Research Article

Weight optimization of hybrid composite laminate using learning-oriented artificial algae algorithm

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Abstract
The optimal design of parameters is vital for the effective use of hybrid composite laminated structures. This is due to a highly dependent property of laminated composite structures strength on its fiber orientation, stacking sequence and the number of ply in each laminate. The main aim of this study is to apply Learning-Oriented Artificial Algae Algorithm for optimization of the weight of rectangular hybrid composite laminated plate subjected to compressive in-plane loading. The design parameters are number of plies and stacking sequence of the laminate. The critical buckling factor is the constraint of the optimization process. The parameters of the hybrid composite plate are optimized using Learning-Oriented Artificial Algae Algorithm with the aim of minimizing weight. The performance of the algorithm was compared with previous studies that employed the GA and ACO algorithms. The Learning-Oriented method is integrated to reduce the number of functions evaluated and in turn reducing computational cost. The results showed that Learning-Oriented Artificial Algae Algorithm outperformed GA and ACO, and hence can be successfully applied in the optimization of laminated composite structures.

Keywords Artificial algae algorithm · Buckling load · Hybrid composite laminate · Weight optimization · Stacking sequence

1 Introduction

Composite materials have been extensively used in different sectors such as automotive industries [1], civil structures [2], aerospace structures [3, 4], marine structures and other engineering applications [5, 6]. Hybrid composite laminates are composed of two or more different reinforcements or fibers to provide a lighter weight and better mechanical properties with a lower cost, for example, Carbon/Glass epoxy composite [7]. Due to their interesting properties such as high stiffness to strength ratio, small weight and density, hybrid laminated composite have been attracting different industries and researchers. The effective use of composite laminated structures depends on optimal design. The strength of the laminated composite structures highly depends on its fiber orientation, stacking sequence and the number of ply in each lamina. However, it is a difficult task to obtain right combinations of these parameters unless optimization algorithm is employed. For that reason many researchers studied the optimization of material usage in terms of fiber orientation, lamina thickness, stacking sequence or geometric parameters [8, 9].

The laminated composite structure design involves design variables like fiber orientation, ply thickness, and stacking sequence. Most commonly used objective functions and constraints are weight, stiffness, ply thickness, vibration, fracture mechanics, as well as buckling loads

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[8, 10]. More specifically, some researchers attempted to minimize the laminate thickness [8, 9, 11–13] or ply angles [11, 14, 15] by considering as a continuous design variables. Other researchers [8, 14, 16], considered the thickness and stacking sequence angles as continuous variables. However, it was recommended that the optimum values should be rounded to the closest distinct manufacturable values.

Lopez et al. [14] studied optimization of laminated composites for weight and material cost minimization of laminated plates. In the study, the plates were exposed to in-plane loads considering Tsai–Wu, maximum stress and the Puck failure criterion as a constraint. GA was used to solve the problem considering the orientation of ply and the number of layers as design variables. The results showed that optimal structures highly varies according to the failure criterion employed and the loading conditions. Sørensen, Lund [17] studied thickness optimization of laminated composite structures using a gradient-based method. They incorporated thickness filters to decrease the number of constraints and design variables.

Praveen et al. [18] proposed multi-objective method for weight and cost optimization of hybrid laminated composite. The weight, stacking sequence, and cost of the hybrid materials made from graphite/epoxy and glass/epoxy were optimized using a modified non-dominated sorting GA.

Fan et al. [19] optimized the global stacking sequence of multi-laminate-panel composite structures with ply-drops using GA. Minimization of the weight of laminated composite plate under different constraints such as frequency constraint, fiber volume fractions and thicknesses of the layers was investigated [20]. Smoothed finite element method named as the cell-based smoothed discrete shear gap method (CS-DSG3) was applied in the analysis and the adaptive elitist differential evolution (aeDE) algorithm was used for optimization.

Feghoul et al. [21] investigated the optimization of structural configuration of laminates by maximization of buckling resistance under the influence of fiber orientation as a constraint and GA was used in the optimization process. The result showed that the buckling factor parameters highly affected by different fiber orientations.

Chen et al. [22] introduced special mutation-interference operators into the PSO algorithm for reliability-based optimization of a composite laminate. The introduction of the operator increases the swarm variety and boost the convergence rate of the algorithm. The analysis of structural reliability maximization and the minimization of the total laminate weight was the focus of the paper in which, the stacking sequence is considered as design criteria. The authors recommended that the investigation of lamination parametric optimization and optimal composite laminate design involving more than one material with different design constraints.

Hemmatian et al. [23] studied the minimization of cost and weight of hybrid-laminated composites subjected to the first natural flexural frequency. The optimization process was done using the multi-objective gravitational search algorithm by considering number of layers and the fiber orientations as design variables. In comparison with GA Ant Colony Optimization (ACO), MOGASA showed better performance.

Most of the studies focused on composite material under different loading conditions with constraints such as fixed fiber orientation angle (for example 90°, ± 45° and 0°) [14, 24–26], fixed ply thickness, for example, 64 layers [24, 26], in-plane loading [8, 12, 14], buckling loading [24, 26–29], with a fixed composite parameters.

In this study, we proposed a Learning-Oriented Artificial Algae Algorithm for weight minimization of an interply hybrid composite laminate that is subjected to in-plane compressive loads with buckling load factor as a constraint. The orientation of fiber (stacking sequence) and number of plies are considered as design parameters. The number of layers of the laminate is not predetermined at the initial stage of the optimization; rather it is determined after the end of the optimization process. The fiber orientation (θ) and number of plies (n) is in the range [− 90, 90] and [1, 20] respectively.

