AN APPROACH FOR MULTI-OBJECTIVE OPTIMIZATION OF HYBRID MATERIAL STRUCTURE FOR MOBILITY APPLICATIONS

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ABSTRACT

The layup optimization for the composite part -in a structure made by metal and composite- subject to 3 components load direction using genetic algorithm method is studied in this paper. The method is demonstrated on the problem to find the optimum stacking sequence with minimal weight and maximal rigidity of structure while keeping the stresses of laminate below the critical level. Material of plies, plies orientation, and their number and thicknesses are assumed as the variable inputs of the optimum stacking sequence in this study.

Fully natural coding approach is used to assign the variable specifications to the laminate. A general software code serves to perform optimization rules and definitions of the related functions based on the genetic algorithm method. The code is coupled with the FEM software in order to analysis the influence of load cases on generated plies and achieving the amount of stress and overall deformation of the structure. Then the objective function will be taking into account as a multi-objectives problem and a weighted sum method is used and evaluated.

Two approaches for reducing the number of analyses required by genetic algorithm are described. First, a selection pattern dictates more competent members in new generation and second makes more valuable characteristic for laminate by using regulated operators of GA. The advantage of developed methods to increase the search ability of algorithm is discussed. The capability of new operators to produce more near optimal design in final iteration is compared with the standard form of GA.

Key words: Optimization, Composite, Multi objective, Genetic Algorithm, Stacking sequence

1. Introduction

The laminate composite materials are being use increasingly in the wide range of industrial fields such as aerospace, marine and automotive industries. The advantages of these materials are summarised as; high strength-to-weight ratio and their flexibilities against to meet specific design requirement by selecting the layers sequence through the thickness.

However, achieving this abilities require to find the optimum size and shape and suitable placement of fiber within the material, while it increases the complexity of the design problem. Regards to material distribution through the part there are 2 different scenarios for design of composite structures; constant stiffness and variable stiffness. This paper has focused on the first case; same stacking sequence over the domain. For optimal layup selection of laminated composite material there are different classification and methods.

The specification and performance of most of them has been precisely discussed by GHIASI [18]. One of the most popular optimization methods in the case of stacking sequence of laminate structure is genetic algorithm. In the recent years wide range of GA (Genetic Algorithm) based approaches have been used for different particle purposes. The advantages of GAs is that they give the designer a family of near optimal design with small variation in their performance instead of a single design, while global optimization method always search for a single global optimal method. Also GA doesn't use any gradient-based information and are insensitive to the complexity of the design space. If the population size is suitably large GA is not at the risk of being stuck a local optimum. However, finding a global solution is not necessarily guaranty to be successful unless an infinite number of iteration is performed [6].

GA for optimization of stacking sequence has being used in different applications; for buckling load minimization of rectangular plate by RICHE and HAFTKA [30], for minimization of buckling load in a rectangular plate with local improvement by KOGISO, WATSON, GÜRDAL, and HAFTKA [22], optimization of a composite cylinder for buckling load using GA with recessive gene like repair by TODORKI and SASAI [4]. Other related studies in [2, 7, 32, 34, 35, 36].

However, GA is known to incur high calculation cost, so the procedure of optimal design becomes ineffective when it is connected with a complex structure analysis model. In order to reduce the calculation cost of standard GA, performance of a micro GA has been introduced by KIM[33], to obtain the optimal stacking sequence with GA using response surface approximation by TODOROKI and ISHIKAWA [5]. Other related surveys in [8, 14, 24, 27]. In section 5 some familiar method for improving the performance of GA will be introduced and some of them will be modified with the case of this paper. Influence of this modification will be discussed in result section.

There are some heuristic optimization methods beside the GA for optimization of stacking sequence in composite structures. They have been classified as direct search method like GA [18]. Exploring of metaheuristic approach called scatter has been used for layup sequence optimization of a rectangular laminate composite plate by RAO and ARVIND [3]. The ant colony method has been evaluated by AYMERICH and SERRA in order to optimal design of stacking sequence of a rectangular plate for maximum buckling load capacity [12]. Optimization of stacking sequence of a rectangular plate for minimization of failure load using TABU search has been studied and its performance has been compared with the GA method by PAIA, KAWA, and WENGB [23]. An integer programing was used by HAFTKA and WALSHT for optimization of stacking sequence for buckling load of a rectangular plate [29]. Other related studies in; [17, 21, 31].

