Optimization Analysis of Rib Placement in Stiffened Laminated Plates Based on the Meshless Method

Dongyan Wei
School of Green Building and Low-Carbon Technologies, Guangxi Technological College of Machinery and Electricity, Nanning, China

Abstract: To achieve the objective of maximizing the fundamental natural frequency of stiffened laminated plates under uniformly distributed loads, the optimization of rib placement in stiffened laminated plate structures is investigated by combining the Meshless method with the genetic algorithm. During the optimization process, the rib positions need to be continuously adjusted. Owing to the fact that the meshless method discretizes the structure using a set of nodes, there is no need to rearrange the nodes as the design variables change, which ensures computational accuracy while significantly improving efficiency. Finally, numerical examples are presented to optimize the rib placement in stiffened laminated plates so as to maximize the fundamental frequency. Comparisons with ABAQUS results demonstrate the effectiveness of the proposed approach.

Keywords: Stiffened Laminated Plates; Genetic Algorithm; First-Order Shear Deformation Theory; Moving Least Squares; Meshless Method

1. Introduction

With the advancement of industrialization and scientific technology, the optimal design of various engineering structures has become a prominent research topic. Accordingly, extensive studies have been conducted on the optimization of stiffened laminated plate structures. Among numerous optimization algorithms, the genetic algorithm (GA) has been widely adopted due to its excellent performance in searching for optimal solutions of both continuous and discrete variables. For example, Montemurro et al. [1] proposed a multiscale two-level GA to simultaneously optimize the geometric and mechanical parameters of skins and stiffeners at different characteristic scales (mesoscopic and macroscopic). An et al. [2] employed a GA-based approach to optimize the stacking sequences of stiffeners and panels as discrete variables. Moradi et al. [3] developed a hybrid optimization algorithm combining particle swarm optimization and GA to determine the optimal fiber orientations of composite stiffened laminated plates under maximum buckling loads. Talele et al. [4] proposed a parallel optimization method for the topology of longitudinal stiffeners and fiber architecture in grid-stiffened traction composite structures to enhance buckling performance. Qiao and Yao [5] established an optimization algorithm for the stacking sequence design of composite stiffened plates by combining the equivalent bending stiffness method with GA. Wang [6] proposed an optimization framework based on surrogate models, layout–size–sequence updating, and a multi-island GA to optimize the stacking sequences of skins and stiffeners in composite thin-walled stiffened plates. Wu and Yao [7] developed a two-level optimization strategy: the first level employed an approximate model-based layout optimization to determine the layout configuration and cross-sectional dimensions of stiffened plates, while the second level combined the equivalent bending stiffness method and GA to optimize the stacking sequence under a fixed number of laminate plies. Li [8] aims to construct an optimization model for building structure design based on genetic algorithm.

In the study of the mechanical responses of stiffened laminated plates, numerical methods constitute the most fundamental analytical tools. Among them, the finite element method (FEM) has received extensive attention due to its efficiency and robustness. However, for problems involving mesh distortion and mesh movement, meshless methods exhibit distinct advantages. Meshless approaches allow for the convenient construction of high-order shape functions, effectively avoid shear locking, improve computational accuracy, and reduce post-processing efforts. At present, several studies have applied meshless methods to composite laminated plates. Cosentino and Weaver [9] proposed a meshless method combining the Rayleigh–Ritz approach with Galerkin techniques and applied it to the buckling prediction of discretely assembled, multi-gap composite stiffened plates. Liew et al. [10, 11] modeled stiffened corrugated plates as equivalent orthotropic plate–beam composite structures and analyzed their free vibration and buckling behaviors using the meshless Galerkin method. Ardestani et al. [12] based on the first-order shear deformation theory, employed the reproducing kernel particle method to investigate the bending behavior of functionally graded stiffened rectangular and circular plates. Zhang et al. [13] significantly improved the buckling performance of Ω-shaped stiffened composite plates by introducing multiple materials and optimizing their distribution and stacking sequences while maintaining structural strength. Sheth and Joshi [14] conducted a static analysis of stiffened laminated plates using a newly developed higher-order stiffened shell element (Higher Order Stiffened Shell Element, HOST9). To date, although a substantial body of literature has applied meshless methods to composite laminated plates, relatively few studies have focused on the mechanical responses of composite stiffened laminated plates using meshless approaches. In particular, investigations employing the moving least squares (MLS) meshless method for the static and dynamic response analysis of stiffened laminated plates remain scarce, which constitutes a primary motivation of the present study.