2 Materials and Methods

2.1 Problem formulation

In this study, a hybrid Carbon/Glass/epoxy rectangular composite plates having length a and width b are used in the optimization. A laminated rectangular plate with simply supported along ends $x = 0, x = a, y = 0$ *and* $y = b$, which is subjected to uniform in-plane compressive load per unit length in the X-direction and Y-direction was considered. The plate geometry and the applied loads are indicated in Fig. 1. According to classical laminate theory, each ply is assumed to be under plane stress condition [30, 31]. When the amplitude parameter reaches a value critical buckling load factor, λ_{cri}, given by (Eq. 1), the hybrid composite plate buckles into two half-waves, m and n, in the x and y directions.

$$\lambda_{cri} = \min_{m,n} \left\{ \frac{\pi^2 \left[m^4 D_{11} + 2(D_{12} + 2D_{66})(rmn)^2 + (rn)^4 D_{22} \right]}{(am)^2 N_x + (ran)^2 N_y} \right\} \tag{1}$$

where D_{ij} is bending stiffness coefficients, and λ_{cri} is called the critical buckling load factor the derivation of the

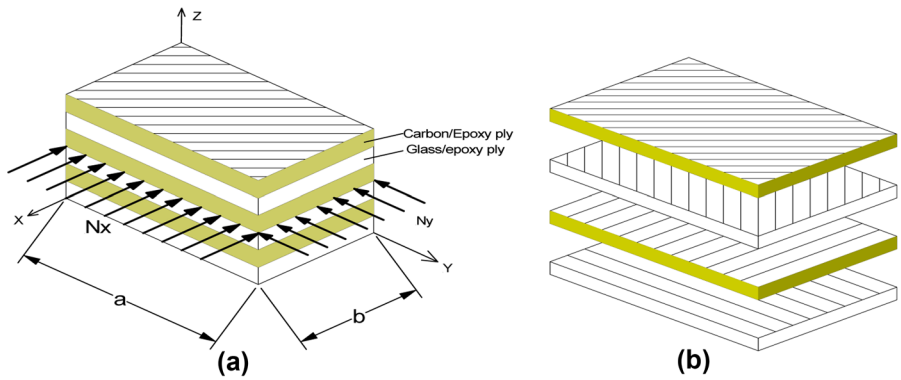

Fig. 1 Composite Laminate with **a** the in-plane loading with their stacking sequence and in-plane loading **b** orientation of the fiber for different Lamina

equation for D_{ij} from classical laminate theory as discussed in Ref. [26]. Details of classical laminate theory is discussed in [16]

$$D_{ij} = 2\sum_{k=1}^{p=24} (\overline{Q}_{ij})_k \left[t_{ok} n_k \overline{Z}_k^2 + \frac{(t_{ok} n_k)^3}{12} \right] \tag{2}$$

where t_{ok} – is the thickness of kth lamina and $\overline{Z}_k$ – is the distance to the centroid of the kth orthotropic lamina

The critical buckling load factor λ_{cri} is chosen as the smallest value of the term in brackets under appropriate m and n values. Lambda governs the maximum load that the laminate can resist without buckling and fluctuates with the plate aspect ratio, loading ratio and type of material. The critical buckling load factor λ_{cri} should be greater than one inorder to avoid sudden failure of the material. According to the report [30], if the plate aspect ratio and bending stiffness coefficients are small, the critical values of m and n should be small.

Accordingly in this study, the values of m and n are taken from the list [(1, 1), (1, 2), (2, 1), (2, 2)] in which, the smallest of λ_{cri} is evaluated. The hybrid composite plate under consideration has length $a = 0.9144$ m and plate aspect ratio $r = {}^{a}/_{b} = [0.5, 1, 1.2, 1.5, \text{and } 2]$. The compressive in-plane loads are [($N_x = 750$, $N_y = 1000$), ($N_x = 1000$, $N_y = 1000$), ($N_x = 2000$, $N_y = 1000$), ($N_x = 1000$, $N_y = 2000$), ($N_x = 1500$, $N_y = 2000$)]. In addition, the ply thickness of each layer is 0.127 mm and the gravitational due to acceleration is 9.81 N/Kg.

The main aim of this study is to apply Learning-Oriented Artificial Algae Algorithm for minimization of the weight of the hybrid composite laminate, which is made of two different fiber with epoxy laminates with different properties under buckling loading. The learning-oriented method is introduced to reduce unnecessary fitness evaluation by the optimizer algorithm. The laminate used in this study is assumed to be symmetric and balanced. The constraint for the problem is the critical buckling load factor (λ_{cri}). Thus, the objective function is expressed as:

Determine: $\{\theta_k, n\}$ *where*, $\theta_k \in [-90, 90]$, *and*, $k = 1, \ldots, n$, *where*, $n-$ is the number of plies

Minimize: Weight

$$W = Mass \times Gravity = mg = \rho \times a \times b \times t_{total} \times g \tag{3}$$

$$W = a \times b \times g \times \rho \times 2\sum_{k=1}^{p=24} n_k t_{ok} \tag{4}$$

Subjected to: ($\lambda_{cri} > 1$)where a is the length of the plate,b is the width of plate, p is the maximum ply number in each lamina, g is gravitational acceleration, ρ is the density of the composite,n_k and t_k are the number of ply and thickness of the kth lamina respectively.

2.2 Material properties

In this study, a hybrid composite made from Glass/Epoxy and Carbon/Epoxy was used. The elastic material properties of these composites are indicated in Table 1. The material properties like Longitudinal Young's Modulus (E1), Transverse Young's Modulus (E2), Shear Modulus (G12), Poison's Ratio, Density and Ply thickness are adopted from [27].

2.3 An overview of Artificial Algae Algorithm (AAA)

Meta-heuristic algorithms, for their stochastic behavior and capability of searching globally, have been used to optimize and solve numerous engineering problems. Hybrid composite laminate involves parameters that should be optimized to produce composite laminate that can satisfy critical buckling load factor constraint. Meta-heuristic algorithms have been applied in optimization of parameters of composite material [18, 22, 23, 27, 31–33]. In this study, we applied the Artificial Algae Algorithm; a recently introduced meta-heuristic algorithm established from helical movement, evolutionary and adoption processes [34]. At the beginning of the optimization, and n are

initialized in the range [−90, 90] and [1, 20] respectively. The initial fitness is evaluated and the size of algal colony is computed as in (Eq. 5 and 6).

$$CS' = \mu_i \times CS \tag{5}$$

$$\mu = \frac{\mu_{\max} S}{K_s + S} \tag{6}$$

where *CS* is the size of the *ith* colony, μ is the growth rate, μ_{max} is the maximum specific growth rate, S is the amount of nutrient which is the fitness value, and *K* is a constant representing substrate half-saturation of the colony.