Most of engineering tasks in automotive branch, involve with multi-objective problems i.e., minimize weight, maximize rigidity, maximize durability, minimize cost, etc. Two existing approaches (i) to use their combination (ii) consider some of them as the constraint, are evaluated in this paper. Then, overall procedure to acquire a single objective function for an optimization study will be demonstrated.

2. Case Study

In the present study, in order to implement the GA to optimize the stacking sequence, situation of A-Pillar assembly -made by composite material- in automotive body has been intended.

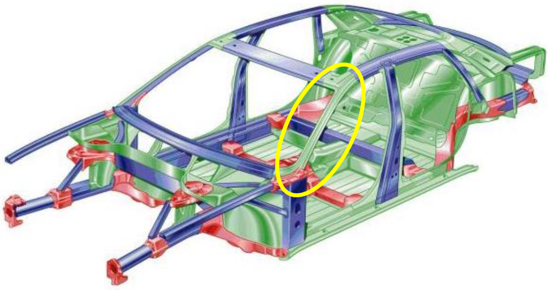


Figure 1: A-Pillar on body-in-white [European Aluminium Association V 2013]

Mostly, mentioned assembly, is integrated with the side-part but here comes an individual assembly. Customary, it consists of two steel parts which has been welded together but in this study, the inner parts has been planned to replace with a laminated composite part. Cohesive bonding method has been used to connect the new part to the metal part (outer), Figure 2.

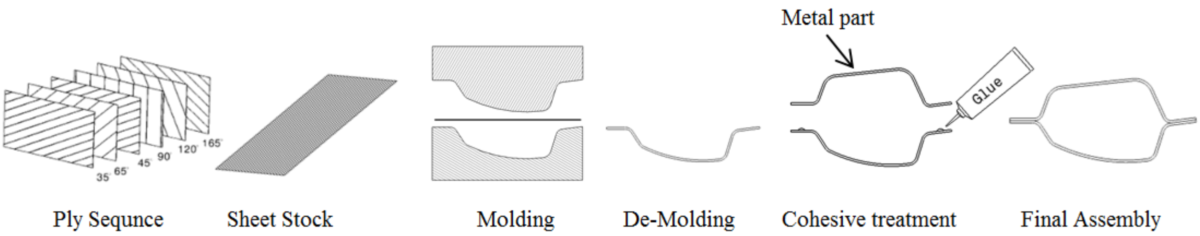
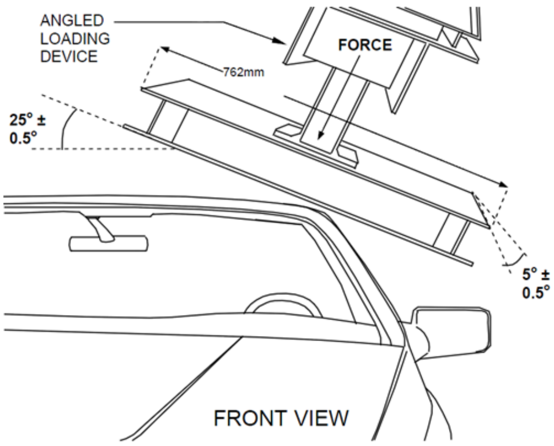


Figure 2: schematic of making a hybrid A-Pillar section

New assembly expected to be lighter and at least has the same rigidity related to the metal assembly. Weight and rigidity of the base model is compared with the new hybrid assembly (steel-composite laminate) at the result section. Most critical accident for this section of car body is rollover, and it assessed by roof crush resistance test according to the *FMVSS No. 216a* procedure, Figure 3.



$$FORCE = \mathrm{GVWR(Kg)} \times 9.81\, {}^{m}/_{s^2} \times 3$$

Where: GVWR = Gross Vehicle Weight Rate = 1,594 Kg

With respect to the force direction:

F_x=3,698 N

F_y=19,979 N

F_z=42,322 N

Figure 3: FMVSS roof crush resistance test procedure

Of course in real world for similar situation, engineers take into account a wide range of load cases like; aerodynamic loads, fatigue and vibration loads, which are not the main subjects of this paper.

The requirements of this test caused to subject a 3D components load in X, Y, and Z direction to the top portion of the A-Pillar assembly. In order to obtain the rigidity and failure criteria under mentioned loads, 3D model of mentioned assembly has been created in CATIA software and then exported to ABAQUS for simulation tasks [10]. For simpler model like plates and tubes and beams with unique section thought the length analytical calculation seems feasible than using FEM software. Analytical method widely used by scientists during the last decades and also has been specifically described in some useful books [11, 20].

