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Artificial Intelligence Approach for Multi-Objective Design Optimization of Composite Structures: Parallel Genetic Immigration

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ABSTRACT

An isotropic mechanical structure cannot withstand shocks, accidents, and mechanical loading. In this perspective, composite structures have been introduced to improve the performance of mechanical structures. We are interested in the study of laminates with the aim to find an optimal structure resistant to vibrations and buckling. To remedy the problem of vibrations and buckling, we use artificial intelligence methods to optimize the design of composite structures. As it is a typical method of artificial intelligence adapted to this studied problem, we use genetic algorithms based on a new genetic operator. In the present article, an optimization procedure based on the new genetic operator called genetic immigration operator is developed to determine the maximum buckling load and fundamental frequency of the laminated plate with plies oriented at -45◦/45◦ ,0◦, and 90◦. The aim of this paper is the use of two different methods for their effectiveness. These optimization works consist of first maximizing the buckling load factor with UGA (Uniform Genetic Algorithm) and a new evolutionary search strategies called Immigration Genetic: SIG (Standard Immigration Genetic Algorithm) and AIG (Improved Genetic Immigration Algorithm) and second of solving a multi-objective problem with minimizing the cost and weight of the hybrid laminate made of the fibers of two composite materials. The resolution of this problem by the proposed genetic immigration approach is reinforced by the optimization of the CPU computation time which is due to the exploitation of the parallel architecture based on the multi-processor parallel computation.

Key words: Artificial Intelligence; Genetic algorithm; Immigration Strategy; laminated Composite Plates; Fundamental Frequency; Buckling Load; Parallel Architecture; Multi-Objective Optimization.

1.INTRODUCTION

New technologies today rely on sophisticated and high-performance industrialization that requires safety and quality. The current development of aerospace and automotive technologies is based on the use of composite materials that meet the requirements of quality and durability. An isotropic mechanical structure cannot ensure the lightness or resistance to accidents and shocks. Therefore, the importance and need to produce mechanical structures composed of more than two materials are at stake. Indeed, to improve the performance of a mechanical structure, it is appropriate to calculate the various mechanical factors likely to prevent any buckling, cracking, or vibrations in the case where these structures are subjected to compressive loads. In addition, an isotropic structure is less efficient because reinforcement for a composite structure is generally involved in the form of fibers so that it can withstand traction, compression and temperature.

The fibers are also known for their low densities and dimensional stability. These fibers may be arranged in orientations relative to the reference axis for each layer of the mechanical structure. Artificial intelligence is oriented towards the deployment of complex problems [1]. It has proved successful algorithms for solving problems of optimization of composite structures. Evolutionary algorithms have proved their adaptations to the constraints of problems and have been able to overcome local minima problems such as GA (Genetic Algorithm) [2], ACO (Ant Colony Optimization) [3] and TS (Tabu search) [4].

Many researches related to optimization of composite structures subjected to mechanical loading have been treated and resolved by various methods of artificial intelligence and specifically metaheuristic methods: GA, ACO and TS. In Ref [5], to optimize the layup of laminated panels for a maximum buckling load the ACO method is used. According to this article, ACO is an effective strategy to exploit the search space which can be described as better if we compare it with the GA method and the TS method. In [6], a genetic algorithm was used for maximizing the buckling and failure load of a laminate by changing its stacking sequence. Recently, the authors in [7] investigated the design optimization of laminated composite plates subjected to buckling loads using a optimization method which combine a mixed integer and continuous design variables. Jing et al. [8] optimize the stacking sequence of laminated composite plates subjected to compressive loadings with the purpose of maximizing the critical buckling load and critical failure load using the Sequential Permutation Table (SPT) method. Kiyono et al. [9] has proposed a new parameterization approach named Normal

Distribution Fiber Optimization (NDFO) for fiber angle optimization.

According to [10], a composite laminate is generally designed depending on the following criteria: the thickness, number and orientations of the layers. For optimal results, optimization techniques including the genetic algorithm (GA) have been implemented. Being advantageous in excluding local minima, this algorithm allows exploring a set of optimal solutions. In addition, the optimization of laminated composites, targets the orientations of the layers which are generally limited to a set of restricted angles due to manufacturing limitations. Many objective functions were used such as buckling load, stiffness, strength, weight, and cost.
Furthermore, a common constraint in the laminates is the cracking of the first layer. In addition to the crack criterion, other mechanical constraints are generally associated with this optimization including the symmetry, the balance of the laminate, and a maximum number of contiguous stacks.

