Title:
An Iterative Generative Design Approach for Multi-Material Components

Authors:
Luca Belluomo, luca.belluomo@uniroma1.it, 'La Sapienza' University of Rome
Michele Trovato, michele.trovato@uniroma3.it, Università degli Studi ROMA TRE
Michele Bici, michele.bici@uniroma1.it, 'La Sapienza' University of Rome
Paolo Cicconi, paolo.cicconi@uniroma3.it, Università degli Studi ROMA TRE
Francesca Campana, francesca.campana@uniroma1.it, 'La Sapienza' University of Rome

Keywords:
Lightweight Design, Topology Optimization, Design Automation, Generative Design, Automotive

DOI: 10.14733/cadconfP.2023.334-338

Introduction:

The lightening of the components [6, 8] is playing an increasingly predominant role in modern industry to reduce energy consumption, and in this process, CAD/CAE tools are a fundamental support for designers. This work presents an iterative and automated Generative Design method based on Topological Optimization to optimize the multi-material distribution of components. Indeed, in the case of multi-material parts, the available commercial tools do not consider the possibility to change the target volume and, most of all, the space distribution related to each material during the optimization workflow.

Currently, to achieve lightweight designs, three macro-techniques are most widespread due to their effectiveness: Topological Optimization (TO), Lattice Structures (LS) design, and Generative Design (GD). These techniques allow to create free-form organic shapes intended to be additively manufactured [9]. TO is the search for the optimal material distribution changing the topology, shape, and size of the part by an iterative removal of ineffective material [1]. This type of study starts with the definition of a target volume, loading and boundary conditions, objective function, and design constraint's ones [4, 7]. LS design is based on repeating patterns of cells in the space; their purpose is to support loads with the least possible weight, to achieve the optimal material distribution. These structures make possible to lighten the components while maintaining good mechanical characteristics [3, 5]. GD methodologies exploit algorithmic methods to translate, in an automated way, the requirements and constraints of the design task into a design space of possible solutions to be evaluated. Compared to previous methods, Generative Design is the method that offers the most freedom to the designer [2].

The methodology has been applied to car seats. The production of seats requires a large use of polyurethane foam, combined with plastic and/or metal frames. The method here developed proposes an optimization loop to consider the influence of the polyurethane foam in the TO of the plastic part of the seat, allowing the possibility to have moving boundaries between the different materials to be iteratively optimized.

Methodology:

The goal of the presented methodology is to iteratively optimize the multi-material (two materials) distribution within a given design volume through a TO based GD approach. The used materials could have different mechanical behaviors. Indeed, as reported in the test case, 'Material 1' has a linear elastic behavior while 'Material 2' has an hyperelastic behavior. The workflow of the proposed methodology is presented in Fig. 1 and consists of a two-level optimization process.

