THE GA OPTIMIZATION OF STRAIGHT AND CURVED LAMINATED COMPOSITE PANELS IN PRESENCE OF A CUTOUT

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1. OVERVIEW

Over the last two decades, laminated composites have been widely used in aerospace, automotive, marine, civil, and sport industries. In most of these applications, the composite laminates are subjected to cut outs especially for aircraft parts where other causes such as weight reduction dictate some openings in the parts structure. So, the design of each panel depends on a substantial number of design variables namely (number of layers, layer thickness, fiber orientation, and the materials for the composite constituents, shape and the geometry of the cutout, etc.).

Aircraft engineers can neither tolerate the added weight inherent with large safety factors nor the dangers to lives implied by a small value of this factor. As a result, high reliability of aerospace components must be assured by detailed analysis and accurate optimization in order to meet minimum weight requirements, while satisfying strength constraints. Here, in this research work, Genetic Algorithm (GA) which is a general optimization tool for searching of large, nonlinear, discrete, and poorly-understood design spaces that arise in many areas of science and engineering like the design and optimization of laminated composite panels, is utilized. However, constrained optimization via the Genetic Algorithm (GA) is often a challenging endeavor, as the GA is most directly suited to unconstrained optimization problems. Note that, traditionally, external penalty functions are used to convert a constrained optimization problem into an unconstrained problem for GA-based optimization studies. Therefore, here, the death, static, linear-dynamic, and a newly developed penalty function so called Two-Part penalty factor are employed for the GA design optimization of two laminated composite test cases. The study is focused on two straight and curved composite panels (1 m long × 0.5m wide) which are to be optimized for minimum weight and deflection in presence of an opening and under several other constraints. Note that the shape and dimension of the cut out are also considered as the design variables.

2. INTRODUCTION

Composite materials are becoming the material of choice in structural applications today and for the future. Although the high strength-to-weight properties of composite materials are attractive, their greatest advantage is that they provide the designer with the ability to tailor the directional strength and stiffness of a material to a given loading environment of the structure.

Designers have been reluctant to use composite materials in aerospace applications where there is a high demand for strong, yet light weight structures, because it is difficult to absolutely determine and design for the range of all possible loading conditions that a structure will encounter. An example of this is the latest and most technically advanced commercial transport aircraft, the Boeing 777. The structure of this revolutionary aircraft, which first flew in 1994, is only comprised of 9% by weight of composite materials [1]. Composite structures usually involve large, non-convex, integer programming problems that are discrete in nature therefore using composite materials in structural components has significantly increased the complexity of the design process. In fact, the numerous variations in ply thickness and orientation have extended the design space and reduced the effectiveness of the general design methods that are usually used with conventional materials. The most challenging aspect within the design and optimization of composite panels is that how to find the global optimum solution, which is usually obscured among a large number of local optimums. Moreover, the discrete nature of the design variables and nonlinearity of the constraints normally lead to more difficulties. Genetic Algorithm (GA) method is recently used as a general optimization tool for searching of large, nonlinear, discrete, and poorly-understood design spaces that arise in many areas of science and engineering [1-5] like the design and optimization of laminated composite panels, which is under consideration here. Constrained optimization via the Genetic Algorithm (GA) is often a challenging endeavor, as the GA is most directly suited to unconstrained optimization. Traditionally, external penalty functions have been used to convert a constrained optimization problem into an unconstrained problem for GA-based optimization studies. This approach requires a somewhat arbitrary selection of penalty draw-down coefficients. In this research work, several static and dynamic penalty functions with changing values for the draw-down coefficients are utilized.

3. GENETIC ALGORITHM

A simple genetic algorithm includes a population of chromosomes. Each chromosome consists of some genes that represent the design variables of a problem under consideration. Several genetic operators such as crossover, mutation, and elitism are implemented to create new chromosomes. During the GA process, the next generation of chromosomes is selected by a specific schema that considers the probability level of survival for each of the chromosomes. In fact, better chromosomes result in higher values for the fitness function. The reproduction process is stopped when some or all of the conditions set by the selected criteria are met and an optimum or near-optimum solution is obtained. However, maintaining the feasibility of the results is among the most important and endeavor tasks in a GA process due to application of the genetic operators that may easily produce infeasible children despite the proven feasibility of the parents.

