- **Symmetry constraint:** The stacking sequence must satisfy symmetry requirements to eliminate extensional-bending stiffness coupling effects.
- **Balance constraint:** The number of plies with opposite fibre orientations must remain consistent (e.g., equal counts for −45° and +45° plies) to eliminate in-plane shear-extensional stiffness coupling phenomena.
- **Contiguity constraint:** Consecutive plies of identical orientation must not exceed three layers, preventing crack propagation and interlaminar edge effects.
- **Adjacency constraint:** The angular difference between adjacent plies must remain below 90° to reduce interlaminar shear stress levels.
- **Minimum proportion constraint:** Each orientation must occupy at least 10% of the total ply count to avoid structural failures induced by secondary loading modes and ensure comprehensive mechanical performance reserves.

The symmetry constraint is inherently satisfied by fixing the design variables to represent half the stacking sequence; the discrete angle constraint is internalized within the data structure through one-hot encoding. Both constraints are naturally incorporated into the design process by the prediction model and genetic algorithm. The remaining four constraint rules are embedded into the offspring screening process through soft-penalty fitness mechanisms, ensuring the manufacturing feasibility of stacking sequence solutions.

2.3 Database Construction

The quality of the training dataset constitutes a critical determinant of the model performance ceiling, directly governing inference accuracy in prediction tasks [22] . Primary evaluation dimensions for database quality encompass annotation precision, distribution completeness, sample diversity, and statistical rationality [23] . These characteristics collectively determine the model's capability to learn mapping relationships between parameters and labels.

The annotation information for the database constructed in this work primarily comprises structural mechanical performance metrics, where mechanical response acquisition remains entirely dependent upon finite element simulation. The substantial computational redundancy causes this phase to occupy over 90% of the temporal cost in the overall optimisation workflow. Consequently, this study established a fully automated batch simulation and post-processing framework based on Python and Abaqus, as illustrated in Figure 1.

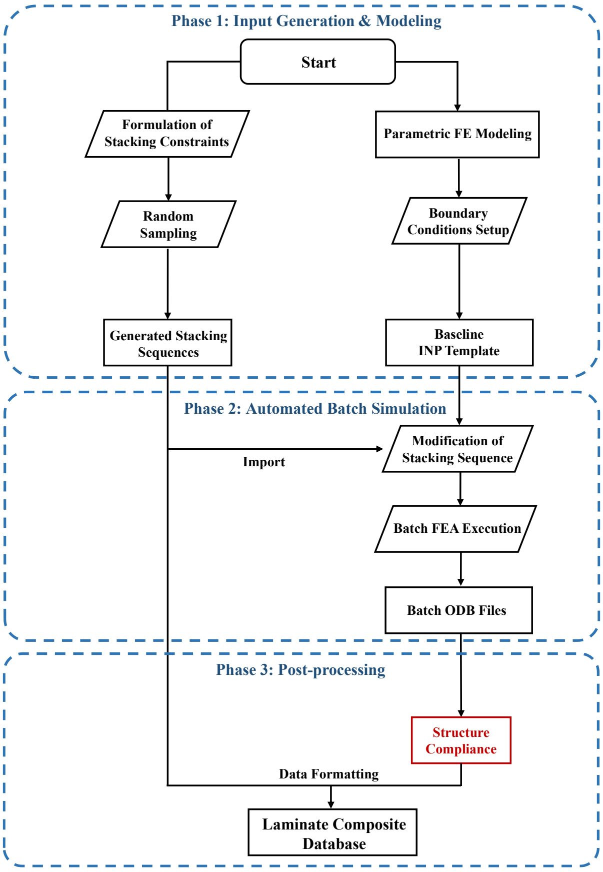

Figure 1: Flowchart of batch FEA simulation and data post-processing based on Python and Abaqus.