Thus, gradient optimization methods are not adequate for optimizing composite structures because they converge to a local optimum and do not adapt to discrete problems [11]. Linear integer programming as a technique for solving combinatorial optimization problems has been used to optimize the buckling load factor of laminates [12]. In addition, TS is a heuristic method that can be applied to solve the laminate optimization problem. It was introduced by [13]. TS is an iterative local search procedure that explores the set of solutions beyond local optimality. This heuristic is based on a memory concept to find good solutions avoiding convergence limitations [14].

Thus, the present investigation deals with the design optimization of static and dynamic analysis of composite rectangular laminates. On one hand, the design objective aims to maximize the buckling load and fundamental frequency using ply fiber orientation angle as design variables. On the other hand, the minimization of cost and weight of hybrid laminate is elaborated. The design problem is formulated as a multi-objective optimization problem. Two studies, one for maximizing fundamental frequency and one for maximizing buckling load, are carried out to demonstrate the efficiency of the developed method in the optimal stacking sequence design. Some of the obtained numerical results are compared with their counterparts in the literature.

This work proposes a new optimization approach called Parallel Genetic Immigration. The proposed approach is based on the new genetic immigration operator [15] and on the Multi-Processor parallel calculation method [4] to optimize the problem of stratified structures. The resolution is thus made by the integration of an immigration operator based on the random selection and an immigration operator via the roulette wheel selection. This manuscript studied the resolutions by UGA, SIG and AIG and the parallel optimization results of laminated composite plates.
This paper is organized as follows: section 2 presents the formulation of the optimization problem. Then the proposed Parallel Immigration Genetic approach is presented in section 3. Ensuing, the numerical results are shown in section 4, and finally conclusions are presented in section 5.

2.MATERIAL AND METHOD

2.1 Optimizationof Laminated Composite Plates

A symmetrically laminated rectangular plate of length a, width b, total thickness h, and made of N plies is shown in Figure 1. Fibers reinforced composite materials are orthotropic along the fibers direction, that is in the local materials axes (x,y) of the plate. The plate is symmetrical, balanced, and simply supported of N layers of thickness hk, consisting of a pair of stacks of 0°-ply, 90°-ply and two contiguous plies of 45° and -45° . A pair of 0° is coded in ‘1’, a pair of 90° is coded in ‘3’, and thus a stack of ± 45° is coded in‘2’.

According to the Classical Laminated Plate Theory (CLPT), the free vibration and buckling load will be expressed in this section [16].
Firstly, we supposed that the plate is subjected to uniformly distributed compressive load λN_x and λN_y in the x and y directions, where λ is a load factor. As a result, buckling waves will be noticed if a buckling load value reaches a critical buckling value λ_{cb}. The buckling load factor [6] is given in terms of flexural stiffness D_{ij}, and loads N_x and N_y as:

$$\lambda_b(m,n) = \pi^2 \frac{[D_{11}\left(\frac{m}{a}\right)^4 + 2(D_{12} + 2D_{66})\left(\frac{m}{a}\right)^2\left(\frac{n}{b}\right)^2 + D_{22}\left(\frac{n}{b}\right)^4]}{\left(\frac{m}{a}\right)^2 Nx + \left(\frac{n}{b}\right)^2 Ny} \quad (1)$$

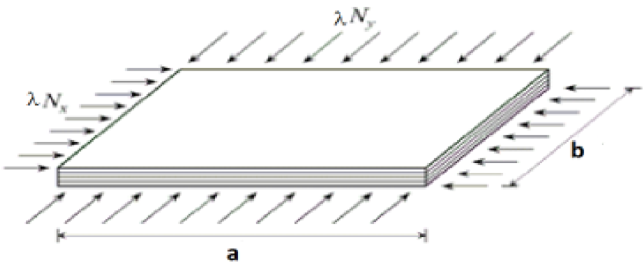

Figure 1: Laminate plate subjected to bi-axial compressive loads

This optimization problem consists of exploring optimal design of laminates according to the criteria of buckling load factor maximization and by altering the orientations of the layers, in situ γxy is zero. The relationship between the principal strains of the i[th] layer and the loads are given as follow [6]:

$$\lambda N_x = A_{11}\,\varepsilon_x + A_{12}\,\varepsilon_y \;,\; \lambda N_y = A_{12}\,\varepsilon_x + A_{22}\,\varepsilon_y \quad (2)$$

ε_x , ε_y and γ_{xy} are the strains considered and A_{ij} are the coefficients of the extensional stiffness matrix.

The components of the extensional and bending stiffness matrix are calculated by the following formula [16]:

$$A_{ij} = \sum_{k=1}^{N}\int_{z_k}^{z_{k-1}} \overline{Q_{ij}^{(k)}}\,dz \;,\; D_{ij} = \sum_{k=1}^{N}\int_{z_k}^{z_{k-1}} \overline{Q_{ij}^{(k)}}\,z^2 dz \quad (3)$$

Where Q'(k) is the reduced stiffness matrix of the layer (k).