In addition, optimization studies on composite stiffened laminated plates have attracted considerable scholarly attention, with most research concentrating on the optimization of dimensions, geometries, and stacking sequences. Some studies have also integrated meshless methods into optimization frameworks. For instance, Tamijani et al. [15] analyzed curved-rib stiffened structures using the meshless Galerkin method and, based on a Kriging surrogate model and GA, determined the optimal stiffener curvature for maximizing buckling load, followed by size optimization under fixed stiffener geometry to minimize structural mass. Domestic studies by Li [16] and Qin et al. [17] also applied meshless methods to the optimization of stiffened plate structures; however, their work primarily targeted isotropic stiffened plates, with minimum deflection as the objective function and GA-based optimization of stiffener layouts. Wang et al. [18] addressed the layout optimization problem of ribs in stiffened plate structures by adopting a robust structural layout optimization method that accounts for load uncertainties, thereby achieving simultaneous optimization of both the layout and dimensions of the stiffened plates. Compared with isotropic materials, composite materials exhibit more complex mechanical properties, rendering their optimal design more challenging. Overall, there remain very limited studies that integrate meshless methods into optimization algorithms for the optimization of composite stiffened laminated plates.

In view of the above, the present study combines the genetic algorithm with the moving least squares meshless method to perform an optimization analysis of stiffener locations in isotropic stiffened laminated plates, with the maximization of the fundamental natural frequency as the objective function. Numerical examples are finally presented to optimize stiffener positions and to verify the accuracy and effectiveness of the proposed method.

2. Theory of Genetic Algorithms

Genetic algorithms are optimization methods based on the principles of biological evolution and genetics, designed to simulate the process of natural selection and survival of the fittest. The algorithm starts from an initial population of candidate solutions and iteratively applies a series of genetic operators, such as selection, crossover, and mutation, to preserve superior individuals while eliminating inferior ones. As the optimization proceeds over successive generations, individuals with higher fitness gradually dominate the population, and an approximate optimal solution to the objective function can ultimately be obtained.

2.1 Encoding Schemes

The encoding schemes used in genetic algorithms are generally classified into binary encoding, symbolic encoding, and integer encoding. Binary encoding is the most commonly adopted scheme. It employs a binary symbol set composed of digits 0 and 1, where a binary string represents a design variable. The length of the binary code is determined according to the required solution precision of the problem under consideration. For a discretized interval [x_1, x_2] with a specified discretization accuracy *p,* the encoding length can be calculated as follows:

$$L = \log_2\left(\frac{x_2 - x_1}{p+1}\right) \quad (1)$$

In practice, the encoding length usually needs to be rounded to an integer. According to the encoding rules, once the encoding length is determined, the binary strings must be decoded to obtain the actual values of the design variables for each individual in the initial population.

Symbolic encoding consists of a set of symbols without numerical values but with predefined meanings, such as {A, B, C}, where each symbol set represents a design variable. This encoding scheme has a limited range of applicability and is mainly suitable for optimization problems in which design variables cannot be expressed numerically. Integer encoding represents design variables using integer strings of a specified length, where the encoding length is related to the number of selected design variables. In general, integer encoding offers greater flexibility and is particularly suitable for problems such as angle optimization.

2.2 Encoding Schemes

In genetic algorithms, the initial population is randomly generated within the search space of the optimization problem, based on the feasible range of the optimal solution. The population size is typically chosen in the range of 20 to 100 individuals. Increasing the population size helps maintain population diversity; however, it may also reduce computational efficiency. Given the predetermined population size and encoding length, the encoding matrix of the initial population can be generated randomly.

2.3 Fitness Function

Fitness is a quantitative measure used to evaluate the quality of individuals in a population. During the evolutionary process of a genetic algorithm, the fitness value determines whether an individual is selected for reproduction or eliminated. Individuals with relatively higher fitness values are more likely to survive into the next generation, whereas those with lower fitness values may be discarded. In general, the fitness value reflects the potential of an individual to approach or achieve the optimal solution.