Upon defining structural load cases and boundary conditions, a baseline finite element model is initially established in Abaqus, encompassing geometric modelling, material property assignment, mesh generation, and load and boundary condition application. During this process, the PythonReader tool is utilized to comprehensively record the complete command tree, enabling development of parameterized reusable analysis scripts for rapid iteration of material definitions and modelling configurations, thereby enhancing analysis iteration efficiency. Subsequently, the pre-configured baseline analysis model is exported in INP format (notably, INP files exhibit significantly smaller volume than CAE model files while preserving all essential information required for finite element analysis). By traversing the stacking sequence database, Python scripts perform batch character replacement of material orientations and interlaminar property blocks within INP files, achieving second-level generation of analysis files with automatic submission to the Abaqus solver. Finally, additional Python scripts conduct post-processing of ODB result files, automatically extracting structural compliance in batch mode. Mechanical performance labels are then merged with corresponding stacking sequences and output as standardized CSV datasets readable by neural networks. This automated workflow completely eliminates manual intervention, substantially improving the acquisition efficiency of high-fidelity finite element data while simultaneously providing tools for rapid verification of final optimised designs.

3 CNN-GA Coupled Optimisation Framework

This section elaborates the neural network predictor-based genetic algorithm framework proposed in this study.

3.1 CNN Predictor Design

Given that composite laminate stacking sequence data constitutes typical structured sequential data, one-dimensional convolutional neural networks (1D-CNN) demonstrate superior performance in extracting interlaminar local features and global spatial correlations from such data through their one-dimensional sliding window mechanism. Consequently, the underlying network architecture in this study is constructed around 1D-CNN as the core component.

The network architecture of the prediction model is illustrated in Figure 2, primarily comprising a convolutional feature extraction module and multi-output prediction heads. The module contains four cascaded convolutional blocks. To avoid spatial information loss associated with conventional pooling operations, this model employs strided convolution strategies for feature map downsampling. Simultaneously, batch normalization (BN), ReLU activation functions, and Dropout regularization (with a dropout rate of 0.1) are introduced at each layer to effectively alleviate model overfitting and ensure stability in multi-task learning.

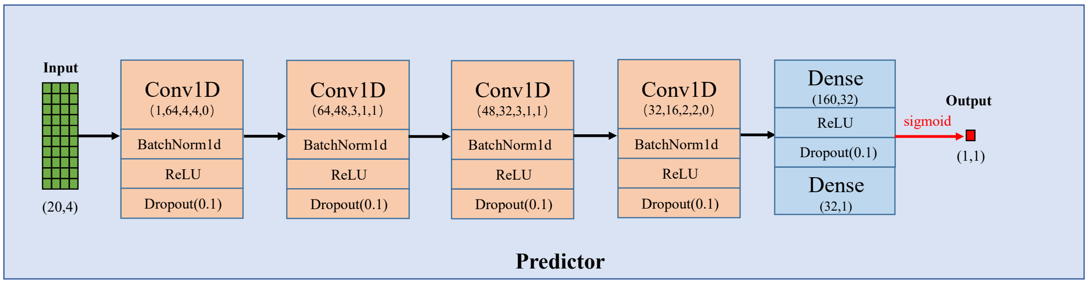

Figure 2: Neural network architectures and hyperparameters of predictor model.

For the mechanical performance regression task, the Huber loss (Equation (3)) is employed. This loss function approximates L2 loss for small errors, exhibiting smooth and easily convergent characteristics; for large errors, it approximates L1 loss, effectively mitigating gradient interference from outliers and demonstrating superior robustness, making it suitable for precise regression of continuous-value indicators. The loss function expression is:

$$Loss_{\mathrm{reg}} = \begin{cases} \frac{1}{2}e^2, |e| \leq \delta \\ \delta\left(|e| - \frac{1}{2}\delta\right), |e| > \delta \end{cases} \tag{3}$$

where e represents the mechanical performance prediction error, and $\delta = 1$ (default parameter for Huber loss).

3.2 Genetic Algorithm Workflow

This study proposes a hierarchical nested optimisation architecture combining the global search capabilities of genetic algorithms with the rapid prediction capabilities of deep neural networks.

The first layer comprises the foundational genetic algorithm architecture, implemented using the PyGAD library for population evolution, responsible for global optimisation within the discrete design space (combinations of ply angles). Population individuals are represented as 20-dimensional discrete vectors, with each gene dimension taking values from the discrete angle set.