3. Implementing of GA

The concept of GA is explained in detail in many publications such as Goldberg [16] and Kaya. It is started with generation of the random initial population which is evaluated to measure the performance of the population in order to make them the better solution. Then they are tested and if optimization criteria are satisfied the process will be stopped and return the solution in current population. If the optimization criteria are not achieved, the new population is created by GA operators until the new population is completed. This new generated population is replaced for a further run of algorithm and steps are carried out continuously until the optimization or termination criteria are met. In order to implement the GA to optimize the staking sequence of inner part as introduced in section 2, following assumptions has been considered to build the laminate.

- Minimum and maximum number of plies per laminate; 4 and 8 respectively.
- Available materials of plies are Glass-Epoxy and Carbon-Epoxy.
- Available thicknesses for individual layers are 0.5, 0.6… 1.4, 1.5 mm.
- No manufacturing limitation for plies orientation.

For individual applications such as tensile-compression, buckling and even bending, special guidelines -obtained from experimental tests- are available. Here, to avoid of matrix cracking phenomenon, an axillary subroutine program continually prevents to produce and duplicate of laminate with more than 4 contiguous plies of same orientation during the implementing of algorithm.

3.1 Creating of initial population

First action of GA is to randomly create initial population from total possible stacking sequences. In this paper a MATLAB code generates an identification code for each layer and consequently for the whole laminate contains every ordinary numbers for layers. Identification code for each layer contains six characters, Figure 4.

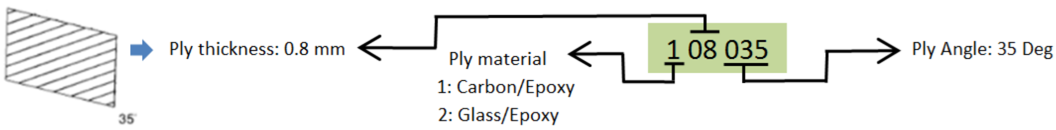


Figure 4: Coding of an individual layer

For instance, an 8 layers laminate will be coded with 8×6 characters (Figure 5, Parent 2). Most recent researchers have used a form of a bit string or integers for permutation to make the laminate with some assumptions related to the ply orientation [4, 5, 6, 13, 14, 22, 30].

3.2 Creating of objective function

Stacking sequence optimization of inner part which provides the minimum weight and overall deflection -while keeping the strength blow than the failure criteria- consider as a multi-objective task. In multi-objective problems the objectives normally have clash together and it is caused to prevent optimum value of objectives simultaneously [2, 7, 19, 25]. One general approach to multi-objective optimization is to combine the individual objective functions into a single composite function.

Weighted Sum method is most practical approach to obtain the objective function (WBGA [1, 25]). The objective function equation (1) is used to assign a fitness value to each laminate [15].

$$\bar{F}(\mathrm{X}) = F(X) + r\sum_{j=1}^{m}\{\max[0, g_j(X)]\}^2 \quad (1)$$

Here, weight and deflection of structure are mentioned as the objectives and TSAIW value is consider as a constraint (Constraint handling techniques has been widely introduced by Coello [9] here a *static penalty* approach has been operated). In TSAI-Wu criterion, a composite ply subject to plane stress continues will fail when a special formulation resultant of stresses being more than one [11, 20].

The objective function needs to dimensionless parameters; Wn, Un, and $TSAIWn$ that represent the normalized amounts of weight, deflection and TSAIW criterion of parts by their maximum and minimum values. This approach is more effective than a formulation that uses directly the weight and displacement value even a simple dimensionless value of this variable divided by a reference value [7, 13, 28]. The normalization formula is given by equation (2):

$$Wn = \frac{(W-W_{min})}{(W_{max}-W_{min})} + 1 \ \ , \ \ Un = \frac{(U-U_{min})}{(U_{max}-U_{min})} + 1 \ \ , \ \ TSAIWn = \frac{(TSAIW-TSAIW_{min})}{(TSAIW_{max}-TSAIW_{min})} + 1 \quad (2)$$