The techniques for handling the constraints within the evolutionary algorithms are classified either as direct (when only feasible elements of the searching space are considered) or as indirect (when both feasible and infeasible elements are used) during the search process [6]. The direct techniques are comprised of the design of special closed genetic operators, the use of special decoders, repair techniques, and the death penalty. However, the indirect techniques include the use of Lagrange multipliers, special selection techniques, and "lethalization" (i.e. any infeasible offspring is assigned a very small fitness value [6]). The most important and widely used schema from among the large number of proposed indirect methods in the literature [7, 8] is the penalty function method, which includes the death penalty, most of the penalty schemes, and "lethalization" [9].

The penalty function method, which originally proposed by Courant in 1940's and then extended by Carroll, Fiacco, and McCormick, is a method that transforms a constrained optimization problem into an unconstrained one. In this way, based on the amount of violation of a constraint [9], a certain value is added to the objective. Usually, for problems with inequality constraints the penalty functions are divided into two exterior and interior categories. For the interior penalty functions, the penalty term forces the generated searching points to always remain within the borders of the design space [10]. However, for the exterior category a penalty value is added to the violating designs considering their distance from the feasible domain and also the number of violated constraints to bring them back to the feasible area. By means of these penalty values it will be possible to reuse the valuable parts (or genes) of the generated infeasible chromosomes in order to steer the optimization progress up toward the optimum solution(s). Eq. 1 depicts the general form of a penalizing function;

$$(1)\quad f(x) = \varphi(\bar{x}) + \sum_{i=1}^{N_{con}} \alpha_i \times P_i(\bar{x})$$

Where f(x) is the fitness function (or penalized objective function, $\varphi(\bar{x})$ is the objective function, and P(x) is a function of the constraints, and α's are positive constants (or rising factors) normally called ''penalty factors''. In all available penalty schemes, the degree of penalty can be further controlled by means of the values for α coefficient. Most of these coefficients are treated as constants during the calculations and their values have to be specified at the beginning of the calculations. The penalty functions with these coefficients are normally called ''static external penalty functions (SEPF)''. These coefficients usually have no clear physical meanings. Thus, it is nearly impossible to know appropriate values for them even by experience. Consequently, for all problems with either similar or different natures, appropriate values of the coefficients are generally obtained by trial and error. Many researchers, however, have tried to suggest the appropriate ranges for the coefficients. Most of these suggestions are obviously doubtful. The reason is simply that the selected values are usually given without any reference to the units used in the problems. Another important concern is that the conventional penalty schemes were not provided appropriate penalty strength during the calculations, as the coefficients used are always kept constant. As a result, sometimes very week or very strong penalty values during different phases of the evolution may occur. This may lead to inaccurate solutions. To overcome this limitation, some penalty schemes that vary the values of the coefficients to adjust the strength of the penalty during the calculation have been proposed [1, 11]. One of these schemes is called linear dynamic penalty function (LDEPF). In this scheme, the penalty function is dependent on the penalty factors which may somehow be related to the generation numbers. Normally, the penalty function is defined in such a way that it increases during the processing time. In general, the problems associated with static penalty functions may also be presented with dynamic penalties. If an appropriate penalty factor is chosen, the GA may converge to either non-optimal feasible solutions for high penalty values or to infeasible solutions for very small penalty values [11, 12].

4. PROBLEMS DESCRIPTION

The design problems under consideration consist of 24 ply laminated symmetric composite straight and curved plates (1 m length × 0.5m width) which are subjected to a concentrated load (P=300 N) at the midpoint of the plates as depicted in Fig 1. There is a cutout at the center of the plates. The shape, size and orientation of the cutout are considered as the design parameters. The cutout shape can be in the form of circle or polygons with three to seven sides and its orientation respect to the center line of the plate can vary from 0 to 180 degrees in increments of 30 degrees. Each ply in the stacking sequence is allowed to be oriented at any angle between 0 to 90 degrees in increments of 15 degrees. The constitutes of the composite plates are also considered as design variables and can be selected from 16 materials which are listed in Table 1.The design parameters and the meaning of each gene in a typical chromosome are summarized in Table 2.