Addressing the strongly constrained nature of composite laminate design problems, a hybrid seeding initialization strategy is adopted. Thirty superior individuals verified to satisfy all manufacturing constraints are extracted from the historical database as initial seeds, while the remaining seventy individuals are generated through random sampling in discrete space. This ensures the presence of feasible solutions in the initial population to guide evolutionary direction while introducing random genes to maintain population diversity and avoid premature convergence. Integer encoding is employed for individuals, with tournament selection for the selection operator, complemented by an elitism strategy that directly preserves the top four individuals from each generation to the next, preventing loss of superior gene segments during crossover and mutation. The two-point crossover operator is selected, which is suitable for maintaining gene block structures within stacking sequences. The population size is set to 100, with evolutionary generations limited to 100. Empirical evidence demonstrates that this approach balances search breadth with computational cost control, sufficient to enable fitness curve convergence to stable levels.

The second layer constitutes the neural network surrogate model layer, where a CNN regression model serves as the surrogate for fitness evaluation. This model maps 20-dimensional stacking sequences to 80-dimensional inputs through one-hot encoding, subsequently predicting laminate structural compliance indicators through convolutional feature extraction. Single forward propagation requires less than 10 ms, achieving four orders of magnitude acceleration compared to conventional finite element analysis, effectively releasing fitness computation cost burdens.

The third layer represents the manufacturing constraint evaluation layer. Addressing the strong manufacturing constraint characteristics in composite design, this study proposes a stepped soft-penalty fitness function to embed four composite manufacturing process constraints into the optimisation workflow, resolving the feasible domain boundary search inefficiency and early evolutionary stagnation issues caused by traditional hard penalty approaches.

This study establishes continuous penalty functions for four manufacturing process constraints, transforming discrete feasible/infeasible judgments into differentiable violation severity metrics:

Rule 1 (Balance constraint): Requires strict equality between the number of −45° and +45° plies. Letting $\Delta n = |n_{-45} - n_{45}|$ represent the quantity difference, the penalty function is:

$$P_1 = \Delta n \times 1.5 \tag{4}$$

Rule 2 (Contiguity constraint): Prohibits consecutive stacking of identical orientations exceeding three layers. Letting $c_{\max}$ represent the maximum consecutive repetition count for an individual, the penalty function is:

$$P_2 = \max\left(0, c_{\max} - 3\right) \times 2.0 \tag{5}$$

Rule 3 (Adjacency constraint): Prohibits angular differences of 90° between adjacent plies. Letting Z_p represent the angular difference for the p-th pair of adjacent layers, the penalty function adopts binary classification values:

$$P_3 = \begin{cases} 3.0, \text{ if } \exists p \in \{1,2,\ldots,19\} : Z_p = 90^\circ \\ 0, \quad \text{otherwise} \end{cases} \tag{6}$$

Rule 4 (Minimum proportion constraint): Requires each of the four orientations to occupy at least 10% of the total. Letting ρ_i represent the proportion of angle *i*, the penalty function is:

$$P_4 = \sum_{i=1}^{4} \max\left(0, 0.1 - \rho_i\right) \times 30.0 \tag{7}$$

The total penalty value represents the sum of individual rule penalties:

$$P_{\text{total}} = \sum_{k=1}^{4} P_k \tag{8}$$

A two-tier fitness function is established to strengthen the manufacturing constraint screening mechanism:

$$F = \begin{cases} 10f, & \text{if } P_{\text{total}} = 0 \\ -P_{\text{total}}, & \text{if } P_{\text{total}} > 0 \end{cases} \tag{9}$$

where f represents normalised objective approaching degree, calculated as:

$$f = 1 - \frac{\left|A_{\text{pred}} - A_{\text{target}}\right|}{\max(A_{\text{target}} - A_{\text{min}}, A_{\text{max}} - A_{\text{target}})} \tag{10}$$

with value range [0, 1], where values closer to the target objective approach 1.