Helical movement is a movement of algal cells to the surface of the water where sufficient light is available. The speed of the movement depends on the friction surface and the energy level it consumed. The higher the friction, the more frequent is the helical movement. Consequently, they can search better locally. The energy level of algal cells depends on the number of nutrients absorbed. Hence, when the algal cell approaches the surface, it means that it consumed more energy than others did. When algae move from its current position to the position of the food source, they burn energy (denoted as energy loss,e_L). However, when the friction surface is less, they cover longer distances and explore better globally. The Artificial Algae Algorithm takes into an assumption that the gravity is zero. The position of a particular algal cell depends on the force dragging its movement in the liquid, which is the shear force, and the friction surface computed using (Eq. 7).

$$\tau(\omega_i) = 2\pi\left(\sqrt[3]{\frac{3CS}{4\pi}}\right)^2 \tag{7}$$

Neighbor algal colony is selected using tournament selection and candidate solution is generated by updating three dimensions according to (Eqs. 8–10).

$$\omega_{ip}(t+1) = \omega_{ip} + (\omega_{jp} - \omega_{ip})(\Delta - \tau(\omega_i))\bar{p} \tag{8}$$

$$\omega_{iq}(t+1) = \omega_{iq} + (\omega_{jq} - \omega_{iq})(\Delta - \tau(\omega_i))\cos\alpha \tag{9}$$

$$\omega_{ir}(t+1) = \omega_{ir} + (\omega_{jr} - \omega_{ir})(\Delta - \tau(\omega_i))\sin\beta \tag{10}$$

where $\omega_{ip}, \omega_{iq}, \omega_{ir}$ are current solutions selected randomly and ω_j is neighbor algal colony identified by tournament selection; α, β ∈ [0,2π], Δ is the shear force;$\tau(\omega_i)$ is the friction surface area of the *ith* algal cell and $\bar{p} \in [-1, 1]$.

In the *evolutionary process*, given that the colony got enough nutrient and light, an alga reproduces into two new algal cells. Otherwise, the algal colony dies after some time. The growing algal colony gets bigger as it continues providing good solutions. On the other side, algal cells that are in the non-growing colony get diminished in size; therefore, they are the smallest colony.

$$BC = \max(CS) \tag{11}$$

$$SC = \min(CS) \tag{12}$$

$$SC = BC \tag{13}$$

where *BC* and *SC* are the biggest and smallest colony respectively.

The *adaption process* is where an algal colony that has not grown sufficiently attempts for survival. In AAA, each artificial algae is initialized with zero starvation value. The colony that has better solution keeps growing. Nevertheless, the colony that does not result in better solution became more starved; therefore, its starvation level is incremented. The algal cell, which is starved most, is chosen for adaption.

$$\phi = \max(A_i) \tag{14}$$

$$\phi(t+1) = \phi + rand \times (BC - \phi) \tag{15}$$

where ϕ is the starving, A_i is the starvation value of the *ith* algal colony, starving represents the colony with a maximum starvation level. The adaption parameter, A_p is a constant between 0 and 1 and determines whether or not to get into the adaption process.

2.4 The proposed approach

Uymaz et al. [34] evaluated the performance of the AAA in optimizing continuous problem and pressure vessel optimization. In AAA, helical movement allows to update three parameters in a single movement. The evolutionary process helps to evolve new solutions based on good performing solutions. In addition, the adaption helps to keeping best performing solutions. These characteristics made it to achieve outstanding results for non-linear problem optimization as compared to Artificial Bee Colony, Harmony Search, Ant Colony, Bee algorithm and Differential Evolution algorithms. Yet, for AAA to be successful in optimizing engineering problems, for example hybrid composite laminate problems, it has to be improved for robust performance. Similar to other meta-heuristic algorithms, AAA generates solutions randomly and fitness evaluations are undertaken. Following that, it does a greedy decision between the previous and current fitness results. However, greedy behavior may lead the algorithm to get stuck to local minima. In addition, in optimization algorithms the maximum number of fitness evaluations is fixed. Hence, for the optimizer to be competitive it has to obtain the

optimal value within the given range of maximum fitness evaluations.

On top of that, obtaining optimal result with minimum fitness evaluation is much preferable in engineering problems. In this respect, Yibre, Koçer [35] introduced Gaussian-based Naïve Bayes algorithm to estimate the potential of a candidate solution for successful fitness updates. The authors has thoroughly investigated the efficiency of the method for continuous optimization problem and revealed the importance of predicting quality of candidate solution is vital in improving the performance of AAA and at the same time save unnecessary fitness computations. Figure 3 illustrates convergence comparison of LOAAA against the original AAA, artificial bee colony, bat algorithm, flower pollination algorithm, bee algorithm, particle swarm optimization algorithm, genetic algorithm and ant colony optimization algorithm. Well-known benchmark functions namely; schewefel2.21, Sphere, Penalized1, Penalized2, Quartic and SumPower were employed. As it can be seen in Fig. 3, the LOAAA has achieved outstanding results for both unimodal and multimodal test suites functions with dimension size. Due to these achievements of LOAAA, we employed it for optimization parameters of hybrid composite material in the search of minimum weight.

In composite optimization, not every trial of fitness evaluation of candidate solution is concluded with successful fitness updates. In such situations, the unwanted fitness evaluations should be minimized so that the optimizer algorithm finds optimal weight of hybrid composite laminates with minimum fitness evaluations. It is computationally preferable to achieve best results with minimum fitness evaluations. In which case the optimization algorithm is capable of finding optimal result with possible minimum iterations. Therefore, we proposed a learning-oriented fitness update mechanism that is integrated with the AAA. Instead of randomly generating candidate solutions and evaluating them, we designed the optimizer to partially behave in an informed manner. The learning-oriented model learns from the history of generated candidate solutions and their successful or unsuccessful fitness updates. Then after building learning model, the optimizer algorithm will partially act in an informed manner. By doing so, unwanted fitness evaluations are avoided or minimized and better parameter values which high probably lead to successful fitness updates are identified. Thus, the proposed method is designed to find a minimum weight of hybrid composite material with relatively minimum fitness evaluation. Figure 2 illustrates the workflow of the proposed method for hybrid composite optimization.

