FINDING THE BEST MATERIAL COMBINATIONS THROUGH MULTI-MATERIAL JOINING, USING GENETIC ALGORITHM

Vahid Ghaffarimejlej[1], Eiko Türck[2], Thomas Vietor[3]

(1-3)Institut für Konstruktionstechnik, Technische Universität Braunschweig
Hermann-Blenk Strasse 42, D-38108 Braunschweig, Germany
(1) v.ghaffarimejlej@tu-braunschweig.de, web page: http://www.tu-braunschweig.de/ik
(2) e.tuerck@tu-braunschweig.de, web page: http://www.tu-braunschweig.de/ik
(3) t.viteor@tu-braunschweig.de, web page: http://www.tu-braunschweig.de/ik

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Abstract

Construction of light weight bodies in automotive industry usually involves excessive challenges to select some subassemblies in a structure and subtracting with lighter materials.

In this study an approach to discover the best combinations of material in hybrid-material joining has been introduced. This method generates a wide possible ambience of geometry and material combination with any number of parts in structure. It also handles varied series of geometrical and manufacturing constraints.

A collection of appropriate structures respect to the predefined objectives and restrictions obtain by evaluating of CAE results and using genetic algorithm. In final assessment optimum combination consider to the manufacturing restrictions is selected within the best results. An approach to apply the influence of some manufacturing complexities in final selection of optimum structure is presented.

Effect of dissimilar constrains in multi-material design problem has been handled corresponding to their behavior through the iterations. In order to increase the speed of optimization process for various existing structures parallel computing has been used. It is demonstrated that some improvements in the default setting of operators enables to using this approach in the wide range of similar applications with the ordinary limitations and objectives.

1. Introduction

Transport industry as the consumer of 30 percent of energy in Europa takes into account the significant source to produce the green-house gas emissions [20]. Automobiles dispose the biggest distribution of this source. For this reason automotive industry looking forward to find solutions to reduce the effects of environmental destruction which created by its productions. Increasing the engines efficiency to reduce the fuel consumption, making more aerodynamic bodies, reducing the energy consumption of electrical components, development of hybrid cars and finally making the lighter bodies are considered as the most significant methods to reduce the emission. Recent observations show that reducing of 100 Kg of weight caused to reduce 8.5 gram Co2/Km [13]. Whereas, based on the current European directives produced CO2 in each 100 Km must not be more than 130 gr. This allowable level will reduce to 95 gr in 2020 [14]. Weight reduction is applicable with substitution the conventional materials like steel with lighter materials like polymers and composites. Because of the production limitations and also the final cost or even the maximum expected strength, direct replacement of lighter parts without any condition and restriction is not easily applicable.

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In most cases it will be necessary to replace a percentage of original part with new materials. By this way a combination of two or more parts will be generated instead of one unique material. Through this process even it is possible that the geometry of original parts be changed. These challenges have been conducted to create and publish applicable strategies in recent years to make lighter structure via using of different materials.

S. Poulikidau and his colleagues have introduced a material selection method to replace materials in a structure with the aim of weight reduction and environmental impact simultaneously [20]. S. Graccobi et al. in multi material design process have improved the filtering operator [19]. Ermolaeva et al. have also implemented a comprehensive study on material selection of an automotive structure with integration of structural optimization and environmental impact [17]. Aly et al. have introduced a method to material selection for a sandwich beam through parameter optimization [16]. Also Ashby and colleagues have explored ways of designing hybrid materials, emphasizing the choice of components, their shape and their scale [15]. J. Singh et al. have used the novel feature to integrate shape and material to model and visualize multi-objective selection problems [10].

Due to the large amount of potential candidate solution in multi material optimization possibility of finding and comparing the effect of all of them in output needs to spend lots of computing time. Optimization algorithms process that a set of input variables is varied automatically to find the more desirable output. These algorithms without necessity of evaluating the effect of all inputs on output able to seek whole design space and find the best combination of inputs. During recent years researchers have tried to use different optimization algorithm in multi material optimization. Most famous and more applicable algorithms method to search in variable discrete space is evolutionary algorithm and especially genetic algorithm.