And :

$$\varepsilon_1^i = \cos\theta_i^2\,\varepsilon_x + \sin\theta_i^2\,\varepsilon_y$$
$$\varepsilon_2^i = \sin\theta_i^2\,\varepsilon_x + \cos\theta_i^2\,\varepsilon_y$$
$$\gamma_{12}^i = \sin\theta_i^2\,(\varepsilon_y - \varepsilon_x) \qquad (4)$$

The critical failure load λ_{cs} [6] is defined as follows:

$$\boldsymbol{\lambda}_{cs} = \min_i(\min(\frac{\varepsilon_1^{ua}}{f|\varepsilon_1^i|}, \frac{\varepsilon_2^{ua}}{f|\varepsilon_2^i|}, \frac{\gamma_{12}^{ua}}{f|\gamma_{12}^i|})) \qquad (5)$$

The factor f means a safety factor of the value 1.5. ε_1^{ua},ε_2^{ua} and γ_{12}^{ua} denotes the ultimate allowable strains values. The failure load factor is for the prevention of any premature cracking of the structure.

The vibration frequencies f_{mn} of the laminate are given by the equation (6) [17]. The values of m and n indicate the vibration modes of the plate. The smallest value of f_{mn} defines the first natural frequency of the structure. This frequency depends on the dimensions a and b of the plate, its total thickness h, the matrix D, and the density ρ. When the laminate consists of different materials, ρ is determined by calculating the ratio of the sum of the densities of each layer and the total number N of layers:

$$f_{mn} = \frac{\pi}{2\sqrt{\rho h}}\sqrt{D_{11}\left(\frac{m}{a}\right)^4 + 2(D_{12} + 2D_{66})\left(\frac{m}{a}\right)^2\left(\frac{n}{b}\right)^2 + D_{22}\left(\frac{n}{b}\right)^4} \qquad (6)$$

The density ρ of the laminate is calculated according the following formula [18]:

$$\rho = \frac{1}{h}\int_{-h/2}^{h/2}\rho^{(k)}\,dz = \frac{1}{N}\sum_{k=1}^{N}\rho^{(k)} \qquad (7)$$

N is the number of layers of the laminate, ρ(k) is the density corresponding to the layer (k), and h is the thickness of the laminate.

The problem studied in this section will focus on optimizing the cost and weight of composite structures. Indeed, this problem includes the study of buckling load factor, as well as natural frequencies of the laminates, for the case of hybrid composite structures consisting of the fibers of two composite materials: Graphite / epoxy and Glass / epoxy. The advantage of using Graphite / Epoxy layers is that this material has a high stiffness-to-weight ratio compared to Glass / epoxy.

We supposed a symmetrical and balanced structure, consisting of N plies of thickness h (Ngr plies of Graphite / epoxy of thickness h1 and Ngl plies of Glass / epoxy of thickness h2. These laminates are then composed of random pairs of plies of material 1 (Graphite / epoxy of density ρ_1) or material 2 (Glass / epoxy of density ρ_1) in which the fibers are oriented at angles 0°, 90° or at angles of -45° associated to 45°. Each two plies of material 1 oriented at 0° and 90° are encoded as '1' and '3' respectively, and each stack of ±45° is encoded as '2'. Thus, for the material 2 each two layers of 0° and 90° are encoded as '4' and '6' respectively and each stack of ±45° is encoded by '5'. This second study, a multi criterion optimization of the hybrid rectangular laminate plate, is an attempt for simultaneously optimizing weight and cost, considering the first natural frequency as the design constraint.

The cost is calculated via the following formula [18]:

$$\boldsymbol{C} = \frac{\boldsymbol{abh(C_1 N_{gr}\rho_1 + C_2 N_{gl}\rho_2)}}{\boldsymbol{N}} \qquad (8)$$

C1 and C2 represent the cost of material 1 and 2 respectively.

The weight is thus calculated by the following formula [19]:

$$\boldsymbol{W} = \frac{\boldsymbol{abhg(N_{gr}\rho_1 + N_{gl}\rho_2)}}{\boldsymbol{N}} \qquad (9)$$

For example, g (g = 9.8 m/s2) is the constant of gravity.
The Pareto-optimal set represents the set of non-dominated solutions defined for a multi-objective optimization problem [20]. In this paper, the Pareto-optimal set is calculated by optimizing a convex combination of the two objectives, cost (C) and weight (W) which are based on a series of values for the multiplier β as follows [19]:

$$\boldsymbol{F = \beta W + (1-\beta)C} \qquad (10)$$

$\boldsymbol{\beta}$ is an optimization parameter. The problem of laminate stacking sequence optimization can be solved according to several metaheuristics, specifically through evolutionary algorithms. In this perspective, genetic algorithms have proved their efficiency and interest. In what follows, an immigration genetic approach is presented for the resolution of laminate optimization problems.