The main goals of the optimization process considered here are to find the shape, geometry and orientation of the cutout and also the stacking sequence and the thickness and sequence of the layers and the suitable material in order to obtain minimum weight and deflection for the panel. Therefore, the considered problems are multi objective functions which consist of non dimensional state variables that their particularly weighted values are linearly combined. The mentioned weighting parameters are selected regarding the significance of each state variable in a real engineering problem. These parameters are selected to be 80% for the non dimensional weight and 20% for the non dimensional deflection. Here, in this study, regarding the pervious studies, the restriction or constrains imposed are as follows:

1) Safety factor must be greater than 1.2

2) The weight must remain under 35 kg

3) The max allowable deflection is 5 cm (at the mid point)

The problem is converted to the standard form of a constrained maximization of a positive objective function in form of Eq.2;

$$Max \rightarrow \varphi(\overline{x}) = 10 - (0.8\overline{w} + 0.2\overline{\delta})$$

$$S.T \begin{cases} S.F > 1.2 \\ \overline{w} < 1.0 \\ \overline{\delta} < 1.0 \end{cases}$$

(2) *where*

$$\overline{w} = w/w_{\max} = w/35$$

$$\overline{\delta} = \delta/\delta_{\max} = \delta/50$$

As mentioned before, the GA is an ideal method for unconstrained optimization problems and constrains are handled by using penalty functions. Therefore penalty term P($\overline{x}$) is used to preserve the feasibility of the solutions and it is subtracted from the maximization problem as in Eq.3;

(3) $$Max \rightarrow F(\overline{x}) = \varphi(\overline{x}) - \alpha \times P(\overline{x})$$

Where P($\overline{x}$) has the form as shown in Eq.4;

(4)
$$P(\overline{x}) = 0.7(\overline{w} - 1) - 0.26(1/S.F. - 0.833) - 0.04(\overline{\delta} - 1)$$

Here, the weighting parameters for the three terms of the penalty function are chosen regarding the significance of each term in achieving the optimum objective value. It could be related to the positive or negative effects of one constraint change on the rest of the related constraints. However, it should be mentioned that choosing these weighting parameters is often arbitrary and not a definite way for it has been set, yet [2, 13 and 14]. For instance, in this example, increasing the panel weight is a disadvantage; however, it could positively affect the process by causing the advantage of decreasing the deflection. Since these state variables (i.e. weight and deflection) are appeared by 80% and 20% weighting factors in the objective function φ($\overline{x}$), therefore it is assumed that any increase in the panel weight could produce a maximum drawback of %80 for the weight and maximum benefit of %20 for the deflection (see Table. 3). It is noted that since the objective function φ($\overline{x}$) appears by the weight of unity in F($\overline{x}$), the weighting factors for the terms of the penalty function P($\overline{x}$) are also calculated such that they add up to unity. Note again that, in this way, the relationship between the weighting factors of the Two-Parts of the fitness function (F($\overline{x}$)) plays a significant role in penalizing infeasible chromosomes. It is reminded that there is not a clear way to define the optimum value for these factors, yet. It is only known that they should be kept as low as possible, just above the limit below which infeasible solutions are optimal [15]. For the problem in hand, the effect of α (see Eq. 3), which is defined as the penalty factor, could be easily highlighted. For doing the analysis, the specially provided GA code is linked with ANSYS FEM software for evaluation of the objective value corresponding to each one of the chromosomes.

5. RESULTS

The effects of the dynamic, static, death, and a newly developed (so called Two-Part) penalty factors on the design of two laminated composite plates are investigated. The first problem consists of a straight laminated composite plate, while for the next test case, the plate is considered to have a curved configuration. In these cases, the geometry, size and orientation of the cutout at center of the plates are also added to the design parameters. Here for the straight plate the effect of all mentioned penalty factors will be compared but for the second case study the attention is focused on the dynamic and Two-Part penalty factors.