Barchini et al. have designed a method which is able to select proper material and geometry simultaneously with the aim of weight reduction. Their method is base on to dedicate an individual library for material and geometry. They have carried out a combination of genetic algorithm and backtracking algorithm to find the optimum geometry and material. [18]. Xintao Cui et al. have used genetic algorithm to find the optimum design in a multi material problem [23]. Vincenti and his collages have developed the genetic algorithm for combinatorial optimizations. They used this algorithm so called BIANCA to optimize the stacking sequence in constrain and unconstraint cases [3]. Author in his last paper has introduced some methods to improve the performance of genetic algorithm to find the optimum stacking sequence of a part belong to the automotive body [22]. Xiu-Juan Zhang et al., used genetic algorithm for material design made of a multiphase material [24].

This paper will try with the mention of carried studies in methodologies of structure optimization and using of strong ability of developed genetic algorithm tool introduces a comprehensive method to find the optimum material combination in a hybrid structure.

2. Proposed Methodology

Efficient strategies to generate and find optimum solutions through variations are explicitly introduced in construction process studies [21]. The main structure of search algorithm in this study follows these strategies as a sub-extracted method. This section explains in detail about the methodology to find the optimum material distribution and geometry through a multi material structure. The method consists of a fully controlled parametric modeling in CAD and optimization loop using genetic algorithm which coupled with CAE as follow:

2.1. Pre-processing step; generates and selects initial structures.
2.2. Evaluating step; calculates the fitness of individuals to satisfy the objectives.
2.3. Genetic algorithm; carries out the optimization loop. If the stopping criteria are not satisfied it continues, otherwise will stop and display the result.

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Depends on the number and variety of population in each problem, implementing of above sections may be different with other problems.

2.1. Pre-Processing

Initial operation in this method is based on the producing of initial geometry of structure. The method dedicates different material to current geometries in the next step of algorithm. This operation needs the complete information of initial geometry of structure to create different geometries with the mentioned dimensions and material variation. Generally this information contains the limitation of all changeable and unchangeable dimensions. Unchangeable dimensions are the positions which respect to design considerations, style, function, and interaction with the other parts, there is no permission or possibility to increase or decrease them. This category of parameters named fixed geometrical restrictions and pre-process algorithm prevent to generate any geometry out of these restrictions. It is necessary to mention that a dimensional parameter could be mentioned as an unchangeable parameter in one optimization study and could be mention as a variable in another.

Other category of geometrical constrains is the changeable dimension within a predefined boundary. Since the effect of diversity of these parameters on the final function of structure is not predictable the algorithm should conduct different procedure against them. These dimensions and their allowable limits are stored in an individual library for every part.

Other constrains which have mentioned in this study is manufacturing limitations. This constrains force algorithm to prevent of generate the not manufacture able geometries. It is necessary to mention that some dimension of parts may cause to make a relative complex geometry but it may have a great effect to improve the final application. Therefore algorithm has been plane to do not prevent generate them. In Figure 1 schematic steps to generate the initial structures has been shown.