2.2 Genetic Approach for Solving Laminate Optimization Problems

Genetic algorithms (GA) are research methods based on the principles of natural selection and genetics (Fraser, 1957, Bremermann, 1958, Holland, 1975) [21]. The GAs encodes the decision variables of a search problem into finite-length strings of alphabets of certain cardinalities. The chains that are possible solutions to the research problem are called chromosomes, the alphabets are called genes, and the gene values are called alleles. To evolve the best solutions and implement natural selection, we need a measure to distinguish the quality of solutions. Measurement can be an objective function that is a mathematical model. Essentially, the adaptation function must determine the relative form of the candidate solution, which will then be used by the GA to guide the evolution of good solutions. Another important concept of AG is the notion of population. Unlike traditional research methods, genetic algorithms rely on a population of candidate solutions [22]. The size of the population, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. For example, small populations can lead to premature convergence and result in substandard solutions. Likewise, large populations lead to unnecessary expenditures in computing time. The GA consists of applying the selection, mutation [23] and crossover operators [24].

The selection operator is the key element ensuring the survival of the most adapted individuals for the next evolving generation. Based on the fitness function's value, this operator consists of choosing chromosomes having the top of fitness value. This is done through a probabilistic selection by selecting roulette or tournament. After applying the selection operator on each offspring, the selected solutions are combined so as to create new individuals [24].

It is possible to combine them with the worst fitness in the population. As it is known, the crossover operator (Figure 2) could be applied according to a single or multi-point of crossing [24].

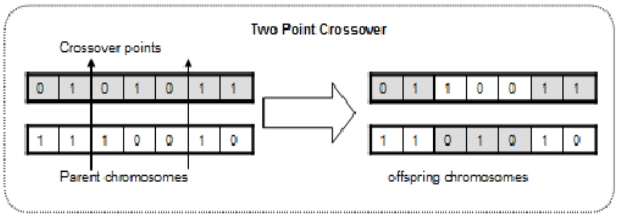

Figure 2: Two Point crossover operator

The main objective of mutation (Figure 3) is to allow disrupting chromosomes by genes chosen randomly since the set of genes of the chromosomes [25].

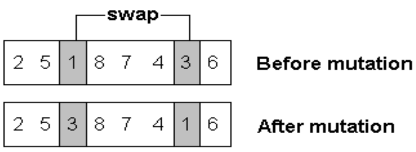

Figure 3: Mutation operator

The genetic algorithm is an evolutionary metaheuristic. It is an iterative algorithm (Figure 4) operating on populations of individuals compounds of chromosome vectors represented in integer, binary or real code [2]. These individuals will evolve from one generation to another to constitute a set of solutions for the problem. By creating an initial population, we proceed to select a percentage of 60% of the chromosomes of each population, which admit a maximum or minimal fitness value depending on the objective of the algorithm. The elitist selection by tournament is based on choosing the best individuals of the population to crossover so as to generate new individuals. The crossover operator must guarantee a diversity of genes as well as chromosomes. It is, therefore, essential to choose a probability of crossover greater than 0.7 and to select more than one crossover point for each of the chromosomes. The mutation operator consists of inserting, for a probability lower than 0.1, a block of random genes concluded since the set of genes of the chromosome. Populations will be sorted according to fitness values.

```
Begin
Initialize population P randomly with constraints
validation
Evaluate population P
i=1
While i<= iter
popS:= Select For reproduction(P, rate)
// rate is 60% of N individuals
popC:= CrossoverPopulation(popS, Pc)
// Pc is crossover probability
popM:=MutationPopulation(popC, Pm)
 // Pm is mutation probability
pop= RankingPopulation(popM)
EndWhile
End
```

Figure 4: Scheme of UGA [15]

The SIG consists of inserting an immigration operator based on the creation of a random population and crossing the population concluded since the uniform evolution and the randomly created population [15]. A mutation operator is also used by replacing a sub-vector of the chromosome with another randomly including gene values from the set of chromosome genes [23].

