APPLICATION OF OPTIMIZATION ALGORITHM FOR COMPOSITE LAMINATE OPTIMIZATION

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Abstract— In this project composite laminate optimization code was developed using genetic algorithm in ANSYS APDL code. Now a day's composite material widely used in many industries like aerospace, automobile, marine, structural industries and many more, due to high strength to weight ratio. The main objective of this research is economically use the composite material by optimization techniques. The strength of the Laminated structures is depends upon the fiber angle, thickness, material, sequence of layer and no of layer. To find the optimized combination of above parameter is very difficult by traditional methods, it may struck in to local optimum. To avoid the above difficulties global searching algorithm like genetic algorithm were used.

KEY WORDS: Laminate optimization, Genetic algorithm, Structural optimization.

1.INTRODUCTION

Composite materials have received substantial attention as manufacturing materials. Although the high stiffness-to-weight and strength-to-weight properties of composite materials are attractive, their greatest advantage is their ability to be designed to satisfy directional strength and stiff nesses for any particular loading, or multi-loading, of the structure. In laminated composite structures, each ply has its greatest stiffness and strength properties, along the direction, through which the fibers are oriented in. By orienting each layer at different angles, the structure can be designed for a specific loading environment. Along with structural performance and weight, cost is an area of great interest when considering optimization studies in structural design. Obviously, reducing the amount of material required for the structure, minimizes the cost of a laminate composite. However, another method for cost reduction is to allow more than one material in the stacking sequence. Thus, it is possible to use layers of low cost material at locations, in the structure, where performance is less important. In general, the problem of composite laminate stacking sequence optimization has been formulated as a continuous design problem, and solved using gradient based techniques. These methods of solution present several disadvantages:

Stacking sequence design often involves design variables, which are limited to small discrete sets of values of ply thickness, orientation angle or material type, due to manufacturing or cost limitations, therefore, these methods require the transformation of these variables into continuous variables, in order that a solution might be obtained, Converting the continuous solutions back to discrete feasible values, often produces sub-optimal, or even infeasible designs, Composite laminate design problems often have discontinuous objective functions, exhibiting multiple designs with similar performances, involving many local optimum designs. Genetic Algorithms are suitable optimization algorithms for problems with discrete design variables. Its implementation does not require any evaluation of gradients which, together with its easiness of implementation, make it worthwhile investigating. Although, Genetic Algorithms require many function evaluations, which reflect in large computational costs, there are many reported applications of Genetic Algorithms to the design of composite structures. Genetic algorithms have been applied to stacking sequence optimization of composite plates, (Callahan and Weeks, 1992), to stiffened composite panel design (Nagendra et al., 1996), design of laminated composite panels (Hajela,1990) (Leung and Nevill, 1994) (Fernandes et al., 1998)(Haftka, 1998).

The design of optimal composite laminates has been shown to be well suited to the defining characteristics of genetic algorithms. Techniques for improving the efficiency of this methodology have been explored for several problems using local improvement, memory, migration, and varied selection schemes [13]. For large structures, such as the design of a wing or fuselage, the optimization is divided into smaller, tractable, sub problems using predefined local loads to constrain the optimization [13], [1], [9]. Isolated local optimization results in widely varying stacking sequence orientations between adjacent panels that causes serious manufacturing difficulties and, hence, generates the need for a globally blended solution. Design of a fiber-reinforced composite laminate requires the specification of the stacking sequence, which is defined by the orientation and material type of each ply layer, creating a discrete optimization problem. It is computationally expensive to design an entire wing or fuselage structure with the panels optimized simultaneously. Instead, local panels are commonly optimized for the specified local loads by ignoring the possible continuity of some or all of the layers from one panel to another across the structure. Soremekun et al.

[18]introduced multiple elitist selection schemes that by nature aid in discovering alternative designs with similar fitness values. In a standard elitist selection strategy only a single member of a parent population can survive the selection process without being modified and be placed in the child population. In a multiple elitist selection strategy the genetic algorithm allows a greater number of high fitness members to survive the selection process at each generation. Application of GAs for optimization of composite structures was reported by Hajela (1989, 1990). Callahan and Weeks (1992) used a GA to maximize strength and stiffness of a laminate under in-plane and flexural loads. Labossiere and Turkkan (1992) used a GA and neural networks for optimization of composite materials. Haftka, Watson, G¨urdal and their coworkers (Nagendra et al., 1992; Le Riche and Haftka, 1993; Nagendra et al., 1993a,b; G¨urdal et al., 1994; Le Riche, 1994; Soremekun, 1997) have developed specialized GAs for stacking sequence optimization of composite laminates under buckling and strength constraints. Sargent et al. (1995) compared GAs to other random search techniques for strength design of laminated plates.