This two-tier fitness function establishes an isolation mechanism: any individual satisfying all manufacturing constraints achieves superior fitness compared to all violating individuals, ensuring priority fulfillment of manufacturing constraints before mechanical performance optimisation. Through soft-penalty guidance, fitness and violation degree form a continuous gradient field pointing toward feasible domain boundaries, guiding population evolution along penalty descent directions and significantly improving feasible domain boundary search efficiency.

3.3 Performance Evaluation

The proposed prediction model is implemented based on the open-source PyTorch library, with training acceleration completed on an NVIDIA GeForce GTX 1660 GPU platform. Network parameters are updated using the Adam optimizer, with batch size set to 64. The ReduceLROnPlateau strategy is employed for dynamic adjustment: when validation metrics cease improvement, the learning rate decays by 5% every 10 epochs, with a lower bound constrained to 1.0×10^{-4}.

The training iteration curves for the prediction model are presented in Figure 3(a)–(b). Training is configured for a maximum of 130 epochs, with overall loss curves for both training and validation sets exhibiting monotonic smooth downward trends, stable convergence processes, and no apparent oscillation or overfitting phenomena. The coefficient of determination (R^2) for the regression task converges rapidly, with prediction fidelity on the test set for the optimal model verified in Figure 3(c). The macroscopic structural compliance outputs from the model demonstrate high linear correlation with true values along the ideal reference line, achieving an R^2 of 0.9846.

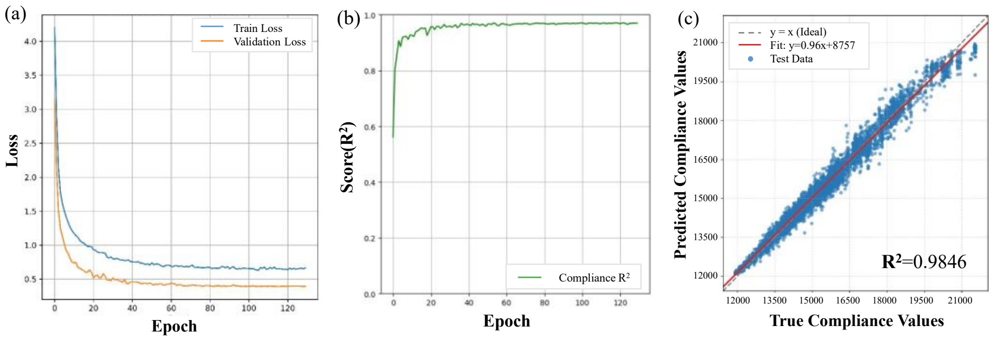

Figure 3: Training iteration curves of the predictor and performance evaluation
results: (a)-(b) Loss iteration curves; (c) Regression task for compliance.

4 Results and discussions

This section applies the constructed neural network predictor-embedded genetic algorithm framework to stacking sequence optimisation design for a typical cantilever beam structure, with effectiveness verification through FEA validation.

4.1 Composite Laminate Cantilever Beam Model and Boundary Constraint Definition

For the composite cantilever beam case study, this section first clarifies structural characteristics and loading conditions, with boundary conditions and design constraints illustrated in Figure 4. Detailed design requirements are specified as follows:

1) **Loading and boundary conditions:** One side plane of the cantilever beam is fully fixed, while the opposite side boundary is subjected to vertical concentrated force F_1 parallel to the Z-axis and horizontal concentrated force F_2 parallel to the X-axis.

2) **Stacking space constraints:** Total ply count is 40 layers, with available ply angles restricted to ±45°, 0°, and 90°.

3) **Optimisation objective:** Minimize macroscopic structural compliance under strict satisfaction of all manufacturing constraints defined in Section 2.2.

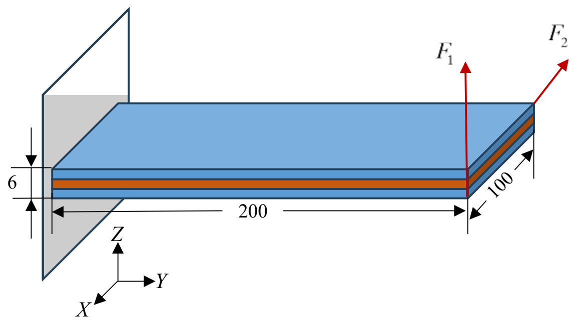

Figure 4: Schematic diagram of composite laminated cantilever beam.