As for the AIG, it consists of operating on immigration populations resulting from the selection operations by the roulette wheel selection. It consists of choosing three best individuals to conclude 60% since the first, 10% since the second and 30% since the third individual in order to create random vectors [15]. It implicates combining the 20% of random individuals from the roulette wheel selection with the best solutions concluded from the elitist selection by tournament. The mutation operation of the SIG (Figure 5) is similar to that of AIG (Figure 6).

```
Begin
Initialize population P randomly with constraints validation
Evaluate  population P
i=1
While i<= iter
popS:= Select For reproduction(P, rate)
  // rate is 60% of N individuals
popC:= CrossoverPopulation(popS, Pc)
// Pc is crossover probability
popM:=MutationPopulation(popC, Pm)
  // Pm is mutation probability
pop= RankingPopulation(popM)
if mod(iter,10)==0 then
      create N random  immigrants
      select 20% of N immigrants randomly
       P:=create population of the selected immigrants  and the
worst individuals of pop
       popS:= Select For reproduction(P, rate)
  // rate is 60% of N individuals
      popC:= CrossoverPopulation(popS, Pc)
 // Pc is crossover probability
      popM:=MutationPopulation(popC, Pm)
// Pm is mutation probability
       pop= RankingPopulation(popM)
Endif
EndWhile
End
```

Figure 5: Scheme of SIG[26]

Begin

Initialize population P randomly with constraints validation

Evaluate population P

i=1

While i<= iter

popS:= Select For reproduction(P, rate)

// rate is 60% of N individuals

popC:= CrossoverPopulation(popS, Pc)

// Pc is crossover probability

popM:=MutationPopulation(popC, Pm)

// Pm is mutation probability

pop= RankingPopulation(popM)

if mod(iter,10)==0 then

create N random immigrants

select 20% of immigrants by roulette wheel selection

P:=create population as recombination of the new immigrants and the best of pop

popS:=Select For reproduction(P, rate)

// rate is 60% of N individuals

popC:=CrossoverPopulation(popS, Pc)

// Pc is crossover probability

popM:=MutationPopulation(popC, Pm)

// Pm is mutation probability

pop=RankingPopulation(popM)

Endif

EndWhile

End

Figure 6: Scheme of AIG [26]

2.3 PARALLEL ARCHITECTURE

Parallel processing is highly demanded especially for the iterative algorithms which prove to be generally expensive in calculations in order to promote real time savings. Indeed, the time spent on n processors is equal to time on one processor divided by n. In addition, the good parallel algorithms are those that can be adapted to the number of available processors [27-28]. There are two methods of parallelization. The first one is subject to simultaneous execution of the same instruction for massive data. The second method, known as parallelism control, consists of concurrently performing simultaneous executions [29]. Data parallelism is a sequential method based on the parallel manipulation of data because at a certain time the execution will be performed sequentially. In contrast, genetic algorithms have been parallelized according to the principle of data parallelization [30]. Thus, the genetic algorithm can be parallelized by assigning to each generation distributed calculation procedures for subpopulations and the corresponding calculation of each subpopulation being assigned to a processor in a parallel computer [3].

The parallel master-slave GA is divided into a master process and several slave processes [4]. The master manages all the operations of genetic evolution. As for the slaves, they are asked to receive the sub-populations from the main process to calculate the adaptation function, and then they respond the results to the master [31].

3.RESULTS AND DISCUSSIONS

3.1 Bucking Load Optimization Results

The genetic algorithm, as a random evolutionary search algorithm, has proved the convergence of its results. Such an algorithm based on probabilistic and random evolution operators is likely to extend and diversify the search space. Moreover, the effectiveness of this algorithm, as it is known, is related to the mutation and crossover probabilities [32]. An elitist selection operator which has been developed consists of selecting a portion of individuals from the population based on the buckling optimization criterion. Optimization will be carried out according to three implementations of the genetic algorithm: UGA, AIG and SIG.

We examine a composite structure of length a, width b subjected to loads N_x and N_y along the axis of x and y respectively. The plate is composed of a laminate of N plies which the material properties of the used composite are as follows:
E_L = 127.59 GPa ; E_T = 13.03 GPa ; G_{LT} = 6.41 GPa ;
υ_{LT} = 0.3; ε_1 = 0.008; ε_2 = 0.029; γ_{12} = 0.015.

The tests concern the load cases as mentioned in table 1.

Table 1 : Data Of Optimization Problem

Load case	N	a(m)	b(m)	N_x(N/m)	N_y(N/m)
1	48	0.508	0.127	175	22
2	48	0.508	0.127	175	44
3	48	0.508	0.127	175	88
4	64	0.508	0.254	175	175

The buckling and failure load factors values for 48 ply laminate and 64 ply laminate are presented in Table 2. The obtained results were compared with the results gained from [6-17].