The applications of GA methods in the field of composite structure optimization include the weight minimization of stiffened panels and shells (Harrison et al., 1995,Nagendra et al., 1996; Kallassy and Marcelin, 1997; Jaunky et al., 1998,Kaletta and Wolf, 2000; Gantovnik et al., 2003b; Kang and Kim, 2005), the strength optimization of plates with open holes (Todoroki et al., 1995,Sivakumar et al., 1998), the improvement of the energy absorption capability of composite structures (Woodson et al., 1995,Averill et al., 1995; Crossley and Laananen, 1996), the optimization of sandwich-type composite structures (Malott et al., 1996,Kodiyalam et al., 1996; Wolf, 2001; Gantovnik et al., 2002b; He and Aref, 2003; Lin and Lee, 2004), the optimization of dimensional and thermal buckling stability under hygrothermal loads (Le Riche and Gaudin, 1998; Spallino and Thierauf, 2000), the strain energy minimization of laminated composite plates and shells (Potgieter and Stander, 1998),maximizing the fundamental frequency of the laminated composite structure (Sivakumar et al., 1998), the stacking sequence blending of multiple composite laminates (Soremekun et al., 2001, 2002; Adams et al., 2003; Seresta et al., 2004; Adams et al., 2004), the optimization of electromagnetic absorption in laminated composite structures (Matous and Dvorak, 2003), the optimization of composite structures considering mechanical performance and manufacturing cost (Park et al., 2004), the optimization of composite tire reinforcement (Abe et al., 2004), the optimization of composites against impact induced failure (Rahul et al.,2005).A GA is a powerful technique for search and optimization problems with discrete variables, and is therefore particularly useful for optimization of composite laminates. However, to reach an optimal solution with a high degree of confidence typically requires a large number of function evaluations during the optimization search. Performance of GAs is even more of an issue for problems with mixed integer design variables. Several studies have concentrated on improving the reliability and efficiency of GAs. The proposed project is the extension of the study by Kogiso et al. (1994b,a), where, in order to reduce the computational cost, the authors used memory and local improvements so that information from previously analyzed design points is utilized during a search. In the first approach a memory binary tree was employed for a composite panel design problem to store pertinent information about laminate designs that have already been analyzed (Kogiso et al., 1994b). After the creation of a new population of designs, the tree structure is searched for either a design with identical stacking sequence or similar performance, such as a laminate with identical in-plane strains. Depending on the kind of information that can be retrieved from the tree, the analysis for a given laminate may be significantly reduced or may not be required at all. The second method is called local improvement

2. GENETIC ALGORITHM OVERVIEW

Genetic algorithms are robust, stochastic and heuristic optimization methods based on biological evolution process. There are several optimization techniques that are used in the context of engineering design optimization. Genetic algorithm is one such technique and is a search strategy based on the rules of natural genetic evolution. The standard genetic algorithm proceeds as follows: an initial population of individuals is generated at random. Every evolutionary step, known as a generation, the individuals in the current population are decoded and evaluated according to some predefined quality criterion, referred to as fitness function. To form a new population (the next generation), individuals are selected according to their fitness. Selection alone cannot introduce any new individuals into the population, i.e. it cannot find new points in the search space. These are generated by genetically-inspired operators, of which the most well known are crossover and mutation. Crossover is performed with crossover probability between two selected individuals. The mutation operator is introduced to prevent premature convergence to local optima by randomly sampling new points in the search space. Genetic algorithms are stochastic iterative processes that are not guaranteed to converge; the termination condition may be specified as some fixed maximal number of generations or as the attainment of an acceptable fitness level.

Genetic operators

Establishing the GA parameters is very crucial in an optimization problem because they greatly affect the performance of a GA [6]. The genetic algorithm contains several operators, e.g. reproduction, crossover and mutation.

(a) Reproduction

The reproduction operator allows individual strings to be copied for possible inclusion in the next generation. After assessing the fitness value for each string in the initial population, only a few strings with a high fitness value are considered in their production. There are many different types of reproduction operators including proportional selection, tournament selection, ranking selection, etc. In this study, tournament selection is selected, since it has better convergence and computational time compared to any other reproduction operator (Deb, 1999). In tournament selection, two individuals are chosen from the population at random, and then the string which has best fitness value is selected. This procedure is continued until the size of the reproduction population is equal to the size of the population.