5.1. CASE STUDY1: STRAIGHT PLATE

DEATH AND CONSTANT PF

To study the effects of the discussed penalty approaches on the efficiency of the GA in optimization of the problem under consideration, here two of the simplest forms of the penalty functions i.e. the death and constant PF's are applied. The Death penalty is implemented by relating a large penalty factor (i.e. 10,000 in this case) to the infeasible solutions. However, the constant PF is assumed to penalize the infeasible solutions with a value that is in the same order as the weighting factor of the objective value i.e. (α=1). This penalty factor is kept unchanged during the whole reproduction process. In other words, neither the penalty function nor the penalty factor is considered to be dependent on the number of generations. Note in this text when the fitness value quoted it may be related to both feasible and infeasible chromosomes. But, when the objective value is quoted the related chromosomes all are feasible. For the applied penalties, Figure 2 shows the maximum fitness values obtained in 200 GA generations. As it is observed, higher maximum fitness values are obtained with the constant PF compared to the death PF but some of the chromosomes in each population for α=1 are found to be infeasible. In other words, using the constant PF benefits the process by fast improvement in the fitness values, but unfortunately it may force the algorithm to converge to infeasible solutions. It is important to note that if the feasible chromosomes of the last population obtained by the two penalties are also compared, the fitness of the solution found by the constant PF (fitness=9.9442) is slightly above the one that is found by the death PF (fitness=9.9361). Also, the placement of the fitness curve of the constant PF above the one for the death PF shows that how the survival of infeasible solutions with employing constant PF robust the searching method. However, for the constant PF, increasing the number of infeasible chromosomes and converging to some infeasible solutions is highly presumable if the value of the penalty factor is not adequately set. It should be noted that since an ideal penalty factor must satisfy the minimum penalty rule, it is not easily possible to select a value for the PF when the design space or objective function is not clearly known.

Linear-Dynamic PF

In order to overcome the mentioned disadvantages of constant PF, two linear-dynamic PF's are utilized to adjust the amount of penalty during the optimization process. In these cases, the value of the penalty factor is linearly increased with increasing the generation number. Eq. 7 presents these dynamic penalty factors which are here named as GN_20 and GN_40 as mentioned in Eq.5;

$$(5) \quad \begin{cases} GN\_20 \rightarrow \alpha = \dfrac{number\ of\ generations}{20} \\ GN\_40 \rightarrow \alpha = \dfrac{number\ of\ generations}{40} \end{cases}$$

Regarding the plots of the maximum fitness value (obtained for 200 generations) vs the generation number (see Fig. 3 and Fig.4) it is clear that, In comparison both cases of the linear-dynamic PF's end up with a higher fitness values found in the last generation than the constant and death PF's. Note that though GN_20 (that implies higher penalty factor) is more robust than GN_40, but not a clear way could be found in the literature for setting the value of the penalty factor. As it can be seen in some generations if the process of GN_40 is stopped, better results than GN_20 could be found. A comparison of all PF's discussed so far shows that in most generations between 1 and 200, GN_20 produces higher fitness values than others. Also, the objective values of the chromosomes in all generations indicates that using a rising PF (either linearly or in any other complicated form) results in survival of infeasible solutions in early generations , while it could relatively ensure the feasibility of the final solutions.

Two-Part PF

The introduced Two-Part penalty factor enjoys the convergence speed of the linear-dynamic penalty factors in early generation. Note this penalty showed a reasonably well performance in previous section. As for the second part of the penalty, an exponentially rising factor with the number of generations is considered as indicated in Figure 5. Note that the exponential nature of this part of the penalty guarantees the swift transition from the dynamic part to the death penalty at higher number of generations by attributing very large penalty values to the infeasible chromosomes. Here, for these test cases, the switching point between the two parts of the penalty is set at the generation number of 130. It is assumed that for generation numbers higher than 130 the death PF is more effective than the others. So at this point the penalty factor is set to start to increase exponentially with the number of generations. In comparison to the linear-dynamic and death PF's, fast convergence to a near-optimum is secured with using the Two-Part PF. Note that this could not be considered as a sole measurement parameter of efficiency for the GA, yet it is seen merely as a sign of relative efficiency. A more close observation of the maximum fitness found by the discussed PF's shows higher accuracy of the results for the Two-Part penalty function, see Figure 6. The figure clearly depicts that, in comparison to other methods, the value of the fitness found after 200 generations (i.e. 9.9498) is also higher for the Two-Part PF, see Table 4.