In ref. [6] corresponds to a multi-objective optimization of a λfunction taking the minimum value of buckling load factor and failure load factor weighted by a penalty equal to 0,8. However, the buckling and failure load factors values according to [17] correspond to a buckling load factor maximization of the laminates using a scatter search algorithm. The results obtained from table 2 prove a good performance of UGA optimization. The error rate corresponding to the first load case is 0.00576%. For the second load case, the error rate is 0.0176% compared to [17] results. The achieved error rate is 1.89% for the third load case. For the fourth load case, the error rate is 0.0107% compared to R (R=a/b). These error rates demonstrate a rapid convergence of UGA.

Table 2 : Optimal stacking sequences for buckling load factor maximisation using UGA

Load case	Presents results				[6]		[17]	
	Stacking sequence	**Buckling load factor**	**Failure load factor**	**Time CPU (s)**	**Buckling load factor**	**Failure load factor**	**Buckling load factor**	**Failure load factor**
1	[2 1 2 3 2 2 2 2 2 2 3 2]$_s$	16119.4652	10215.7804	667.3123	14618.12	13518.66	16120.38	5099.60
	[1 3 2 3 3 2 2 1 2 3 3 2]$_s$	16119.4652	10215.7804		14134.76	13518.66	15982.86	8088.92
	[2 3 1 2 2 2 1 2 2 3 2 2]$_s$	16119.4652	10215.7804		14013.71	13518.66	16008.29	8467.68
	[2 2 2 3 2 2 3 2 2 2 2 2]$_s$	16119.4652	10215.7804		13662.61	13518.66	15974.94	8563.07
2	[1 3 2 2 2 2 2 2 2 2 2 3]$_s$	13430.5124	8296.9195	669.6658	12725.26	12678.77	13432.89	7880.62
	[2 2 2 2 3 2 3 2 2 2 2 3]$_s$	13430.5124	8296.9195		12698.4	12678.77	13418.4	8283.52
	[2 1 1 3 2 3 3 2 2 2 2 3]$_s$	13430.5124	8296.9195		12743.45	12678.78	13399.34	8424.34
3	[1 1 2 3 2 2 1 3 2 3 2 2]$_s$	9979.7466	9826.2049	672.8334	9976.58	10187.93	9998.7	10403.75
	[1 3 2 3 2 2 3 2 2 3 3 3]$_s$	9979.7466	9826.2049		9998.19	10394.81	9998.66	9282.54
	[1 1 2 1 3 1 2 2 2 3 3 2]$_s$	9979.7466	9826.2049		9997.6	10187.93	9996.5	9802.62
	[3 2 1 1 2 3 2 1 2 3 2 3]$_s$	9979.3891	10219.8272				9995.20	10403.74
4	[3 2 2 2 3 3 3 2 3 2 3 2 3 1 2 2]$_s$	3975.6033	12506.5624	795.6751	3973.01	14205.18	3957.22	10733.33
	[3 2 1 2 3 2 3 2 3 1 2 2 2 2 2 3]$_s$	3975.5578	13370.5139		3973.01	8935.74	3953.01	11620.92
	[1 2 2 2 3 2 3 2 2 3 3 2 3 2 1 3]$_s$	3973.4357	8722.8419				3977.12	8934.13

The results obtained from table 3 demonstrate the optimality of SIG buckling optimization results compared to [17] results. The execution time of this implementation is more expensive in CPU time than that of the UGA implementation. Thereby, the SIG implementation integrate an immigration operator that creates a random population and randomly inserts a portion of 20% of individuals in the population concluded since the operations of selection, crossover and mutation for each 10 iterations.

The quality of SIG optimization results is better than that of UGA optimization. Corresponding to the fourth load case, the error rate of the achieved buckling load factor is 0.023% compared to the buckling value of 3977.12, while for loading cases 1, 2 and 3, the obtained results are similar to UGA optimization. However, it is obvious that for laminates having 64 stacks, the convergence time is more expensive in CPU time.

Table 3 : SIG Optimization results

Load case	Buckling (*)	Failure (*)	Time CPU(s)
1	16118.5624	6265.1087	825.6262
	16114.1753	6287.5703	
2	**13430.5124**	**8296.9195**	798.7109
	13422.8787	**7894.7031**	
	13422.1153	7894.7031	
3	9979.3891	10219.8272	824.6419
	9977.4137	10435.8748	
	9977.2406	10435.8748	
	9976.8305	10219.8272	
4	**3967.3151**	**11775.8682**	1027.0493
	3957.488	**10134.7984**	

(*) Results of the present work

The results from table 4 are thus optimal with a faster convergence time than that of SIG optimization. Indeed, the AIG implementation consists of inserting a population resulting from the roulette wheel selection for each 10 generations. It consists of selecting three random individuals from each population to constitute new random immigrants then forming a so-called immigration population.