Consider new ω_i be candidate solution, which is a combination of n and θ is generated according to (Eqs. 8–10). The new solution is a vector with dimension D. The conditional probability of the candidate solution to give better and feasible fitness can be predicted using Naïve Bayes as in (Eq. 16).

$$P(\Upsilon|\omega_{i1\ldots j}) = \frac{P(\Upsilon_i)P(\omega_{i1\ldots j}|\Upsilon_i)}{P(\omega_{i1\ldots j})} \tag{16}$$

where $P(\Upsilon_i)$ is class conditional probability; $P(\omega_{i1\ldots j}|\Upsilon_i)$ is the probability of each parameter given the class; Υ_i is the class labeled according to their fitness quality, and $i = 1\ldots m$, $j = 1\ldots D$. The weights are real-valued, thus, the Gaussian method can be used to compute the probability of the new solution as in (Eq. 17).

$$P(\omega_{ij} = \varphi|\Upsilon_i) = \frac{1}{\sqrt{2\pi^2}} e^{\frac{-(\varphi-\delta)^2}{2\sigma^2}} \tag{17}$$

where φ is the value of the ith alga at the jth dimension, σ^2 and δ are the variance and mean of the vector ω_i respectively. The vector ω_i that end up with successful fitness update is grouped to class 1, whereas those that did not are grouped to class 0. Therefore, ω_i is assigned to the class $\hat{Y}$ whose Gaussian probability is the maximum using (Eq. 18).

$$\hat{Y} = \begin{cases} 1, & P(\omega_i|Y_i = 1) > \mathrm{P}(\omega_i|Y_i = 0 \\ 0, & otherwise \end{cases} \tag{18}$$

2.5 Constraint handling

While searching for optimal parameters that can minimize the weight of hybrid composite laminate, the critical buckling load factor is the constraint that should be handled. The critical loading factor, $\lambda_{cri} > 1$, must be satisfied so that solutions be considered as feasible. In this study, we have employed, the death penalty constraint handling method. For its simplicity, ease of implementation and computational efficiency, death penalty is popular constraint handling technique [36]. Hence, solutions that do not satisfy the critical buckling load factor are ignored.

3 Results and Discussion

Numerical simulations were carried out in order to evaluate the performance of the proposed algorithm for hybrid composite laminate applications. The parameter setting for the LOAAA are shown in Table 2.

The numerical simulations are executed for three different cases as indicated in Sects. 3.1–3.5. In the first case, the proposed approach is compared with previous works of hybrid composite optimization with the GA and ACO

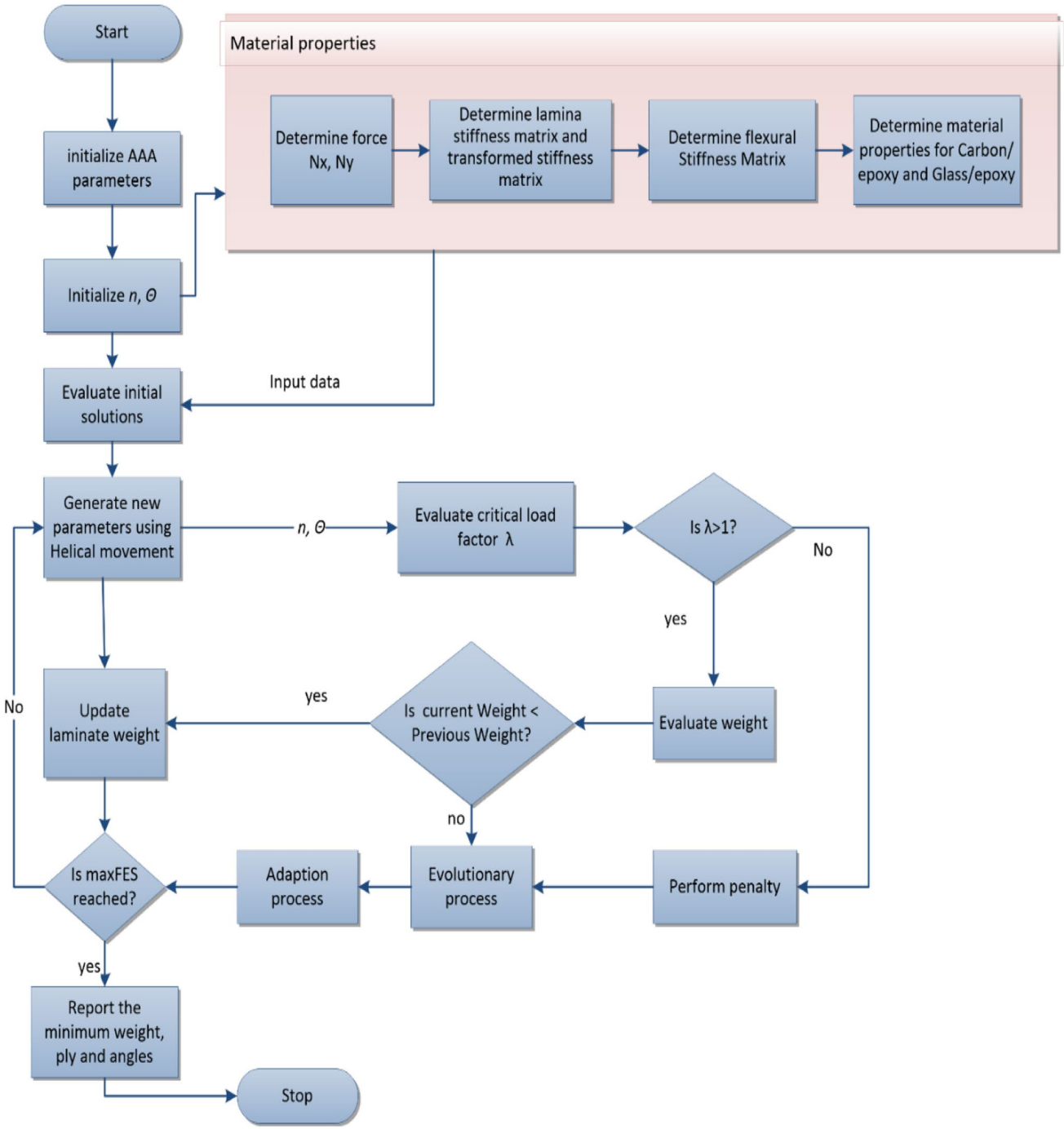

Fig. 2 Working framework of learning oriented AAA for hybrid composite laminate optimization

Table 1 Material properties of carbon/epoxy and glass/epoxy

	E1 (GPa)	E2 (GPa)	G12 (GPa)	Poison's Ratio (ν)	Ply THICKNESS (mm)	Density $\rho\left(\frac{kg}{m^3}\right)$
Carbon/epoxy	138.0	9.0	7.1	0.3	0.127	1605
E-Glass/epoxy	43.4	8.9	4.55	0.27	0.127	1993