Minimum and maximum value of weight can be obtained with consider to the initial assumptions and material densities. Minimum weight is related to the smaller density means Glass-Epoxy and minimum number of plies, obtain; $W_{min} = A \times t_{min} \times \rho_{Glass/Epoxy}$ where A, is the area of the inner part by mm^2, $\mathrm{t_{min}}$ is the minimum total thickness of the laminate by mm, and $\rho_{\mathrm{Carbon/Epoxy}} = 1.54\mathrm{e}^{-6}\ \mathrm{Kg/mm^3}$ [26], acquire Wmin = 0.493 Kg. And for heavier part with $\rho_{\mathrm{Glass/Epoxy}} = 1.8\mathrm{e}^{-6}\ \mathrm{Kg/mm^3}$[26] and maximum allowable thickness, acquire Wmax = 3.456 Kg.

Maximum deflection belongs to the weakest laminate with the minimum number of plies and weakest material (Glass-Epoxy) and worst sequence of plies. Because of complexity of shape and load cases it is relatively difficult to determine the angle of plies associated to the weakest laminate. Here all plies angel are assumed 90° related to the part length and calculated deflection from ABAQUS simulation acquires 48 mm. A safety factor of 1.2 is applied to eliminate of every underestimation. Same method can be applied for minimum deflection related to the strongest laminate, gets 25 mm. Max and min values for TSAIW criterion have been assumed 5 and 0.1 respectively.

The objective function contains 2 objectives has been weighted by a factor (α) which controls the emphasis of each objectives in optimization task. So the first term of equation 1 can be written as [15]:

$$\mathrm{F(X)} = \sum_{k=1}^{k} W_k F_k(X) \quad (3)$$

For the case of this paper equation (1) can be arranged as:

$$\bar{F}(\mathrm{X}) = \propto W_n + (1-\propto)U_n + Penalty \quad (4)$$

Where: $0 \leq \propto \leq 1$

Penalty = TSAIW $_n$ if TSAIW < 1

Penalty = TSAIW $_n + r(TSAIW)^2$ if TSAIW ≥1

In this study, more priority has been planned for deflection of the structure than the total weight, therefor α takes into account as 0.4. Optimum value of r respect to the current values of objective function has been assigned 2.

3.3 Selection patterns

In order to form successive generation, parents are chosen from the current population based on their fitness function. Parents' selection is performed using roulette wheel concept. Selection operator chooses the pair of parents to crossover and produce children and of course fitter individuals have higher opportunity to be a parent. *Fitness-Ranking* for every sample is calculated as equation (5):

$$Fitness\_Ranking = (\bar{F}_i^{max}(X) - \bar{F}_i(X))/(\sum_{i=1}^{P}(\bar{F}_i^{max}(X) - \bar{F}_i(X))) \tag{5}$$

Where P is the population size, $i = 1, \dots, P$, and $\bar{F}_i^{max}(X)$ is the max fitness value of population. This method of selection has been compared with the result of *Linear-Ranking*. In *Linear-Ranking* all laminate must be ranked from best to worst according to their fitness value and take a rank with equation (6).

$$Linear\_Ranking = 2(P - i + 1)/(P^2 + P) \tag{6}$$

Assessment the final result of two ranking methods shows that finding a local optimum instead of the global optimum has more probability in Fitness-Ranking than the Linear-Ranking. Because of this, here the Linear-Ranking method has been used for pair selecting in next process.

3.4 Stopping Criteria

Stopping criteria check some quality characteristics of current population. If at least one of them is reached the optimization process is stopped and the best sample of the last population takes into account as the optimum result. First stopping criterion in this study is to achieve a number of iteration and the second is to sense no improving of the best design. In this study, maximum number of iteration per run and maximum number of iteration without any improving of best result have been set on 30 and 7 respectively. Another stopping criteria may use in special cases such as: small improvement of generation (stagnation), and to reach a specific point of searching space.

3.5 Crossover

Crossover allows member of population to exchange characteristics with a typical probability of Pc = 0.6 – 0.8 [15]. It is usually the primary operator with mutation serving only as a mechanism to introduce diversity in the population. However, there are a number of crossover operator that have been used on GAs such single point, two points and uniform crossover. If crossover is dictated the lamina position will be exchange to make new children.

Selecting the pair of parents is executed by roulette wheel and parents with the better fitness value have higher chance to mate together. Two crossover types have been used here and Probability of implementing of each type is determined by random numbering between 1 and 2.

First type; exchanges the layers of 2 selected parents afterward a random number between 1 and the length of shorter parents. Figure 5 shows the crossover result of two parents with 6 and 8 layers and the section point is 2.