E_1/GPa	E_2/GPa	G_{12}/GPa	G_{13}/GPa	G_{23}/GPa	v_{12}	Thickness/mm
131	9	5.4	5.4	4.5	0.33	0.15

Table 1: Material properties of CFRP laminates.

For the aforementioned loading conditions, the database is constructed according to the methodology described in Section 2. A total of 30,185 samples are generated, among which 8,053 feasible samples satisfying all manufacturing constraints account for 30%. As illustrated in Figure 5, the minimum structural compliance in the global sample space is 12,038 J; however, when constraining the space to the subset "satisfying all manufacturing constraints" the minimum compliance degrades to 13,145 J. Evidently, significant performance gaps exist between randomly generated process-feasible samples and theoretical optima, representing the potential improvement space targeted by the optimisation methodology proposed in this paper.

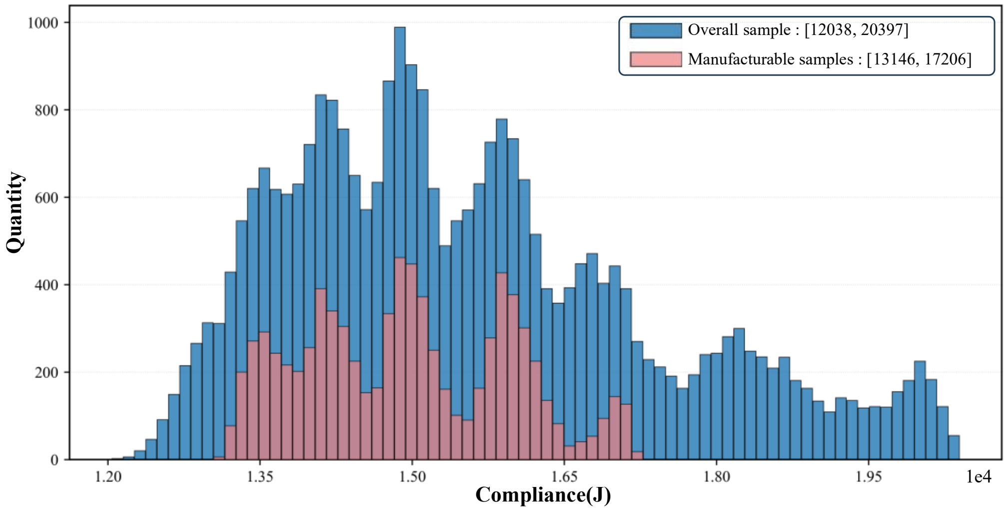

Figure 5: Compliance distribution of database samples.

4.2 Optimised Design Scheme and Verification

Based on the aforementioned database, with minimization of overall structural compliance as the optimisation objective, 30 samples satisfying manufacturability with superior performance are selected from the initial database and mixed with 70 randomly generated samples as the genetic algorithm parent generation. The optimisation target is set to 12,000 J, with design optimisation conducted under satisfaction of all manufacturing constraints. As illustrated in Figure 6, the offspring process-compliant ratio rises to 80% within 20 steps, demonstrating that the algorithm establishes reliable constraint satisfaction mechanisms in early stages. After 30 steps, the population stabilizes within a high-quality feasible solution region, with evolutionary trajectories precisely conforming to the design principle of "ensuring manufacturability satisfaction first, then optimising structural performance." Ultimately, fitness values stabilize at 9.610, with the population establishing stable manufacturing-performance levels.

Superior performance design schemes satisfying manufacturing constraints are extracted from offspring results. To verify optimisation result reliability, Abaqus finite element software is employed for simulation verification of optimal samples. As presented in Table 2, relative errors between predicted and simulated values remain below 1%. Compared with the best manufacturability-feasible sample in the original database (compliance 13,146 J), the optimal sample generated by the proposed method achieves performance improvements up to 6.43%.