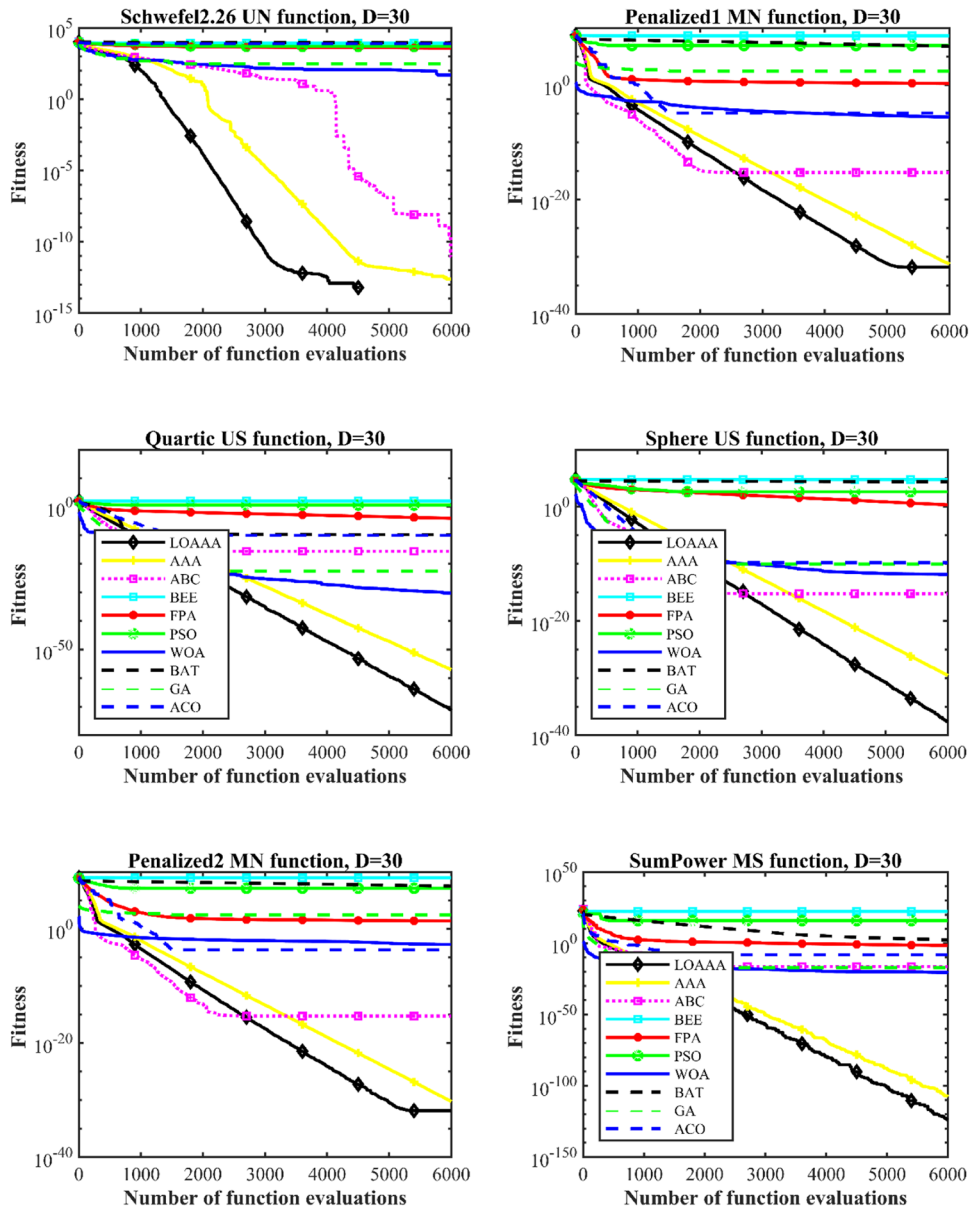

Fig. 3 Convergence curves comparisons involving six well-known unimodal and multi-modal benchmark functions

Table 2 Parameter setting for the optimization algorithm

Parameters	Parameter value
Population size	50
Maximum fitness evaluation	2300
Shear force (Δ)	3
Adaption parameter (A_p)	0.3
Energy loss (e_L)	0.1
Dimension of the problem (D)	48

algorithms. In the second and third cases, the effects of in-plane loading and plate aspect ratio on the weight of the plate are investigated respectively. Moreover, experiments are executed using higher in-plane loading with different plate aspect ratio combinations.

3.1 Comparison LOAA with GA and ACO

Table 3 shows the comparison of the proposed algorithm with GA and ACO, which were used for the optimization of the weight of the composite laminated plate using similar materials as is in this study. The results obtained using the GA and ACO algorithms were taken from Ref. [27]. According to the literature, the optimization was undertaken with a fixed number of plies (48), the stacking sequence angles were selected within the range (± 90, ± 45) and In-plane loads as,$N_x = N_y = 175$. In addition, the plate length and width were set as a = 0.9144 m and

Table 3 Comparative results of weight, stacking sequence and total ply number

Authors	Algorithm	λ	No. Ply	N_x	N_y	Weight	FES[a]
This study	LOAAA	150	40	175	175	67.2	2300
Girard cited in [20]	GA	150	48	175	175	79.73	23,945
Koide et al. [20]	ACO	150	48	175	175	79.73	23,744

[a] *FES* function evaluations

Table 4 The weight (in Kg) of the plate at different in-plane loads (N_x/N_y) and plate aspect ratio (r)

In-plane loads	750/1000					1000/1000				
Plate ratio	1.2	2	1.5	1	0.5	1.2	2	1.5	1	0.5
Weight	39.77	24.31	31.78	47.88	96.55	40.4	24.07	31.4	49.16	95.15
In-plane loads	1000/2000					1500/1000				
Plate ratio	1.2	2	1.5	1	0.5	1.2	2	1.5	1	0.5
Weight	39.47	24.21	31.86	48.98	95.87	39.64	24.14	32.23	48.01	98.07
In-plane Loads		2000/1000								
Plate ratio		1.2		2		1.5		1		0.5
Weight		39.81		23.8		31.89		47.88		95.22

b = 0.762 m respectively. However, in the current study, the number of plies and the stacking sequence angles are considered as a continuous values in which the number of plies varies in the range between 1 and 24 for each layer and the stacking sequence angles were set in range [− 90, 90]. The in-plane compressive loads and the buckling load factor, λ > 150, are similar to [27].