The formulation of the fitness function is closely related to the objective function of the optimization problem and can typically be classified into the following two categories:

(1) For optimization problems with a maximization objective, the fitness function is defined as:

$$F(x) = \begin{cases} f(x) + C_{\min}, & \text{if } f(x) + C_{\min} > 0 \\ 0, & \text{if } f(x) + C_{\min} < 0 \end{cases} \quad (2)$$

In Equation (2), $F(x)$ denotes the fitness function, $f(x)$ is the objective function, and $C_{\min}$ is an estimate of the minimum value of $f(x)$, which is usually taken as 0.

(2) For optimization problems with a minimization objective, the fitness function is defined as:

$$F(x) = \begin{cases} C_{\max} - f(x), & \text{if } f(x) < C_{\max} \\ 0, & \text{if } f(x) \geq C_{\max} \end{cases} \quad (3)$$

In Equation (3), $C_{\max}$ can be chosen arbitrarily, but it is usually taken as 1.

2.4 Selection

After calculating the fitness values as described in Fitness Function, the genetic algorithm performs natural selection on the individuals of the previous generation. Typically, natural selection can be implemented using either the roulette wheel method or the ranking method. In this study, the roulette wheel method is employed. The relative fitness of each individual compared to the total population determines its probability of survival—the higher the proportion, the greater the likelihood that the individual will be selected. The procedure is as follows:

(1) Sum the fitness values of all individuals to obtain the total fitness.

(2) Divide each individual's fitness value by the total fitness to obtain the normalized fitness for each individual.

(3) Calculate the cumulative fitness and map it onto a roulette wheel.

When the roulette "spins," a random number is generated. The individual whose cumulative fitness first exceeds this random number is selected to advance to the next generation. It should be noted that the population size determines the number of individuals selected, and after the selection operation, the population size remains unchanged.

For example, assume a population of three individuals: the selection probability of individual 1 is 0.2, giving it a subinterval of [0, 0.2); individual 2 has a probability of 0.3, corresponding to [0.2, 0.5); and individual 3 has a probability of 0.5, corresponding to [0.5, 1]. If three random numbers generated are 0.65, 0.8, and 0.1, the selected individuals would be individual 3, individual 3, and individual 1, respectively.

2.5 Crossover

Crossover is a critical operation in genetic algorithms, as its implementation significantly affects the convergence speed of the algorithm. Crossover involves exchanging segments of genetic material between two individuals in the population to produce two new offspring. The procedure can be illustrated as follows: suppose two parent genes are 101001 and 100101, and a crossover point is randomly selected at position 3. The sequences after this point are swapped, generating two new offspring: 101101 and 100001. The selection of crossover points should follow a uniform distribution. This type of crossover is known as single-point crossover.

After natural selection reduces the population to a subset of individuals, crossover restores the population to its original size. The new population contains individuals from multiple generations, as the offspring generated through crossover are added to the existing individuals. The advantage of single-point crossover is that it preserves favorable traits within the genes. However, as the number of crossover points increases, the likelihood of disrupting well-adapted gene structures rises, which can negatively affect the performance of the genetic algorithm. Typically, the crossover probability is set between 0.4 and 0.99.

2.6 Mutation

Mutation simulates the genetic variations that occur in biological evolution. It involves altering the alleles of individuals in the population to generate new offspring. The effectiveness of mutation influences both the termination of the algorithm and the ability to approach a global optimum. For example, using binary encoding, suppose a gene 011001 satisfies the mutation condition, and a mutation point is randomly selected at position 2. The value at this position is flipped, resulting in the mutated gene 001001.

Mutation is applied only to the newly generated offspring; parent individuals are not mutated. Because mutation changes the genetic encoding of individuals, the mutation probability is usually set relatively low, typically between 0.001~0.1.

3. Numerical Example

To verify the accuracy of the optimization algorithm developed in this study, a numerical example is conducted using a single rib in the x-direction as the design case. The placement of the rib in an isotropic stiffened laminated plate is optimized to maximize the fundamental natural frequency, as shown in Figure 1. The geometric dimensions and material properties of the laminated plate and rib are consistent with those specified in Section 3.3.2.2, and the laminate stacking sequence is [0°/90°/0°]. To ensure the convergence speed and computational accuracy of the optimization algorithm, the following parameters are adopted: crossover probability P_m=0.05, mutation probability, number of genetic iterations = 20, and population size = 20. Using ABAQUS to model the plate with the rib located at the center, the fundamental frequency is 1430.2 Hz, and the rib's y-coordinate is 0.127 m.