5.2. CASE STUDY 2: CURVED PLATE

Linear-Dynamic and Two-Part PF's

Figure 7 shows the fitness values obtained in 200 generations for a curved plate using GN-20 and GN-40 PF's. It is clear that in this case GN_40 produces better results during the whole process because the graph of fitness value is placed above the graph for GN_20. As mentioned before there is not any obvious way for setting the value of penalty factor. Figure 8 also shows the fitness values obtained in 200 generations for a curved plate using GN-40 and Two-Part PF's. It is clear that in this case also GN_40 produces better results than Two-Part during the whole generations. Note that the Two-Part in comparison to GN-20 produces better results

5.3. Quantitative Comparison of the Results

For measuring the accuracy of the results the global optimum should be known, but for the current test cases this information is not in hand. Therefore, for such situations, it is recommended that the accuracy to be approximately studied through the efficiency measurement. In this way, a method that finds a better solution in fixed number of generations is considered to be more efficient. Note that the maximum number of generations is selected by the user and also it is considered to be constant for all cases. So the computational cost or the number of required evaluations is equal for all the trials assumed. Therefore, the trial that runs always above the others is considered to be more effective rather the one that finds a better optimum in a haphazard jump in the last generations. As a result, the confined area by the progressive rout of the average of maximum fitness and the axis of generation number as in Figure 9 and Figure 10 is assumed as a proper quantity for such a comparison. Based on these results, the Two-Part penalty factor improves the accuracy and efficiency of the GA analysis and ranked first among all of the studied PF's in the first case study but in the second one as it is shown the GN_40 improves the accuracy and efficiency of the GA.

5.4. Optimum plates

Table 4 summarizes the characteristics and properties of optimum straight plates obtained by different penalty factors. It is noticeable that the plate obtained by the constant penalty factor is not feasible because its safety factor in less than 1.2. However it could be concluded that the material must be Ultrahigh modulus Graphite/Epoxy (material number 6) or High modulus Graphite/Epoxy GY-70/493 (material number 15). Another point that can be concluded is the total thickness of the plate. Multiplying the number of layers by the thickness of each layer the total thickness of the plates are found to be between 2.4 to 3.0 mm.

Table 5 also summarizes the optimum curved plates obtained by different penalty factors. It is very clear when the plate is curved all penalty factors lead to very thin and light plates with thicknesses lower than 0.5mm and weights below 700gr, but like the straight plate materials are number 6 or 15.

5.5. Cutout geometry

Figure 11 shows the cutout geometry of the straight plates obtained in different runs. Comparison of these cutouts shows that for the constant, GN-20 and two-part penalty factors the optimum plates obtained have circular cutout shapes with very similar geometries. But for the Death and GN-40 polygons cutout shapes are found which in geometry are very near to two-part cutout shapes.

Figure 12 shows the cutout geometry of curved plates obtained from different penalty factors. Comparison of these cutouts shows that all three curved plates have small cutouts and none of them has regular circular cutout shape. Comparison of the two case studies here clearly shows that the optimum curved plates have smaller cutouts than straight plates (about 5% to 10% smaller) and also it is noticeable that the optimum curved plates are thinner than straight ones (about 7% to 17%).

6. CONCLUSIONS

1. In laminated composite plates the optimum cutout shapes are not necessarily circular and the size and geometry of the optimum cutout are controlled by the material, number of layers and stacking sequences of them.

2. There is a significant difference in optimum cutout shape and thickness of the straight and curved plates with the same size and constrains. The optimum curved plates are much thinner than the straight plates with smaller cutouts.

3. A smart use of conventional penalty factors could lead to superior results which may rule out the necessity for define and application of complex penalties.