(b) Crossover

Crossover is the next operation in the genetic algorithm. This operation partially exchanges formation between any two selected individuals. Crossover selects genes from parent chromosomes and creates new offspring.

(c) Mutation

This is the process of randomly modifying the string with small probability. Mutation operator changes 1 to 0 and vice versa with a small probability of mutation (Pm). The need for mutation is to keep diversity in the population. This is to prevent solutions in the population from being trapped in local optima as the problem is solved.

3. Implementation of Genetic Algorithm in ANSYS software

a. First create the model in Ansys software or import the model from any modeling software.

b. Apply the loading and boundary conditions.

c. Then run optimization algorithm in Ansys software

d. Automatically Meshing is created and solution is solved in the software .The best result (stress and volume)for each iterations (reproduction, crossover,

mutation, addition, deletion and alteration) is stored in separate file.

4. Optimization Algorithm

Composite laminate optimization was carried out for different practical problems with following design variables (no of layers, thickness, material, angle and sequence of layers)

The procedure is given below

(a) Reproduction (iteration 1)

In this process laminate design variables are randomly generated and results were stored for different combinations.

(b) Crossover (iteration 2)

The best sequence from previous iteration was selected based on high fitness

Fitness[i] =1-stress[i]/stress [max] or

Fitness[i] =1-volume[i]/volume [max]

In this iteration, laminate sequence were randomly changed from one sequence (parent1) to another sequence (parent2) for producing new sequences (child1 and child2).This concept is applicable for material, angle and thickness sequences.

Sequence1 Sequence2 Before crossover

1 3 4 2 5 8 7 8

After crossover

1 3 4 7 8 8 2 5

For example two materials (M1,M2), three thickness(5mm,10mm,15mm) and three angles(0,45,90) were taken for crossover operation

The best sequence1 (parent 1)

Total no layer = 5

Position		1	2	3	4	5
Material Sequence	=	M1	M2	M1	M2	M1
Thickness Sequence	=	5	5	10	10	15
Angle	=	45	0	90	90	45

Sequence

The best sequence 2 (parent 2)

Total no layer = 5

Position 1 2 3 4 5

Material Sequence = M2 M2 M1 M1 M1
Thickness = 5 15 10 5 5

Sequence

Angle = 45 90 45 90 0 Sequence

After cross over (child 1)

Total no layer = 5

Position		1	2	3	4	5
Material Sequence	=	M1	M2	M1	M1	M1
Thickness Sequence	=	5	5	10	5	5
Angle Sequence	=	45	0	90	90	0

After cross over (child 2)

Total no layer = 5

Position		1	2	3	4	5
Material Sequence	=	M2	M2	M1	M2	M1
Thickness Sequence	=	5	15	10	10	15
Angle Sequence	=	45	90	45	90	45

The above process is called single point crossover with right side shifting

Crossover operations are classified into

1. Single crossover with right shifting
2. Single crossover with left shifting
3. Single crossover with left to right cross shifting
4. Single crossover with right to left cross shifting

The best results from above four operations are stored.

(c) Mutation

The best sequence from previous iteration was selected based on high fitness. In this process variables are randomly exchange in between the single sequence itself. It is shown in below

Sequence1

Before Mutation	After Mutation
1 3 4 2 5	1 3 5 2 4

The above process is repeated for all best sequences and result was stored.

(d) Addition

The best sequence from previous iteration was selected based on high fitness. In this process variables are added randomly in the best sequence It is shown in below

Sequence1

Before Addition	After Addition
13425	1342523

The above process is repeated for all best sequences and result was stored.

(e) Deletion

The best sequence from previous iteration was selected based on high fitness. In this process variables are deleted randomly in the best sequence It is shown in below

Sequence1
Before Deletion After Deletion

134251325

The above process is repeated for all best sequences and result was stored.

(f) Alteration

The best sequence from previous iteration was selected based on high fitness. In this process variables are altered randomly in the best sequence It is shown in below

Sequence1
Before Alteration After Alteration
1 3 4 2 5 1 3 2 2 5

The above process is repeated for all best sequences and result was stored. This is called one generations.

Finally the over all best result from above six operations was plotted and stored. The same process was repeated for 50 numbers of generations. The optimization algorithm is shown in following Fig 1.