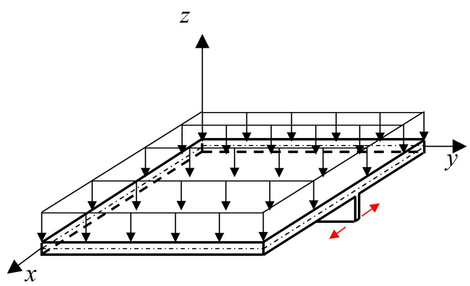

Figure 1. Isotropic Stiffened Laminated Plates under Uniform Loads

The genetic algorithm is used to optimize the rib position in three independent runs. The optimal x-direction rib placement results and the corresponding mode shapes are presented in Table 1 and Figure 2. As seen from the table, the relative errors between the optimized results and ABAQUS calculations are all within 5%, and the fundamental frequency mode shapes in Figure 3 closely match the ABAQUS results. This demonstrates the accuracy of the genetic algorithm in determining the optimal rib placement in isotropic stiffened laminated plates. Although the results of the three runs differ slightly due to the same algorithm parameters, repeated optimization shows that the fundamental frequency generally converges toward a stable value, which most likely corresponds to a local optimum. This variability can be attributed to the inherent randomness in the genetic algorithm, including the generation of the initial population and the selection process. The optimization curve is shown in Figure 3. Around the 19th iteration, the central deflection of the stiffened laminated plate approaches its optimal value, indicating the high efficiency of the algorithm in searching for the rib's optimal position. It can also be observed that larger deviations occur at iterations 3, 8, 13, and 17. Such deviations are likely caused by the early stages of the genetic algorithm, where individuals with higher fitness are repeatedly selected for reproduction, leading to excessive replication within the population and premature convergence to a local optimum—a phenomenon known as "premature convergence."

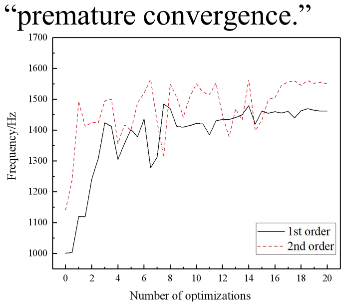

Figure 2. The Optimization Process of Rib Location for Stiffened Laminated Plates with One Rib

Table 1. Optimization Results of Rib Location for Isotropic Stiffened Laminated Plates

No.	*y-Coordinate of Rib in x-Direction (m)*	Fundamental Frequency (Hz)	Relative Error (%)
1	0.1277	1460.1	2.091
2	0.1265	1460.3	2.104
3	0.1255	1459.0	2.013

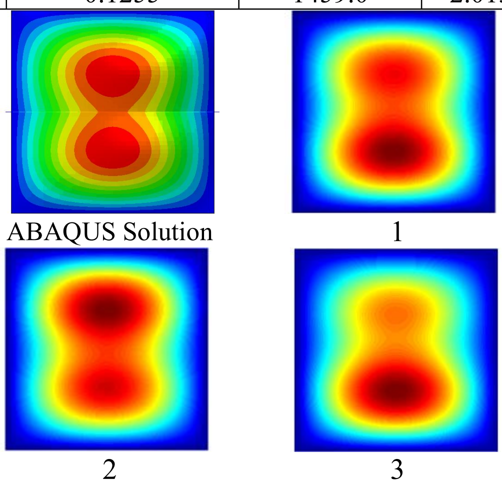

Figure 3. The Frequency of Optimization for Rib Location

4. Conclusion

This study first introduces the fundamental principles of the genetic algorithm and applies it to the optimization of isotropic stiffened laminated plates, with the rib position as the design variable and the maximization of the fundamental frequency as the objective function. Building on this, the stacking sequence of laminated ribs in composite stiffened plates is further optimized. By combining the meshless method with the genetic algorithm, significant advantages are achieved in optimizing both rib placement and laminate stacking. As design variables change, there is no need to redistribute the plate nodes; only the transformation matrix T_p needs to be recalculated. This approach ensures computational accuracy while improving efficiency. The numerical example demonstrates that the genetic algorithm is effective in optimizing the rib positions of isotropic stiffened laminated plates.