The immigration principle is not based on the selection of the best adapted. The error rate of the achieved buckling load factor is 0.011%, 0.017%, 0.193%, 0.24% for the 1, 2, 3 and 4 load cases respectively comparing with the optimization results according to [17].

Corresponding to laminates with 64 stacks, the convergence time of the AIG optimization is more expensive in terms of CPU time than that of the UGA optimization and faster than that of the SIG optimization. In addition, AIG optimization results are less relevant than those of SIG optimization.

Table 4 : AIG Optimization results

Load Case	Buckling (*)	Failure (*)	Time CPU (s)
1	**16119.4652**	10215.7804	1342.4851
2	**13430.5124**	**8296.9195**	1328.4039
3	9979.7466	9826.2049	1806.2326
4	**3976.2048**	**11629.4415**	1943.335
	3976.1209	13370.5139	
	3975.8813	12506.5624	
	3975.6033	12506.5624	
	3975.6033	**9403.9174**	
	3974.5873	**10741.8235**	

(*) Results of the present work

3.2 Optimization Results of Hybrid Laminate Composite Panels

In this study, the UGA optimization of the cost and weight of the hybrid laminate composite panels are subjected to mechanical loads N_x=175N/m and N_y=80N/m as well as evaluated by the buckling load factor and vibration frequencies. The data and properties related to the second problem are presented in table 5.

Table 5 : Data and properties of problem 2

Properties	Graphite/Epoxy	Glass/Epoxy
Longitudinal modulus E_1	140.6 GPa	43 GPa
Transverse modulus E_2	9.13 GPa	9.07 GPa
In-plane shear modulus G_{12}	7.24 GPa	4.54 GPa
Poisson-ratio ν_{12}	0.3	0.27
Density	1605.434 Kg/m^3	1992.95 Kg/m^3
Thickness h	0.000127 m	0.000127 m
Cost factor (U/kg)	8	1

Table 6 : Multi-objective optimization of both weight and cost using AIG with frequency and buckling constraints of bi-Material laminate composite

β	N	Presents results					[17]			
		Stacking sequence	Weight (N)	Cost	Buckling load factor	Freq. (Hz)	Weight (N)	Cost	Buckling load factor	Freq. (Hz)
0	48	$[5\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 6]_s$	83.29	8.49	83.23	27.90	82.1517	8.3828	98.075	26.5387
0.8	44	$[2\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 5\ 6]_s$	74.95	11.61	91.59	30.68	64.6565	38.1109	92.735	29.0887
0.9	40	$[2\ 2\ 2\ 5\ 5\ 5\ 5\ 5\ 5\ 6]_s$	65.24	18.54	102.70	34.51	61.804	26.0023	103.4084	35.611
0.94	36	$[2\ 2\ 2\ 2\ 2\ 2\ 2\ 5\ 5\ 6]_s$	54.15	29.30	93.38	35.64	54.958	25.3037	98.7855	32.5641
0.96	36	$[2\ 2\ 2\ 2\ 2\ 2\ 2\ 5\ 5\ 6]_s$	54.15	29.30	93.38	35.64	54.958	25.3037	92.9752	31.5919
1	36	$[2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2]_s$	49.93	40.76	95.38	37.28	50.9645	36.7137	83.2223	31.038

The multi-objective evaluation of minimizing the cost and weight of laminates according to a uniform genetic algorithm is elaborated. The symmetry and balancing constraints allow an implementation of N/4 of genes of each chromosome.

An elitist selection by tournament is implemented by choosing 60% of the best individuals. In addition, the UGA implementation introduces PMX crossover operator with the rate of 0.8 and a mutation operator with the probability of 0.01, allowing combining chromosomes and disrupting chromosomes by a set of genes ranging from 1 to 6.

The reformulation of problem 2 (Figure 7) is as follows:

Minimize: W and C
By altering: the orientation of fibers θ_k and the material of layers mat_k
With, $\theta_k = \{0°, \pm 45°, 90°\}$
and *mat_k = {graphite/epoxy (1), glass/epoxy (2)}*
constraints: contiguity, Symmetry and laminate balancing

Figure 7 : The formulation of problem 2

The given results in table 6 are corresponding to the multi-objective minimization of cost and weight of hybrid laminate composite panels according to [17] using a scatter search. The UGA optimization results of problem 2 are described in the table 7.