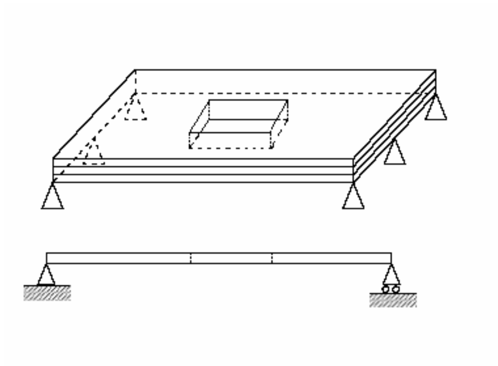

FIG 1. Schematic of Problem

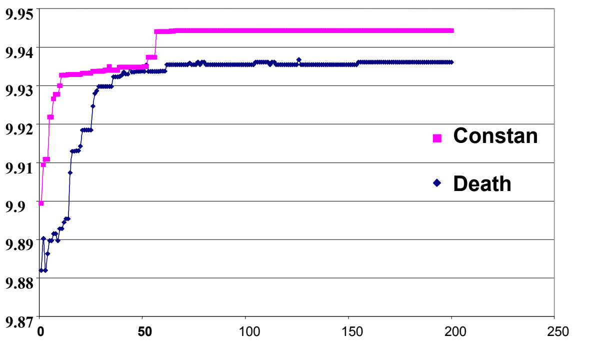

FIG 2. Max Fitness for the Death and Constant PF for the Straight Plate in 200 Generations.

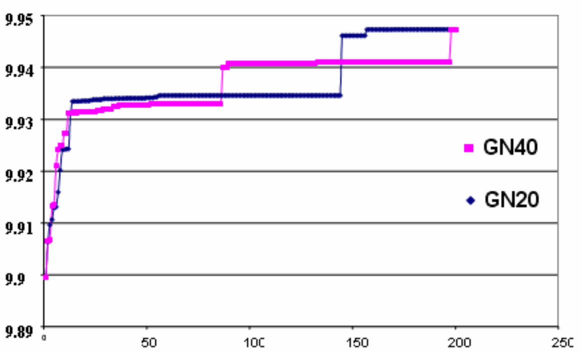

FIG 3. Max Fitness for Linear Dynamic PF's for the Straight Plate in 200 Generations.

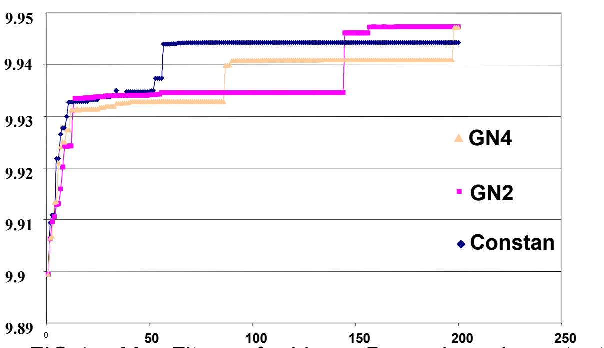

FIG 4. Max Fitness for Linear-Dynamic and constant PF's for the Straight Plate in 200 Generations.

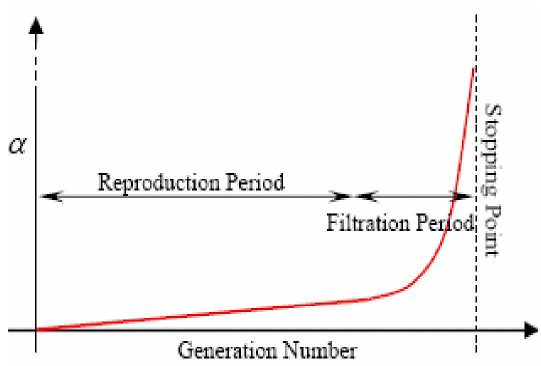

FIG 5. Schematic of Two-Part PF

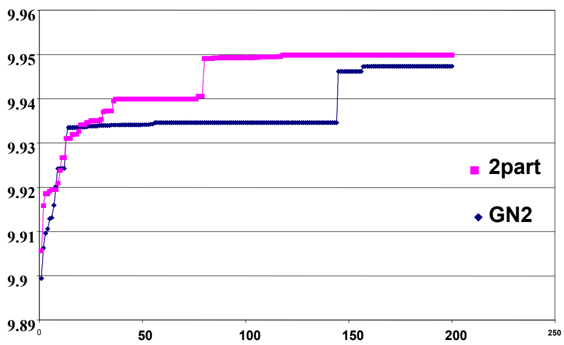

FIG 6. Max Fitness for GN_20 and Two-Part PF's for the Straight Plate in 200 Generations.