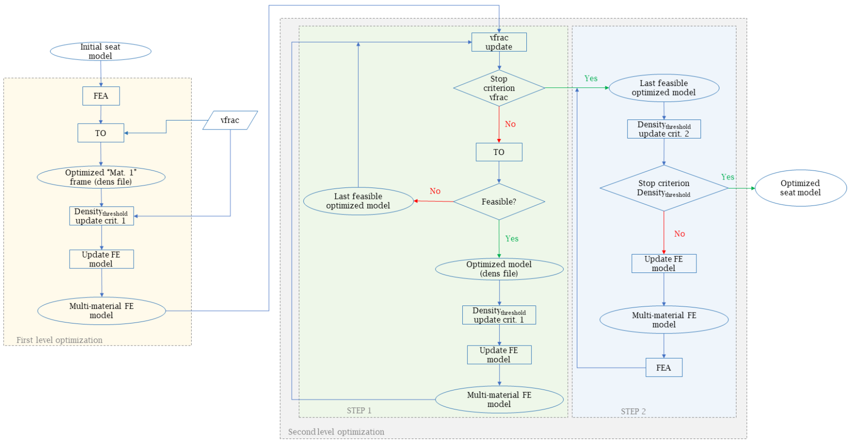

Fig. 1: Workflow of the methodology

The methodology starts considering an initial design volume (i.e., the volume of the designed shape of the seat excepting the external covering tissues) made by 'Material 1'. The first level optimization pertains to the definition of the finite element model to be used to perform the static and/or modal analysis considering multiple load cases (different usage scenarios of the seat), and the following TO. The design objective of the TO is to minimize the weighted compliance of the overall system (design and non-design spaces). The design constraints are set on the upper limit of the volume fraction ($vfrac$) of the design space and, as for the selected test case, on the lower limits of the frequencies of the first $N = 3$ normal modes. The volume fraction constraint is the percentage of material to be retained at the end of the TO algorithm. The initial value of this design variable must be carefully chosen to reduce the number of iterations (computational cost) and to provide meaningful designs also with less effort in the post-processing phase. Other constraints could be set over the maximum stress, strain, etc. In addition, manufacturing constraints as minimum element size and/ or overhangs, etc. can be considered in this stage. Once carried the TO with the assumed volume fraction $vfrac_1$ constraint (iteration 1), it is available the list of all the E elements of the FE model with the associated element densities of the SIMP algorithm ('dens' file). A python script takes the 'dens' file as input and sorts the E elements in ascending order of the densities. The density value corresponding to the e element (Eqn. (2.1)) of the list is retained as density threshold value $density$ (criterion 1 for the density threshold update).

$$e = (1 - vfrac_j) \cdot E \qquad density_j = \text{density}(e) \tag{2.1}$$

The density threshold parameter $density$ is used by the script to update the FE model by switching the material (from 'Material 1' to 'Material 2') for all the elements of the model with an element density lower than the threshold value. Since, in the considered case, 'Material 2' as an hyperelastic behavior, it is necessary to conduct non-linear analyses and optimizations starting from iteration 2. It has to be noted that the elements with 'Material 2' are set to non-design space.

The output of the first level optimization is the FE model available for the second level optimization, which could be a non-linear automated optimization loop. The first iteration of this level takes the

Proceedings of CAD'23, Mexico City, Mexico, July 10-12, 2023, 334-338

volume fraction value $vfrac_2 = vfrac_1$. The TO is carried out and an updated 'dens' file is available as output. The algorithm updates the *density* value according to the volume fraction constraint applied on the current iteration and the FE model for the next one is available. The iterations continue up to the infeasibility of the TO at iteration $i = lnfto$ due to the violation of the design constraints. At this point the Python script updates the $vfrac_{i+1}$ value by considering the average value between the $vfrac_1$ at iteration i and $vfrac = 1$.

The FE model is updated according to the density threshold value and the TO is performed. Based on the result of this optimization, the volume fraction at iteration $i + 2$ updates as follows in Eqn. (2.2):

$$vfrac_{i+2} = \begin{cases} \frac{vfrac_{i+1}+1}{2} & \text{if (Top. Opt.)}_{i+1} \text{ infeasible} \\ vfrac_{i+1} & \text{if (Top. Opt.)}_{i+1} \text{ feasible} \end{cases} \tag{2.2}$$

The iteration stops when the change in the volume fraction value with respect to the volume fraction upper bound is lower than a termination threshold value, retaining the last feasible TO iteration $lfto$. It follows the the further refinement of the optimized model with an update of the density threshold. The $density_k$ value at iteration k is set equal to $density_k = density_{lfto}$, carrying an analysis instead of an optimization and evaluating if the design constraints are satisfied or not. If the analysis is feasible, the loop ends and the optimized model is available for post processing. Else, the density threshold is updated according to the criterion (criterion 2 for the density threshold update) in Eqn. (2.3). This process ends when the termination criteria is reached.

$$\begin{aligned} density_{k+1} &= \frac{density_k}{2} \\ density_{k+2} &= \begin{cases} \frac{density_{lfa}+density_{lfto}}{2} & \text{if the last analysis is feasible } (lfa) \\ \frac{density_{lfa}+density_{lnfa}}{2} & \text{if the last analysis is infeasible } (lnfa) \end{cases} \end{aligned} \tag{2.3}$$

Elementary case study and results:

The proposed methodology has been applied to a simple case study to optimize the material distribution within the initial design volume. The initial volume consists of a rectangular parallelepiped which represent the seat's cushion assembly. The used materials are Acrylonitrile-Butadiene-Styrene (ABS) for 'Material 1' and Polyurethane Foam (PF) for 'Material 2'. Used individually, they do not guarantee appropriate usability. Indeed, ABS alone is too stiff, and the soft foam needs a structural frame.

Model, analysis, and optimization setup:

To perform the TO, it is necessary to divide the initial volume in design and non-design spaces and mesh the CAD model (Fig. 2(a)). Non-design space is the region of the initial volume to be preserved to apply loads and boundary conditions. It is necessary to define the loading conditions of the seat. For this task, 5 load collectors have been defined to consider different sitting scenarios (two pressure load collectors are reported in Fig. 2(b) as example). The loads are applied as uniform pressures on different sectors of the top seat' surface, considering a person with mass $m = 100Kg$. These load collectors are associated to linear static analysis load cases only for iteration 1, while from iteration 2 they are associated to non-linear static analysis ones, being Material 2 hyperelastic. In addition, the load case to analyze the first $N = 3$ natural frequencies have been set. To simulate the anchorage of the seat to the seat main frame, the elements of the non-design space region located in the bottom part of the model have been constrained locking all their DOFs, along the entire depth, for sake of simplicity, as reported in Fig. 2(b).