As indicated in Table 2, the proposed method has achieved minimum weight compared to GA and ACO algorithms with 2300 function evaluations (FES), which is much lesser compared to the 23,945 function by GA and the 23,744 function evaluations by ACO. GA and ACO algorithms obtained equal minimum weight and plies, 79.73 kg and 48 respectively. However, the proposed method obtained 67.2 kg with 40 plies. This is due to the learning-oriented technique used with AAA, which enables the algorithm to search for solutions in an informed manner. The results demonstrated that the proposed method is appropriate for optimization of hybrid composite laminate problems.

3.2 The effect of in-plane loads on the weight of hybrid composite laminate

In this section, in order to evaluate the efficiency of LOAAA for hybrid composite laminate optimization, we executed additional experiments involving different plate aspect ratios and higher in-plane loadings subjected to the critical load factor, as depicted in Table 4. The in-plane loads were varied according to the ratio

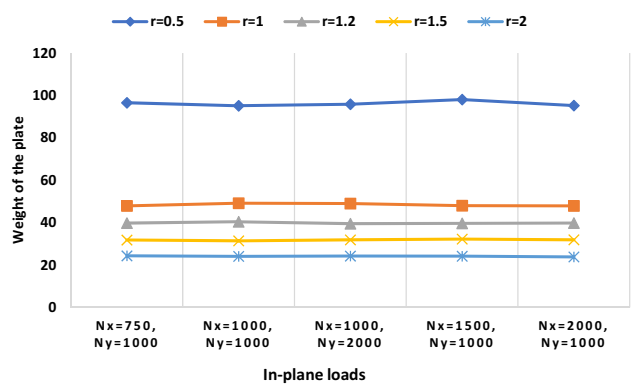

Fig. 4 The effect of in-plane loads on the weight of the plate at different plate ratio

[N_x/N_y = 0.5, 0.75, 1, 1.5 and 2] and the plate aspect ratios are r = [0.5, 1, 1.2, 1.5 and 2]. Moreover, the critical buckling load factor is set as, $\lambda_{cri} > 1$. The critical load factor and thus, the weight of the laminate was highly affected with the plate aspect ratio and the applied in-plane loading.

Figure 4 illustrates the effect of the force on the weight of the hybrid laminate at different plate ratio. Here the effect of the force on the weight of the hybrid laminate was very small. This is because the closeness of the applied in-plane loads to each other. In addition, the plate thickness was increased as in-plane load ratio increased. This makes the plate to resist to the in-plane loads; therefore, the effect was insignificant.

3.3 The effect of plate aspect ratio (r) on the weight of the hybrid laminate

The numerical simulations revealed that, the minimum weight varies with the plate aspect ratio. As illustrated in Fig. 5, the weight of the hybrid laminate decreases as the plate ratio (r) increases for all in-plane loads cases. In other words, as the width decreases, the weight of the plate decreases as well. This result complies with previous works of Kassapoglou [37]. The maximum weight was obtained when the plate ratio, r = 0.5 and it was minimum when r = 2. Therefore, the results again revealed that the competing performance of the LOAAA for optimization of hybrid composite plate.

3.4 Stacking sequences with different in-plane loading plate aspect ratio

Table 5 shows the stacking sequence angles of the hybrid composite laminate under in-plane loading and plate aspect ratio. The results are approximated to the nearest manufacturable values. The arrangement of the stacking