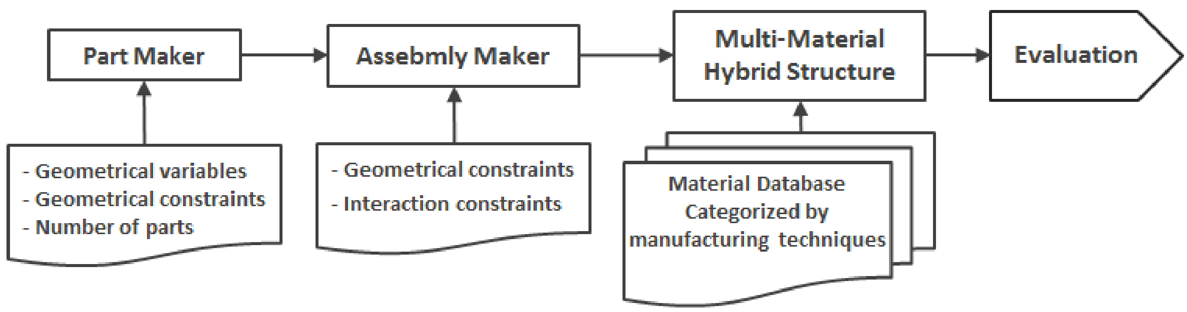

Figure 1. Schematic of steps to generate the initial structure

Since the effect of different combination of dimensions on final behavior of structure is not predictable and the design space for these dimensions is extremely huge, there is no possibility to find a fix rule to make parts and assemblies from the table of dimensions. Therefor algorithm uses a statistical base method to select the dimensions within the acceptable boundaries. Part-Maker (Figure 1.) dedicates a random number between 2 and n to identify the number of parts in structure. Then provide other random number relate to the initial geometry of every part and generate a sample for each part of structure. Assembly-Maker (Figure 1.) respect to the sequence of constrains and the parts interaction produces a structure from received parts. This algorithm has a vital and complex responsibility because, any inaccuracy in parts connection method cause to generate unusable and wrong structures. In the section of material assignment material properties of every part is attached to the part geometry. In order to do this, algorithm will randomly select a material from material library respect to the manufacturing technology like sheet metal, die-cast, injection, extrude, composite laminate and so on for every part and dedicate it to the mentioned part. It is normal that algorithm will not select the

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materials which are not suitable for candidate part. As an example aluminum material in grade of die-cast is never candidate to assign a sheet metal part with 1 mm thickness.

The final output of pre-processing step will be a structure with ordinary number of parts with different manufacturing technology and tailored material. Pre-Processing algorithm will continue to produce structure with different number of part and different geometry and distribution of material until the predefined number of structure in algorithm is reached.

2.2. Evaluation

Before the introduction of the mechanism of evaluating the individuals it is necessary to explain about the circumstances of writing and forming of a multi objective and constrained problem. In this study optimization of several objectives has been plane to carry out therefor the objective function is assumed as multi-objective function. There are some famous methods to write the multi-objective fitness function [1] and 3 of them are more popular than the others; *Weighted sum approach*, *Altering objective function*, and *Pareto-Ranking approach.* This paper uses the weighted sum approach to calculate the objective function.

Since evaluation of most engineering problems without consider to existing limitations is meaningless, it is necessary to utilize objective function to clarify the effect of constraints. Garret in his book has comprehensively introduced the executing of constraints as a penalty function [8].

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

Coello [5] has mentioned 8 different methods to establish the penalty function and explicitly described their strong and weak points simultaneously. In current study adaptive penalty approach which takes feedback from the search process has been used instead of traditional static penalty method [4, 2]. It means that, the second term of equation (1) could be written as follow:

$$\lambda(t)\sum_{j=1}^{m} g_j^2(X) \tag{2}$$

Where $\lambda(t)$ is updated every generation t in the following way:

$$\lambda(t+1) = \begin{cases} (1/\beta_1).\lambda(t) \quad if\ case\ \#1 \\ \beta_2.\lambda(t) \quad if\ case\ \#2 \\ \lambda(t) \quad otherwise \end{cases} \tag{3}$$

Where case#1 and case#2 denote situations where the best individual in the last k generation was always case#1 or was never case#2 feasible, $\beta_1, \beta_2 > 1, and\ \beta_1 \neq \beta_2$ (to avoid cycling). In the other words, the penalty component $\lambda(t+1)$ for generation $t+1$ is decreased if all best individuals in the last k generations were feasible or is increased if they were all infeasible. If there are some feasible and infeasible individuals tied as best in the population, then the penalty does not change.

The objectives of engineering structures in automotive body usually deal to obtain stiffness and strength for complex geometries lead to high volume of analytical calculation. Therefor the FEM codes will help to carry out them faster and more reliable. So algorithm runs the FEM analysis to generate the predefined objectives.

In evaluation process algorithm involves with analysis and dedicate a fitness to every individual to identify its position within the current population. Fitness value of every individual will be compare with the target fitness. The algorithm will be stop if there is an individual with the fitness value less than fitness target. Otherwise algorithm leads the population toward the mating step. In mating process a new population will be generated which have been made from stronger genes of previous population.