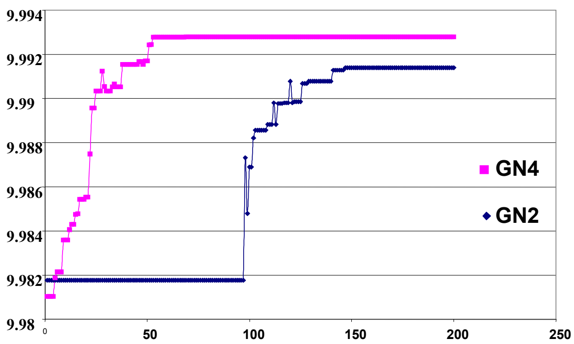

FIG 7. Max Fitness for Linearly Dynamic PF's for the Curved Plate in 200 Generation.

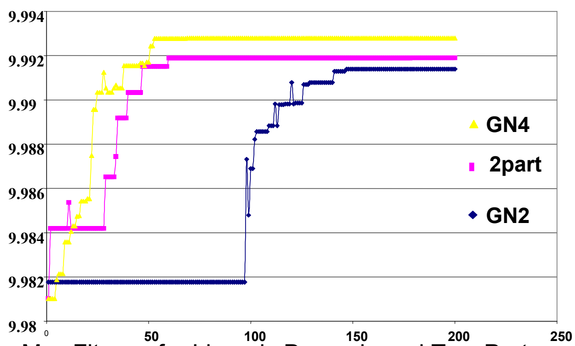

FIG 8. Max Fitness for Linearly Dynamic and Two-Part PF's for the Curved Plate in 200 Generations.

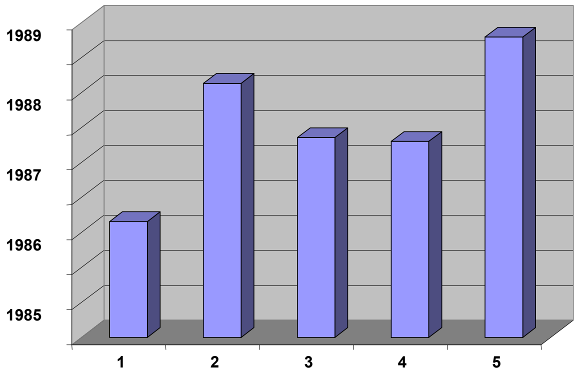

FIG 9. Comparison of robustness of the Straight Plate.
(1: Death, 2: Constant, 3: GN_40, 4: GN_20, 5: Two-part)

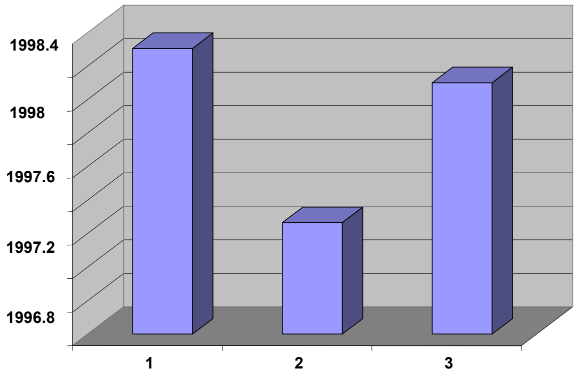

FIG 10. Comparison of robustness of the Curved Plate.
(1: GN_40, 2: GN_20, 3: Two-part)

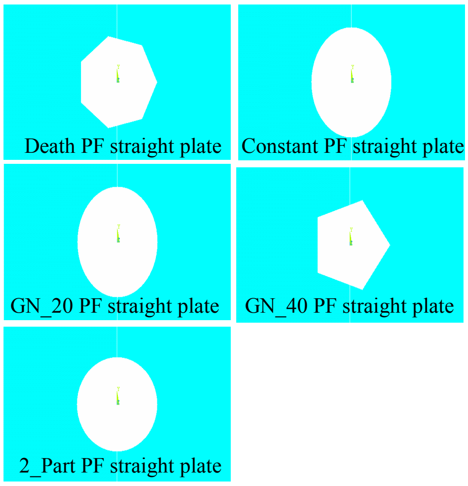

FIG 11. Optimum Cutout Shapes for Straight Plate.