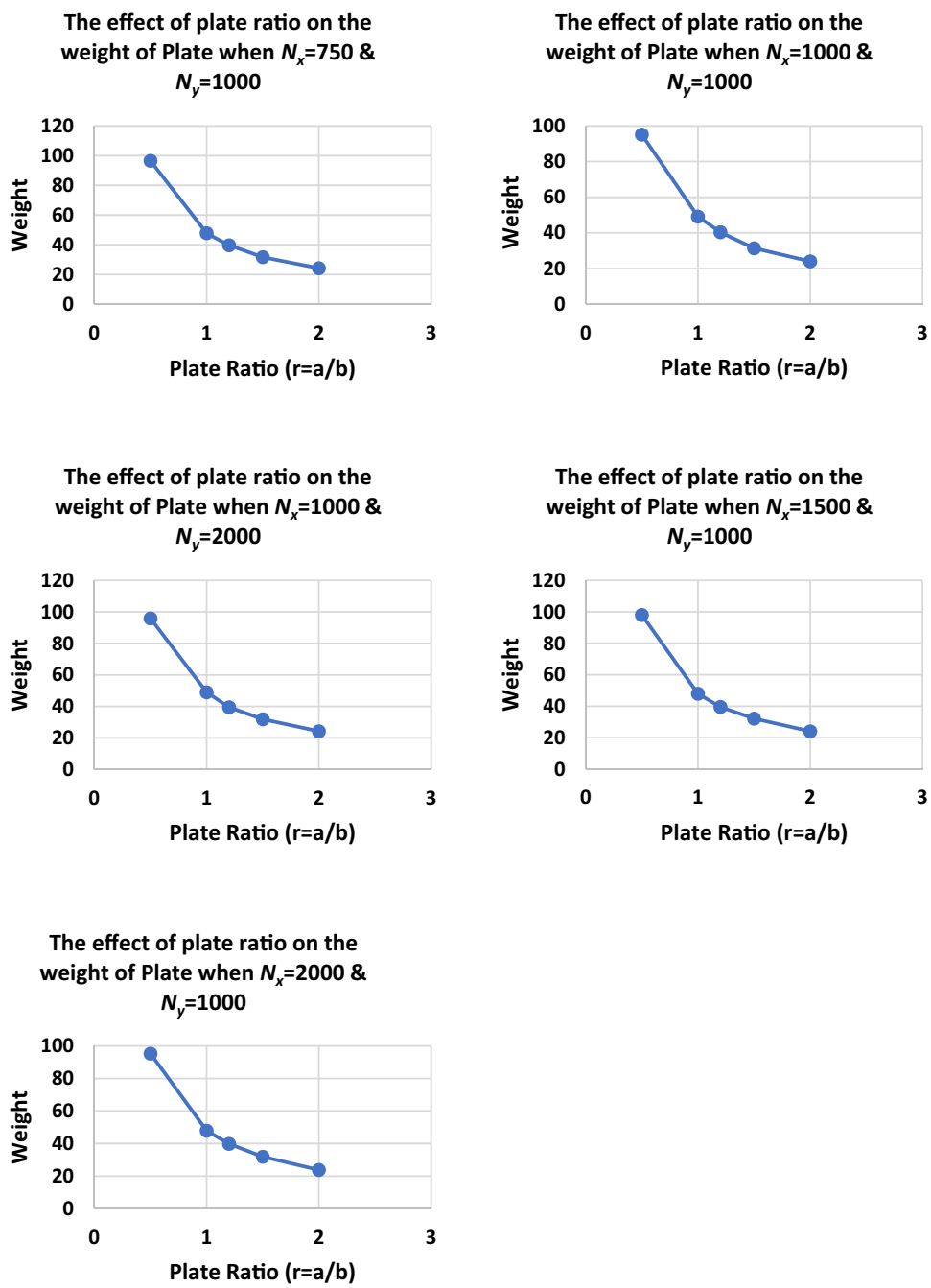

Fig. 5 Graphs showing the effect of plate ratio (r) on the weight of the plate with a variety of in-plane loads

Table 5 Stacking sequence results of half laminate with different in-plane loads and different aspect ratios

N_x	N_y	r	No. of ply	Stacking sequence of half laminate [carbon/glass]
750	1000	1.2	52	[80/-68/90/86/90/90/90/-90/90/90/45/-90/81/-90/90/-90/90/-88$_3$/90/90/90/-87/-90/-47]
		2	48	[90/-90/90/90/-90/69/-48/-90/52/90/53/53/51/90/43/74/90/90/-59/-90/-31/-90/25/90]
		1.5	54	[-81/90/90/-64/90/-90/90/90/-90/-89/90/-90/-70/-90$_4$/90/82/-64/90/89/-90/-90/-90/-90/-90]
		1	58	[81/40/-90/90/89/90$_2$/-26/-90$_4$/90/-90/-83/90/-90/77/90/46/83/72/-90/90$_2$/-90/90/-90/-90]
		0.5	68	[90/-78/-55/-90$_4$/-90/60/88/-90/90/-53$_4$/-82/90/90/-61/-90/90/90/90/-90$_3$/90/-90/90/90/90$_3$]
1000	1000	1.2	52	[90/-90/90/73/-24/34$_2$/-90/86/36/90/-90/48/-90/90/-90/-76/90/-90/-49/-90/90/90/-90/-90]
		2	48	[90/90/-90/90/-90/-90/-90/77/82/90/90/90/-90/-90/90/90/90/90/90/90/-90/-90/77/-90]
		1.5	54	[90/57/-90$_3$/90/-90/90/90/90/90/50/62/-62/90/-90/90/90/-64/90/-85/-32$_2$/61/-90/-88/50]
		1	58	[-90/-41/-36/90/90/44/34/-90/-90/58/-90/-90/-90/90$_3$/90/90/90/90$_4$/-15/-90/66/90/19/90]
		0.5	60	[-90/-90/0/-90/83/90/54/90/-90$_3$/90/90$_2$/-90/90/90/-89$_5$/90/68/82/-66/-90/-90/90/-90/48]
1000	2000	1.2	52	[-90/-50/-85/90/-44/-90/-86/-90/-61$_2$/61/-90/-90/90/-90/-90/0/-27/-90/-90/90/87/-35/90$_2$/-90]
		2	48	[-90/-90/-90/-44/90/90/90/90/-90/-90/90/90/-58/90/-90/-84/50/-62/-90/-90/90/0/82/43]
		1.5	54	[90$_2$/-90/-90/35/90/-90/-90/90/80/90/90/-90/-90/-90/-44/90/76/54/90$_2$/33/90/-90/90/-90]
		1	58	[90/90/53/90$_5$/90/90/90/-90/90$_2$/-90/90/-90/-90/90/-90/-71/-90/90/64/-80/46/-90/-90/90]
		0.5	62	[-90/90/-90/90/-90/-90/-51$_3$/89/-90/-51/25/-88/-90/90$_4$/90$_2$/90/90/90/90$_2$/90/87/-29/-47/-34]
1500	1000	1.2	52	[90/-90/-90/90/-90/-90/-86/90/74/-70/90/-68/90/90/-90/-13$_3$/90/-90/90/-90/-90/-88/-74/87]
		2	48	[90/90/-90/90/86/90/-90/77/82/-90/-90/80/88/89/-90/90/64/90/-90/-89/-90/-15/0/-90]
		1.5	54	[-90/90/-75/78/-57/43/90/-90/64$_3$/-90/90/-63/-90/-81/66/67/33/-90$_2$/-71/90/90/-84/90/43]
		1	58	[90/49/-59/90/-90/90/-90/90/90/90/-90/90$_5$/-24/90/49/-90/90/-90/90/-82$_2$/83/90/81/90]
		0.5	64	[90/90/90/53/-90/90/90/-78/90/90/90/90/90/-88/90/-90/90/90/90/-43/90$_9$/90/-79/-19]
2000	1000	1.2	52	[80/-90/-80/90/-80/-90/-86/90/90/90/90/90/-90/90/90/22$_3$/90/71/-90/80/90/-90/90/90]
		2	48	[-90/-81/83/90/-47/90/29/-90/53/-55/-27/-90/90/-90/-90/-90/90/90/-90/90/-90/90/-84/90]
		1.5	54	[-45/90/59/-90/-90/90/57/90/90/-89$_3$/0/-66/-90/90$_2$/-85/50/-90/-90/84/-90/-90/-90/90/61]
		1	58	[-90$_2$/90$_3$/90/-90/90/37/-90/23/90/90/-90/-90/90/-78/90/-83/-90$_3$/90/74/-90/90/-88/86/90]
		0.5	64	[90/-79/-90/90/82/-43$_5$/90/53/-84/76/-90/-33/65/-90/87/-90$_5$/90/-90/-64/-23/-79/-90/-43/-25]

sequence of the laminate is shown as follows: [CE$_f$/GE/CE/GE…..n] = [90$_f$/30/30/90] where CF is the Carbon epoxy, GE is the Glass epoxy, and the subscript f indicates the repetition of that lamina angles at the kth laminate.