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It is necessary to mention that algorithm uses also some other criteria in every iteration to allow or do not allow to continue to mating process. Receive to a specific number of iteration is one of the most common stopping criteria. If the optimum fitness value won't be improved considerably through the iteration it stops the optimization loop as a stopping criterion. Performance and operation of mentioned stopping criteria has been discussed in previous study of author [22].

2.3. Genetic algorithm operations (Parallel GA)

As described in last part adaptive penalty approach has been used in this study in order to handle the amount of penalty through the iterations. Implementing of adaptive penalty technic and existence of different individuals with dissimilar number of genes requires substantial computational effort and computer memory. Therefor during recent years has been tried to decrease the time consumption of computers with different approaches. One of the most applicable methods is parallel processing [11, 9, 7]. There are three main types of parallel GAs: global single-population master-slave and fine-grained GAs, and multiple-population coarse grained GAs [6]. Multiple-population (or multiple-deme) GAs are more sophisticated, as they consist on several sub-populations which exchange individuals occasionally. Exchange of individuals is called migration and it is controlled by several parameters.

Migration is applied at a specific migration period and some samples migrate from one population to another. Migration probability is defined to determine the number samples which must be exchanged among the populations. Migrates are choose randomly in their sub-population.

3. Case Study

A metal structure belong to automotive body has been candidate to evaluate the performance and operation of introduced algorithm in multi-material design study. During recent years the B-Pillar structure -because of having a vital role to observe the side crash energy- has been extremely improved and reinforced with various approaches. Figure 2.a shows the conventional appearance of B-Pillar and 2.b, 2.c, 2.d show the possible alternatives with lighter and stronger geometry and materials. Overall length and position of every part is generated by fully controlled rules in pre-processing step.

Figure 2.a conventional appearance, **2.b, 2.c, 2.d** some possible material distribution of B-Pillar

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3.1. Variety of cross sections

Independent how many parts the B-Pillar structure has, it can make with different cross sectional profile. It is normal that these profiles must be located inside the fix and variables constrains which has already defined at the first of every project. Definition of mentioned constrains is applied in CATIA and by dedicating random numbers -inside the lower and upper levels- algorithm is able to generate different number of parts with various profiles.

3.2. Variety of material distribution

The individual parts of B-Pillar structure may have different length and different position through the length of structure. This length and position are determined by two random numbers which allows every part to be shorter or longer and move in any direction.

3.3. Variety of Material

Wide ranges of material types is necessary to be stored in the material library consist of complete specification of every material. Material library must be divided into different category based on the manufacturing technology. Any time, algorithm refers to library to catch a material from a given category it generate a number between 1 and the number of materials in mentioned group and takes one to assign a part. Algorithm never refers to a category of material which is not related to the manufacturing technology of selected part. So there is already a guaranty to assign right material to every part of structure.

3.4 Variety of structures

Algorithm will have n number of multi-parts structure after concluding the previous step. In this case study n=100 and possible number of part is between 2 and 4. According to random generated number 28 structure with 2 parts, 42 structure with 3 parts, and 30 structures with 4 parts have been created in initial population of genetic algorithm.

3.5 Evaluation of structures

Evaluation of structures in terms of stress analyses and reaction forces under a multi axial loading are executed in ABAQUS. Reaction moment of structure around principal axes (RM_x, RM_y, RM_z) determined the rigidity of structure as the primary calculation of overall strength of structure in fitness function. Since the number of objective in this study is not more than 2 objectives, instead of weighted sum approach the proportion of objective is assumed to determine the fitness of structure. By dividing weight to resultant of reaction moment $\left(\sqrt{RM_x^2 + RM_y^2 + RM_z^2}\right)$ obtain a ratio which is called the stiffness of weight with dimension of $Kg/N.m/Grad$ [12]. Amount of $RM_{resultant}/Grad$ and weight of structure for every sample is extracted from ABAQUS results. Constraints are assumed the maximum valuable stresses for every material which is specified in mechanical property. Depending on the material type related failure criteria is used to identify the failure initiation. For sheet metal and laminate parts ductile and TSIW criteria has been selected respectively as the failure criteria. As mentioned in previous sections adapted penalty function is used to penalize the out of range constraints. Thus, if all current samples are feasible by applying $\beta_1 = 3$ the amount of λ reduce around %33 and if all samples are infeasible by applying $\beta_2 = 2$ the amount of λ will increase %200.