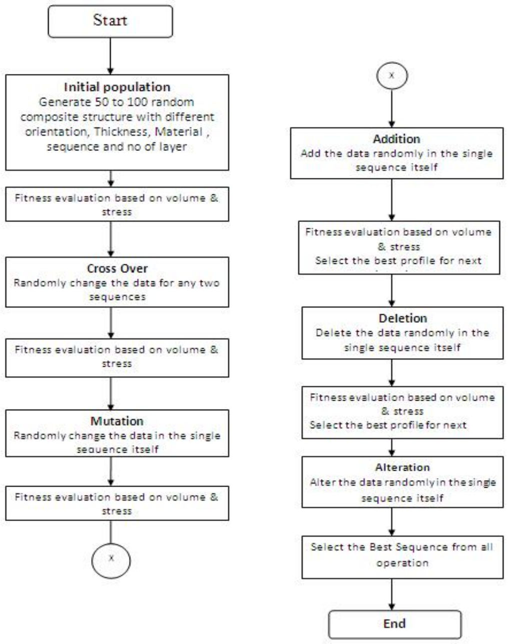

Figure 1. Genetic Algorithm for composite laminate optimization

4.CASE STUDIES

Genetic algorithm successfully implemented in following practical problems. The details of the inputs are shown below

1. Number of Material

2. Maximum Number of layer
3. Number of thickness
4. Number of angle
5. Loading & Boundary conditions
6. Model imported / created
7. Number of generations

All problems considered with following material properties E1= 10,000 N/mm2, E2=

10,000 N/mm2,E3= 250,000 N/mm2, 12=0.25, 23=0.01, 31=0.25,G12=2000 N/mm2,G23=5000 N/mm2,G31=5000 N/mm2, =7850 Kg/mm3

4.1 Plate with hole

A plate is subjected to biaxial load (1000 N) as shown in Figure 2. Following inputs were used

1. Number of Material =1
2. Maximum Number of layer (N) =8
3. Number of thickness =1 (2mm)
4. Number of angle =2 (45,-45)
5. Number of generations =50

The best results obtained in the 35th iteration as shown in below table 1

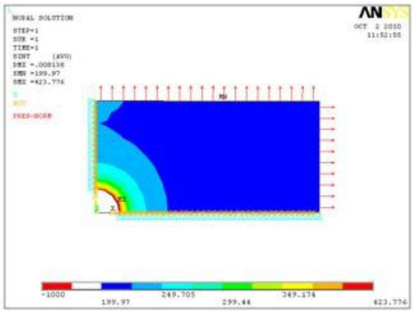

Figure. 2a

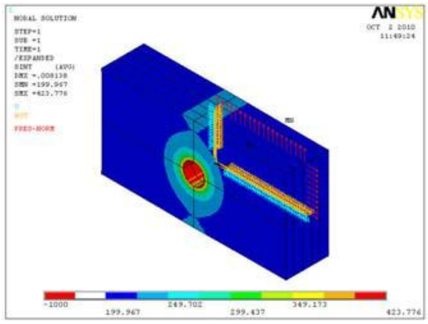

Figure 2a,b. Optimized stress distribution of plate with hole

4.2 Bumper with front & side load

A bumper is subjected to biaxial load (10000 N) as shown in Fig. 3. Following inputs were used

1. Number of Material =1
2. Maximum Number of layer (N) =4
3. Number of thickness =1 (3mm)
4. Number of angle =3 (0,45,90)
5. Number of generations = 50

The best results obtained in the 23rd iteration as shown in below table 2.

Table 1.Optimum results at 35th iteration

GA operators	Number Of Layer	Material	Thickness	Angle	Stress N/mm^2	Volume mm^3
Reproduction	4	1,1,1,1	2,2,2,2	45,-45,-45,45	528.77	10222.43
Cross over	5	1,1,1,1,1	2,2,2,2,2	-45,45,45,-45,-45	423.02	12303.65
Mutation	5	1,1,1,1,1	2,2,2,2,2	-45,45,45,-45,-45	423.02	12303.65
Addition	5	1,1,1,1,1	2,2,2,2,2	-45,45,45,-45,-45	423.02	12303.65
Deletion	5	1,1,1,1,1	2,2,2,2,2	-45,45,45,-45,-45	423.02	12303.65
Alteration	5	1,1,1,1,1	2,2,2,2,2	-45,45,45,-45,-45	423.02	12303.65

CONCLUSION:

The global optimized genetic algorithm plays major role in composite optimization. The above algorithm can applicable for any type of problems with known loading and boundary conditions. Further the computation time will be reduced by using cluster based optimization i.e many computers simultaneously involved in optimization process. In future this work may extended to failure criteria approach and dynamic problems.

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