3.5 Comparisons LOAA vs GA based on different loading and aspect ratios

In this section, the effectiveness of LOAAA and genetic algorithm for hybrid composite laminate optimization is included. The maximum number of function evaluation for the two algorithms is set to 15E + 03 and population size is 50. Figure 6 illustrates convergence rate sketches of LOAAAA and GA for different in-plane loading and aspect ratios. The experiment is aimed at showing the comparative effectiveness of the two algorithms using different testing conditions.

As depicted in Fig. 6, the proposed method has shown superiority over genetic algorithm on various in-plane loadings. In order to further investigate the performances of LOAAA and genetic algorithm, the LOAAA is executed using two different critical buckling factor constraints i.e. $\lambda > 1$ and $\lambda > 50$, whereas genetic algorithm is executed for $\lambda > 1$. A hybrid composite laminate with higher critical buckling factor value entails that it has to resist from buckling than composite laminate with lower value. When the critical loading factor, $\lambda > 50$, the weight of the tested hybrid composite laminate increases. This is due to the increment of the laminate thickness, which in turn increases the weight. The proposed method is able to optimize the parameter of the hybrid composite laminate plate so that it can resist in-plane loading without buckling and at the same time achieving a comparatively lower weight than genetic algorithm with lesser function evaluations.

4 Conclusion

In this study, Learning-Oriented Artificial Algae Algorithm is employed in the optimization of hybrid composite laminate rectangular plates. The proposed method is able to obtain minimum weight that can satisfy the critical load factor constraint. The death penalty approach is utilized to check the feasibility of solutions, in which parameters that do not satisfy the constraint are rejected. The

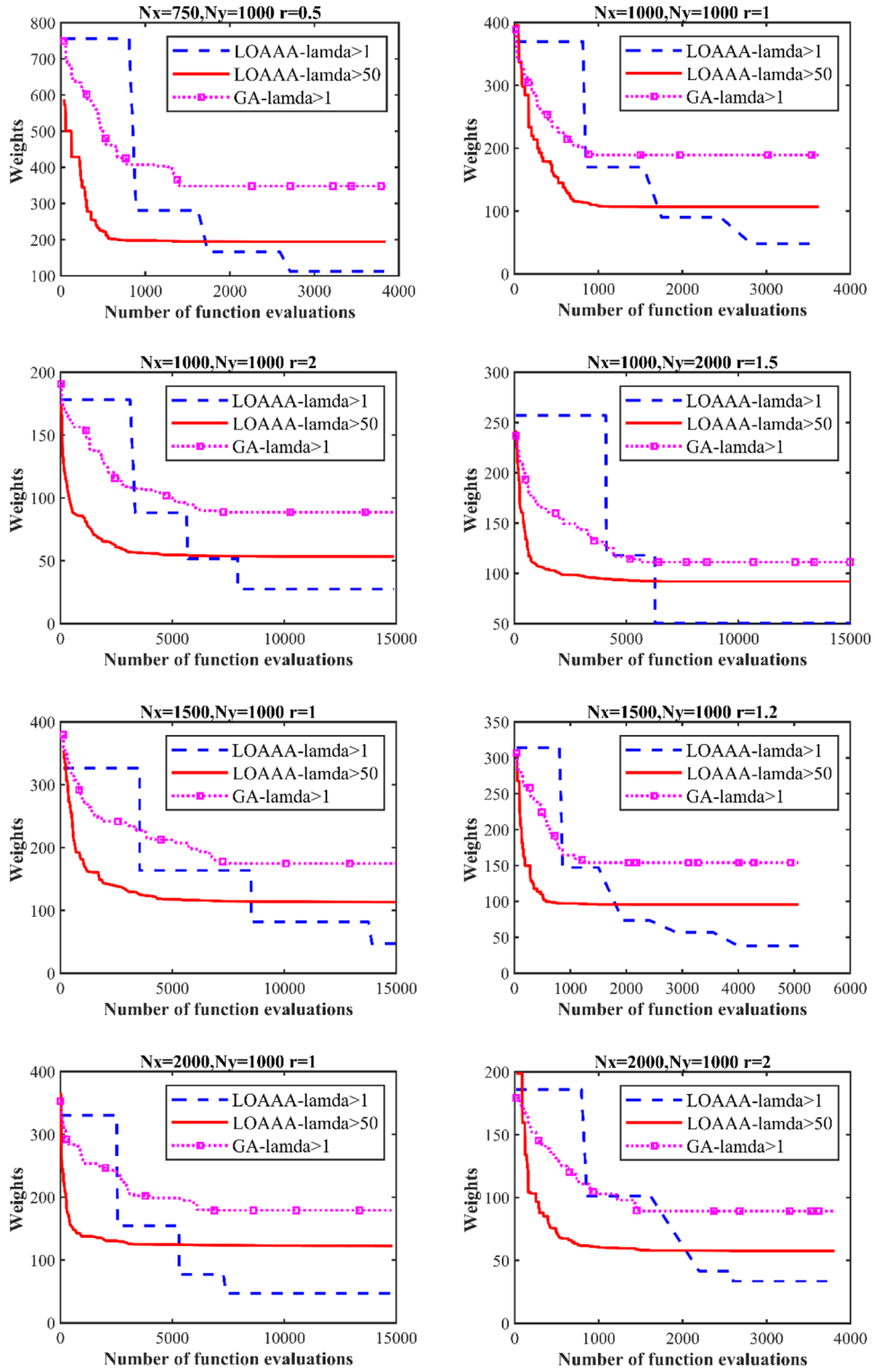

Fig. 6 weight convergence comparison of LOAAA against genetic algorithm

efficiency of the proposed algorithm has been compared with the results of hybrid composite laminate parameters optimized using ACO and GA. The proposed method has shown superiority in terms of weight compared to ACO and GA. In addition, provided that same material property, the proposed approach obtained less number of plies, which in other word can be lesser cost of the new composite material. In addition, the learning capability integrated with AAA minimized the weight to 67.2 kg with 2300 function evaluations, which is 10 times less than functions

evaluated by ACO and GA. That is because the proposed method behaves in an informed manner to evaluate the fitness quality of candidate solutions generated at certain iteration. The learning-oriented approach, since it is able to finding minimum weight with lesser function evaluations, is comparatively computationally efficient than the compared algorithms. Moreover, the effect of in-plane loads and plate aspect ratio have been analyzed and the results testified that the Learning-Oriented Artificial Algae Algorithm could be successfully applied in the optimization of hybrid composite laminates.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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