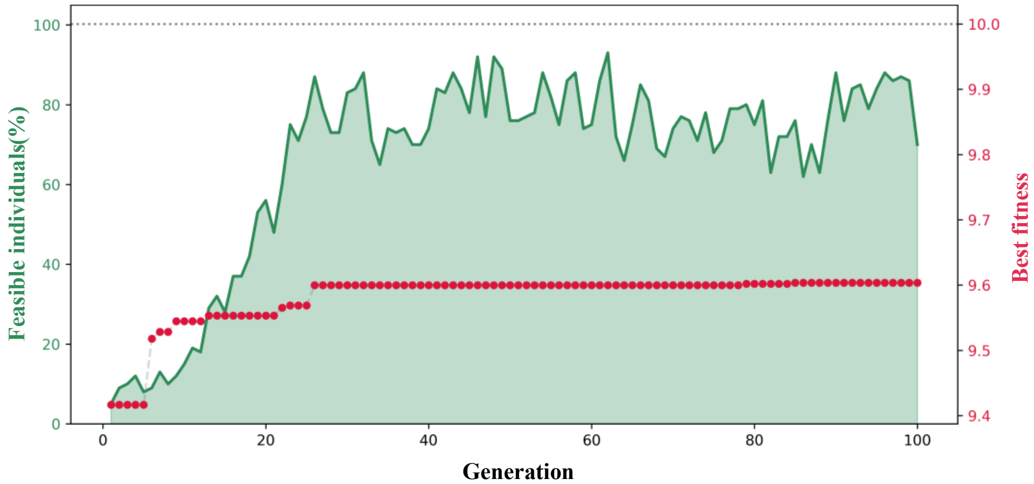

Figure 6: Iteration process of genetic algorithm based on stepwise soft penalty strategy.

No.	Stacking Sequence	Predicted Compliance	Simulated Compliance	Prediction Error	Actual Optimizaiton
1	$[-45/90_2/45/0/45/90_2/-45/90/45/90/-45/0/45/90_2/-45/90_2]_S$	12339J	12301J	-0.31%	6.43%
2	$[-45/90_2/45/0/45/90_2/-45/90/45/0/-45/90/45/90_2/-45/90_2]_S$	12477J	12358J	-0.96%	5.99%
3	$[45/0/45/90/45/90_2/-45/90_2/45/0/-45/90/-45/90_2/-45/90_2]_S$	12554J	12504J	-0.40%	4.88%
4	$[90/-45_2/90/45_2/0_2/45/90/45/90/-45/90_2/-45_2/90]_S$	/	13146J	/	/

Table 2: Optimised stacking sequence results and verification comparison.

5 Conclusion

Addressing the critical challenges of prohibitive computational costs and manufacturing constraint integration difficulties in carbon fibre reinforced polymer (CFRP) laminate optimisation, this paper proposes a genetic algorithm optimisation framework based on one-dimensional convolutional neural network surrogate models. By constructing data-driven surrogate models to replace traditional finite element analysis (FEA) and designing stepped soft-penalty mechanisms to handle complex manufacturing constraints, efficient structural stiffness optimisation for laminates under manufacturability prerequisites is achieved.

Compared with conventional heuristic algorithms, the primary innovative contributions of this research include: (1) Designing a four-layer cascaded convolutional neural network architecture tailored to the structural characteristics of stacking sequence data, achieving approximately four orders of magnitude acceleration compared to traditional finite element analysis while maintaining prediction errors below 1%, thereby validating the advantages of data-driven methodologies. (2) Establishing an innovative stepped soft-penalty fitness function that quantifies four manufacturing constraints as violation severity metrics, resolving the boundary search inefficiency issues caused by traditional hard penalty approaches.

In summary, the CNN-GA coupled framework proposed in this paper overcomes the computational bottlenecks caused by traditional genetic algorithm reliance on finite element analysis, providing a solution that balances computational efficiency with engineering practicality for intelligent composite laminate design.

Acknowledgements

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