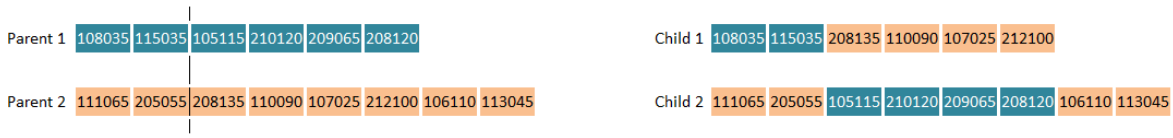


Figure 5: one-point crossover in position 2

Second type is two-point crossover; it exchanges two groups of layers between parents, Figure 6.

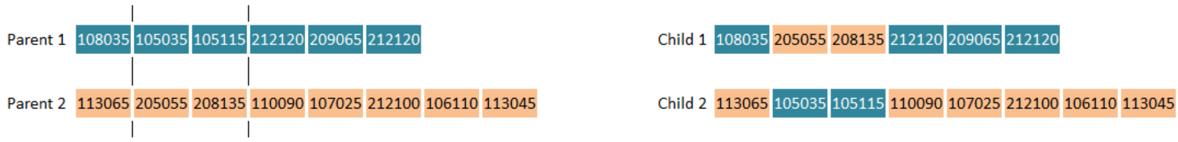


Figure 6: two-point crossover in positions 1 and 3

In section 6.2 a developed crossover method has been introduced and its influence to improve the performance of GA will be evaluated in result section.

3.6 mutation

Mutation is performed with a typical probability of Pm = 0.0 – 0.02 [15]. Its responsibility is to alter the genetic diversity of the population by introducing new information in every selected layer of children after it is created by the crossover operation. These operations provides a random search capability to GA, which may be useful to find promising area in the design space and prevent crossover to lose its effect due to a standardization of the population.

Whereas using of the natural coding method in this paper, here mutation operator changes the layer property of children with 2 approaches. First is to change the material of layer to the other possible material whatever it is. Second is to rotate 90 degree of the layer angle. Probability of executing approach one or two or both of them is randomly determined. Position of mutation through the length is randomly determined as well, Figure7.

Figure 7: mutation for a six layers laminate in position 5 and applying of both methods

3.7 Elitism

In standard GA, Elitism is a selection method that forces the GA to retain some number of the best individuals at each generation. Such laminate can be lost if they are not selected to reproduce or if they are destroyed by crossover or mutation. Many researchers have found that elitism significantly improves the GA performance. In section 6 an improved method of elitism has been introduced.

3.8 Permutation and inversion

A permutation method has more advantages over mutation operator and has been suggested to be used with a high probability [30]. Permutation and inversion, involve with the order of the bits between two random positions of laminate.

BOYONG [6] hasn't suggested using Permutation for natural coding because of generating duplicate or missing allele values. He suggested others methods for crossover and mutation instead of the conventional crossover and mutation, named *Mapped* and *Gene-Rank* crossover. Since, this paper uses fully natural coding identification, concept of permutation and its relevant (Mapped and Gene-Rank crossover) have been developed for natural coding and has been introduced in section 6.2.

4. Criteria for comparative study

GA has been known as an expensive algorithm. In case of high cost for individual analysis, as the situation of this paper, total cost will be considerably increased. Trying to reduce the cost of FEM analysis, makes to occur additional inaccuracies to find the correct requested results. Therefore, remained solution is to reduce the number of analyses to achieve the ending results and it is only possible by tailor setting of GA operators. *Cost* and *Richness* criteria are determined to evaluate the performance of GAs algorithm.

Cost of analysis is the average number of analyses which is needed to achieve a given number of reliability. *Reliability* is calculated by dividing the number of runs which have found any given value of global optimum per total accomplished runs [6, 14]. For example, if 10 runs have accomplished and 8 of them reached to the given number, reliability will be 80 percent and algorithm cost is the average number of applied analyses.

$$Cost = \frac{\sum_{i=1}^{n} N_i}{n} P \qquad \text{Where: } \begin{cases} N_i: \text{ Number of applied iteration in the } i^{th} \text{ Run} \\ n: \text{ Number of Runs to obtain given "Reliability"} \\ P: \text{ Number of population} \end{cases}$$

$$Reliability = \frac{N_R}{n} \qquad \text{Where: } N_R: \text{ Number of Runs which found result less than } FT$$

$$\text{Where: } FT: \text{ Fitness Target value (using of equation (3) respect to the minimum values of weight, displacement and TSAIW criterion.)}$$