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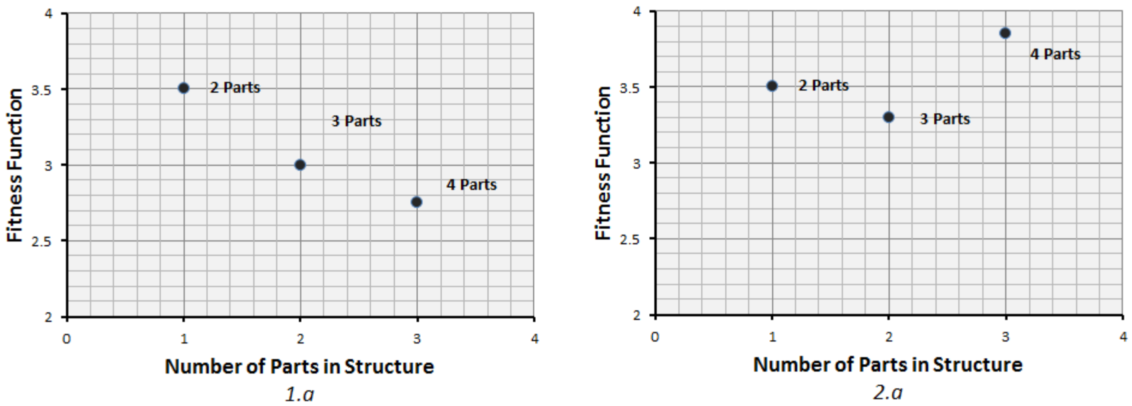
3.5. Operating of GA

Based on multi-population definition of parallel GA, 3 different groups of structures are organized to put in three individual sub-populations. First group contain of 2-parts structures and second group contain 3-parts structures and third group contain 4-parts structures. Every group is divided into 4 sub-groups to evaluate and implement of GAs operators. Migration between same families is executed with probability of 10%. It means that 10% of individuals have the chance of exchange genes with neighbors. Evolution of generation will continue until one of the stopping criteria is satisfied. Optimum result -which has the lower fitness value- for every group of structure, has been illustrated in graph 1.a and one of the 4-Parts structures is the best.

3.6. Manufacturing limitation

As mentioned in section 2.1 before making the final decision to select a structure as the optimum design the manufacturing limitation must be implemented. Consider to the wide deviation range of manufacturing technologies and the number of needed operation to produce parts and assembly's determination a similar and unique parameter to measure the manufacturing limitation is too complex. Because of this total complexity of operations obtain by gathering the needed cost of their preparation. For instance, tooling costs to make individual parts and assembly fixtures, machine investments, manpower, and transportation represent manufacturing cost as a negative ratio for a crowded structure. Optimum structure through the whole groups after executing the effect of manufacturing limitations is a 3-Parts structure show in graph 1.b.



Graph 1 Optimum structure before (1.a) after (1.b) applying the effect of manufacturing limitations

4. Conclusion

A comprehensive methodology to find the optimum geometry and material combinations in multi-material structures has been introduced. Because of multiplicity and diversity of variable parameters consist of dimensional parameters, mechanical properties of materials and interaction variety, using genetic algorithm -having high ability of search and handling of high volume of variables- has been presented. Adaptive penalty function has been used to apply the suitable effect of constraints like allowable level of stresses in materials. Because of being various numbers of genes in different structure and necessity to update the adaptive penalty ratio function through the iterations, several genetic algorithms have been served in parallel to find optimum structure in every sub-group. B-Pillar structure as one of the most vital members of automotive body has been selected to study and demonstrate the presented methodology. An approach to apply the influence of some manufacturing complexities in final selection of optimum structure has been studied.

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