Table 7 : Sequential UGA optimization results of problem 2

NG	Weight (N)	Cost	Buckling load factor	Frequency (Hz)	Time CPU (s)
1000	**82.1517**	**8.3828**	**83.3786**	24.4696	3731.6114
1250	82.1517	8.3828	81.6359	24.2125	3877.7704
2000	82.1517	8.3828	82.0341	24.2715	5491.1896

The cost and weight optimization results are optimal comparing to [17] results. In this case, the quality of the solutions depends on the optimization parameter β (Eq.10). Indeed, by using two fiber materials in each layer of the hybrid laminate, more frequencies are noticed for the laminates of small thicknesses and less weight. Indeed, the contiguity constraint involves sequences of stacks with at most 4 similar genes that succeed one another. The resolution of [17] violates the constraint of contiguity of the stacks.

Thus, the optimization of cost and weight of laminated structures also involves evaluating the buckling load factor and vibration frequencies while respecting the constraints of the contiguity of stacks, balancing and symmetry of the laminates. The buckling values and vibration frequencies are optimal by comparing with the resolution by the scatter search given in ref. [17].

In this work, the concept of multi-core parallelism is presented by means of an SPMD execution (Single Program Multiple Data) in MATLAB, where the genetic evolution algorithm is executed for NG/5 in such a way that NG is the number of generations. Corresponding to four cores present in the machine, four populations are concluded of the best individuals.

Thus, a replacement operator is applied to insert the best individuals of each population into a population of the same size that will sequentially evolve according to the UGA to conclude a most optimal solution.

Table 8 : Parallel UGA optimization results of problem 2

NG	Weight (N)	Cost	Buckling load factor	Frequency (Hz)	Time CPU (s)
1000	**82.1517**	**8.3828**	**83.1997**	24.4433	**1047.3**
1250	82.1517	8.3828	84.8922	24.6907	**1440.7084**
2000	82.1517	8.3828	**83.01**	24.4155	**3172.0612**

For a parallel genetic algorithm in table 8, a reduction in CPU time of 71.9% compared to the sequential genetic algorithm was achieved for the case of 1000 iterations.

Corresponding to the case of 1250 iterations, a CPU time optimization of 62.8% was achieved. Moreover, for the case of 2000 iterations, a reduction of 42% was obtained. This approach implements a parallel genetic optimization of the cost and weight of hybrid laminates, resulting in a faster convergence than sequential optimization. The concept of parallelism is present through a distribution of the same implementation on four cores of the machine, which will be run in parallel. The results will be crossing and subjected to a uniform genetic evolution sequentially. It is a parallel concept of the genetic algorithm so-called master-slave.

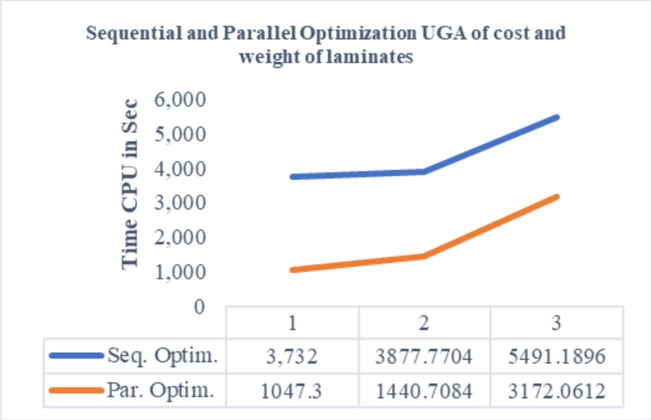

Figure 8 : Sequential and Parallel optimization UGA of cost and weight of laminates

The graph (Figure 8) represents two CPU time variation curves for the case of sequential UGA optimization (in blue) and for the parallel UGA optimization case (in red). Parallel UGA optimization is effective especially that genetic algorithms require a large search space and regular operations on chromosomes to converge towards the best solutions.

4. CONCLUSION

This paper deals with buckling load and vibration frequencies optimization of symmetrically simply supported laminated composite plates under biaxial compressive loads. The fiber orientation is taken as design variable. The main goal of the present work was to show the performance of parallel genetic immigration in the buckling and vibrations optimization problems. Additionally, the optimization problem is applied to the laminated plates for different aspect ratios and load ratios. Applicability and usefulness of the presented method are shown by solving different problems. In the solved problems, the influences of material properties, axial loads and aspect ratios are studied.
The Evolutionary genetic operators should ensure more opportunities for crossover, mutation and replacement such as immigration operators via random selection (SIG) or improved selection (AIG). The goal is to achieve rapid optimality. Metaheuristics can be used to solve optimization problems of composite structures. It is not limited to evolutionary algorithms, but it is necessary to integrate new bio-inspired methods [33, 34] to improve the quality of the obtained solutions. The integration of these methods coming from artificial intelligence requires parallel processing especially when the flow of data or instructions increases.

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