Acknowledgments

This paper is supported by Natural Science Project of Guangxi Technological College of Machinery and Electricity: "Study on the Linear Mechanical Behavior of Stiffened Laminated Plates Based on Meshless Method" (2023YKYZ009)

References

[1] Montemurro M, Pagani A, Fiordilino G A, et al. A general multi-scale two-level optimisation strategy for designing composite stiffened panels. Composite Structures, 2018, 201: 968-979.
[2] An H, Chen S, Huang H. Multi-objective optimization of a composite stiffened panel for hybrid design of stiffener layout and laminate stacking sequence. Structural and Multidisciplinary Optimization, 2018, 57(4): 1411-1426.
[3] Moradi S, Vosoughi A R, Anjabin N. Maximum buckling load of stiffened laminated composite panel by an improved hybrid PSO-GA optimization technique. Thin-Walled Structures, 2021, 160(6): 107382.
[4] Talele M, Haupt M, van Tooren M, et al. Concurrent stringer topology and skin steered fiber pattern optimization for grid stiffened composite shell structures. Composite Structures, 2021, 266: 113804.

[5] Wei Qiao, Weixing Yao. Equivalent bending stiffness method for stacking sequence optimization of composite stiffened panel. Chinese Journal of Computational Mechanics, 2011, 28(1): 158-162.
[6] Ru Wang. Analysis and Optimization Design for Thin Wall StiffenedComposite Panels. Dalian: Dalian University of Technology, 2014.
[7] Lili Wu, Weixing Yao. Two-Level Collaborative Optimum Design Method forComposite Stiffened Panel. Journal of Nanjing University of Aeronautics & Astronautics, 2011, 43(5): 645-649.
[8] Li Y .Optimization Method of Building Structure Design Based on Genetic Algorithm. Procedia Computer Science, 2025, 262(000):1344-1351.DOI:10.1016/j.procs.2025.05.180.
[9] Cosentino E, Weaver P. Buckling of stiffened composite panels with stringer terminations. Journal of Mechanics of Materials and Structures, 2010, 4(9): 1505-1533.
[10] Liew K M, Peng L X, Kitipornchai S. Vibration analysis of corrugated Reissner-Mindlin plates using a mesh-free Galerkin method. International Journal of Mechanical Sciences, 2009, 51(9-10): 642-652.
[11] Liew K M, Peng L X, Kitipornchai S. Buckling analysis of corrugated plates using a mesh-free Galerkin method based on the first-order shear deformation theory. Computational Mechanics, 2006, 38(1): 61-75.
[12] Ardestani M M, Soltani B, Shams S. Analysis of functionally graded stiffened plates based on FSDT utilizing reproducing kernel particle method. Composite Structures, 2014, 112(6): 231-240.
[13] Zhang J C, Jia W Q, Peng X, et al. Buckling analysis and structural optimization of multiple-material omega stiffened composite panel. Mechanics of Advanced Materials and Structures, 2024: 1-17.
[14] Sheth K, Joshi R. Development of higher order stiffened shell element (HOST9) for the static analysis of stiffened laminated plates. Civil and Environmental Engineering, 2024, 20(1): 217-232.
[15] Tamijani A Y, Mulani S B, Kapania R K. A framework combining meshless analysis and adaptive kriging for optimization of stiffened panels. Structural and Multidisciplinary Optimization, 2014, 49(4): 577-594.
[16] Linyuan Li. Optimal Design of Rectangular Stiffened Plate by Meshless Method. Nanning: Guangxi University, 2016.
[17] Xia Qin, Shanshan Liu, Yajing Shen et al. Rib Meshless Optimization of Stiffened Plates Resting On Elastic Foundation Based On Genetic Algorithm. Chinese Journal of Theoretical and Applied Mechanics, 2020, 52(1): 93-110.
[18] Xuan Wang, Zilu Sheng, Xiang Chen, et al. Robust layout optimization of stiffened plate structures considering load uncertainty. Journal of Chongqing University, 2025.