High amount of richness is the power for search ability of the algorithm to find the optimum result. Richness can be calculated by counting the number of close results to the given optimum value divide by product of total runs and population size. For example if population size were 50 and 10 runs applied to obtain the given reliability and 40 answers have small deviation with optimum value, then richness is 40/500=0,08.

$$Richness = \frac{\sum_{i=1}^{n} N_L}{n \times P} \qquad \text{Where: } N_L: \text{ Number of Laminate in final population of each Run with a small deviation(here is 3\%) from } FT$$

5. Tunning of GA

Two difference categories take into consideration to enhance of GA performance. First is the *selection procedure* and second is *developing of GA operators*.

5.1 Selection procedure

In standard process of GA, new generation are made by influence of GA operators. Essentially, there is no warranty to produce more competent children than the parents, unless different rules are found and applied on standard form of operators. G. Soremekun [14], has advised some methods that provide an ability to produce new generation not only from the output of operators, but also made of a combination of more fitter parents and children. He also proposed that the amount of parents percentages, N_k, which cooperate in new generation has been mentioned as a variable and let it to change during the running of algorithm from a given minimum number to maximum possible number (100 percentage, means all of parents population). In case of convergence the algorithm, founded value is considered as the optimum percentages value for parent attendance.

First method of *multiple-elitism* (*ME1*) with $N_k = 5$ has been carried out in this study. Then a wide search was executed to find the optimum N_k and number 18 was found as the ideal percentages of parent attendance. Result of improving the performance of algorithm is shown in Table 1.

5.2 improving of Operators

Variable values for probability of crossover and mutation has been studied and their optimum values have been used to evaluate the performance of standard GA in result section.

GENE-RANK crossover for permutation coding has been introduced by BOYONG [6]. Each parent has a weight and each lamina of parents has a position through the thickness. Assigning a number to above definitions makes a rank for each lamina. Then inner layer of a child laminate will be made from lower ranked lamina. Simultaneously, the higher ranked lamina locates in the outer most layers. In this paper *GENE-RANK* method has been developed for natural coding of laminate with various numbers of plies and introduced by the name of *PLY-RANK*. Whole layers of initial population take a rank by the product of the fitness value and layer position (outer layer of a laminate, has bigger position number). For example, the 8^{th} layer of a laminate with the fitness of 0.08 takes a rank of 0.64. If there is another layer with the same orientation in other laminate with fitness of 0.076 in the 5^{th} layer, then it takes a rank of 0.38. The total rank of mentioned layer will be 1.02, Figure 8.

	10	9	8	7	6	5	4	3	2	1
Ranked ply angles	000135	000040	000140	000125	000030	000115	000120	000025	000130	000035

Figure 8: First top 10 layers, ranked from 100 laminate

PLY-RANK operator with a probability of 0.05 reorders the orientation of selected laminate and generated children are directly sent to new population. One laminate from each group of laminate with the same number of layers -as the representative- has a chance to be reordered by *PLY-RANK* operator. Figure 8 shows one 5 and one 8 layers laminate -which have been selected from the all laminate with 5 and 8 layers- after implementing of *PLY-RANK* operator.

Child 5 layers	115115	105120	212025	209130	212035			
Child 8 layers	205140	211125	110030	107115	214120	106025	113130	109035

Figure 9: 5 and 8 layers laminate after *PLY-RANK*

Addition to the regular mutation, a similar operator is used to exchange the position of two plies of one child with a given probability. It is called *LAMINA-SWAP* and provides a chance to allocate the better position of layer with different material and orientation. Position of two mentioned plies is determined by generating of two unequal random numbers between 1 and the length of laminate.

Before LAMINA-SWAP	115115	105120	212035	209130	212025
After LAMINA-SWAP	115115	105120	212025	209130	212035

Figure 10: *LAMINA-SWAP* operator on a 5 layers laminate in positions 3 and 5

6. Result and discussion

Table.1 shows the values of cost and richness related to the different methods which were used for tuning the standard form of GA. Population number is similar for every type of GAs.