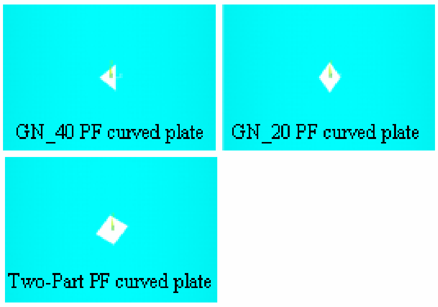

FIG 12. Optimum Cutout Shapes for Curved Plate

	Material Name	No	Material Name	No	Material Name
1	Glass/Epoxy E-Glass	7	Glass/Epoxy E-glass	13	Standard graphite/Epoxy AS43501.6
2	Glass/Epoxy S-glass	8	Glass/Epoxy S-Glass	14	Intermediate modulus graphite/Epoxy IM6/1081
3	Boron/Epoxy	9	Boron/Epoxy B4/5505	15	High modulus graphite/Epoxy GY-70/934
4	High-strength Graphite/Epoxy	10	Boron/Epoxy B5.6/5505	16	Standard graphite/Epoxy
5	High modulus graphite/Epoxy	11	Aramid/Epoxy Kevlar 49		
6	Ultrahigh modulus graphite/Epoxy	12	Standard graphite/Epoxy T300/5208		

TAB 1. Materials which are used to optimization.

Gene No	Meaning	Allowable Range			Binary Length
		Lower Limit	Increment	Upper Limit	
1	Number of layer	1	1	12	4
2	Layer Thickness (mm)	0.1	0.1	1.6	4
3	Material	1	1	16	4
4	Cutout shape(sides)*	2	1	6	3
5,6	Cutout size(scale)**	0.5	0.25	1.75	3
7	Cutout orientation	0	30	180	3
8-20	Fiber Orientation in Layers 1 through 16	0°	15°	90°	3

*Cutout shape can vary from 2(circle) to 7(polygon with seven sides)
** To set cutout size the basic shape scaled in x and y direction by this scale factor

TAB 2. Meaning, allotted values and binary code length of genes in a typical chromosome.

Violating Const.	Con	Pro	Con/Pro	Weighting Coef.
Weight	Weight↑ (max. 80)	Deflection↓ (max. 20)	80/20	≈0.72
Safety Factor	Failure↑ (max. 100) Deflection↑ (max. 20)	Weight↓ (max. 80)	120/80	0.23
Deflection	Deflection↑ (max. 20)	Weight↓ (max. 80)	20/80	≈0.05
			Total	1

TAB 3. Defining weighting parameters for $P(\bar{x})$.

	Death PF	Constant PF	GN_40	GN_20	Two-Part
Fitness Value	9.936099	9.944279	9.947217	9.947325	9.949875
Number of layers	10	10	14	10	24
Thickness	0.3 mm	0.3mm	0.2mm	0.3mm	0.1mm
Material	6	15	15	15	6
Fiber orientation	[0/ 0/ 90/ 45/ 0]s	[0 /0 /90 /60 /90]s	[0 /0 /90 /0 /0 /30 /30]s	[0 /0 /75 /90 /90]s	[0 /0 /90 /0 /0 /0 /0 /90 /0 /45 /45 /60]s
Weight	4.08 kg	4.12 kg	3.90 kg	3.825 kg	3.20 kg
Deflection	1.7 mm	2.2 mm	2.06 mm	2.16 mm	2.42 mm
Max Stress	68.5 MPa	83.1 MPa	80 MPa	88 MPa	115.3 MPa
S.F.	1.5	1.108	1.21	1.36	1.25

TAB 4. Optimum designs found for different PF's straight plate.

	GN_40	GN_20	Two-Part
Fitness Value	9.992793	9.991393	9.991891
Number of layers	2	2	2
Thickness	0.1mm	0.2mm	0.2mm
Material	15	6	15
Fiber orientation	[0]	[0]	[15]
Weight	0.324 kg	0.690 kg	0.644 kg
Deflection	0.87 mm	0.17 mm	0.28 mm
Max Stress	22.2 MPa	12.11 MPa	11.3 MPa
S.F.	4	3.34	5.8

TAB 5. Optimum designs found for different PF's curved plate.

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