	Type of GA	Cost		Richness	
1	GA-S*	412.6	---	0.484	---
2	GA-PR-PS**	372.4	10 % ▼	0.658	26 % ▲
3	GA-ME-PR-PS***	338.5	18 % ▼	0.818	20 % ▲

* GA-S: Genetic Algorithm with Standard operators
Elitism probability = 0.03, Crossover probability = 0.7, Mutation Probability = 0.1

** GA-PR-PS: Genetic Algorithm with PLY-RANK and PLY-SWAP operators
PLY-RANK for all laminate group, Crossover probability = 0.7, PLY-SWAP Probability = 0.1

*** GA-ME-PR-PS: Genetic Algorithm with Multiple Elitism for selection method and PLY-RANK and PLY-SWAP operators
N_k = 18 for ME selection and PLY-RANK for all laminate group, Crossover probability = 0.7, PLY-SWAP Probability = 0.1

Table 1: Performance comparison of different GAs (Reliability for all types is 90%)

Figure 8 shows the convergent rate of *GA-ME-PR-PS* algorithm regards to the stopping criteria as explained in section 3.4. It means that in 26th iteration, algorithm hasn't detected any improving of the best result repeatedly for 7 times and has been stopped.

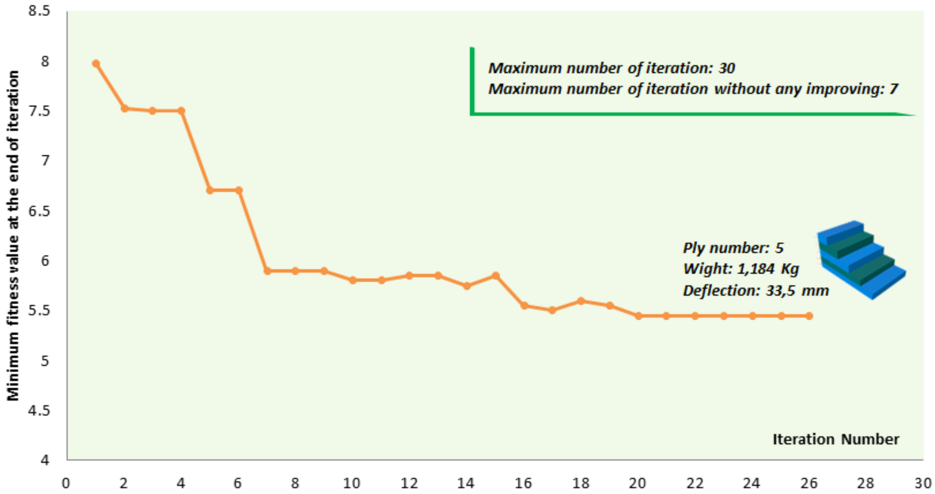


Figure 11: convergent rate of modified algorithm and optimum result

Minimum weight and deflection related to the optimum design of hybrid structure made by steel-composite laminate have been obtained as 1.184 Kg and 33.5 mm respectively. Compare with the result of original structure made by steel material for both inner and outer part, it shows better resulting for weight and deflection, Table 2.

material	Weight (Kg)		Deflection (mm)*	
Steel-Steel	1.572		38.2	
Steel-Composite Laminate	1.184	24.7 % ▼	33.5	12.3 % ▼

*Deflection has been measured on a node related to the inner part which has same designation between two structures

Table 2: Result of metal structure compare with hybrid structure

7. Conclusion

In this study optimization of a metal structure belongs to the automotive body under a 3 axial force components has been evaluated by substituting with a composite part. Minimum weight and maximum rigidity of structure were considered as the multi-objective target and a weighted sum method was used to obtain a single objective function.

In order to designation of composite laminate a natural coding has been introduced and used for design the layer number, layer material and thickness and its orientation. A general code programing was used to generate the laminate sequence, implementing the simulation in FEM, and evaluating the result. A standard form of genetic algorithm was used with the aim of finding the optimum sequence of laminate respect to the objectives and failure criteria. In order to increase the performance of GA in terms of CPU time and reliability, several surveys with numerous probabilities of GA operators was applied and optimum values was found and used for calculating the cost and richness of standard algorithm. Then improving of 2 groups of operators consisting of *selection methods* and *operators function* was considered and performance of tuned algorithms was compared with the GA standard.

Evaluating the rate of converging shows that developed algorithm with modification on selection mechanisms and mating methods of pairs, able to search a large space of total potential cases with the lowest probability of premature convergence to find the optimum result, even a small number of initial population was chose.

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