According to the design variables for the TO defined in the 'methodology' section, the objective function is to minimize the weighted compliance of the overall component, while the constraints are on

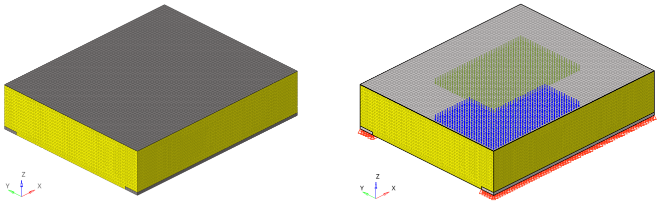

Fig. 2: (a) FE model, non-design volume (grey) and design volume (yellow), (b) boundary constraints (red) and pressure load collectors (blue and green).

the upper limit of the volume fraction of the design space and on the lower limit of the first $N = 3$ natural frequencies. The last constraint is set according to standards and comfort requirements, also considering a factor of safety. Indeed, the first $N = 3$ natural frequencies of the system have been constrained to be above $90Hz$ to prevent dangerous frequency ranges for the human body. Two test cases (TCs) are considered: TC1 with $vfrac_1 = 0.95$ and TC2 with $vfrac_1 = 0.7$. This is done to show the relevance of this parameter on the result in terms of both the computational cost and post-processing operations.

Results:

TC1 runs 16 iterations while TC2 runs 12 iterations. Fig. 3 reports the trend in the ABS reduction at each iteration and its feasibility for each TC while in Fig. 4 it is possible to visually compare the two optimized solutions by slicing the models.

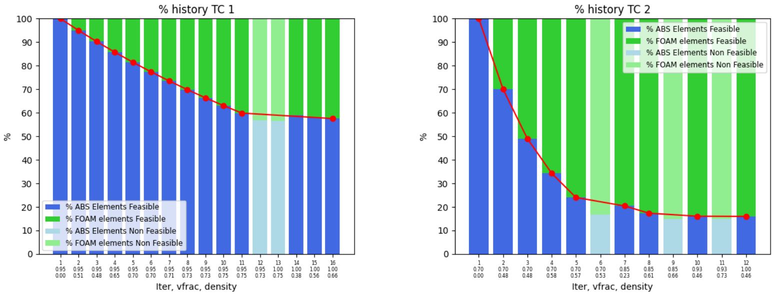

Fig. 3: TCs history bar plots: (a) TC1, (b) TC2.

From the visual inspection of the solutions, Case 1 presents ABS (yellow) sections thicker than the Case 2 ones. Furthermore, Case 1 presents more sparse elements of ABS within the Foam material (red) compared to Case 2, which may result in a more time-consuming post-processing operation to filter out the disconnected elements. Finally, both the solution satisfy the design constraints, however, solution 2 is lighter than solution 1. This highlights the need for an accurate selection of the initial volume fraction vfrac parameter.

Conclusions and future developments:

This abstract presents a novel methodology for considering a multi-material design layout iterative optimization powered by a TO based GD algorithm. The methodology considers non-linear TOs and automatically updates the FE model to fill non-structural elements with the other material, which could also be modelled with an hyperelastic behavior. The methodology has been applied to a simple case of an automotive seat whose frame is intended to be additively manufactured to test its effectiveness in

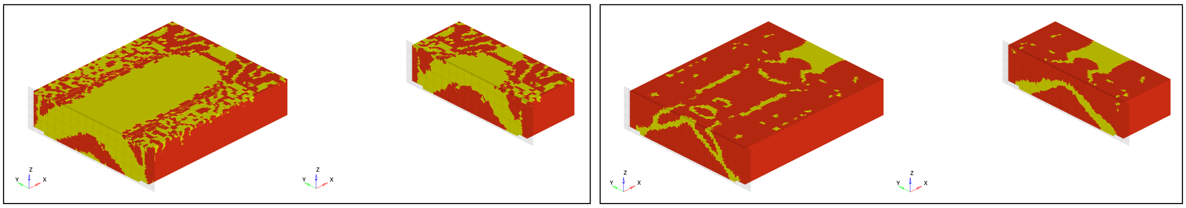

Fig. 4: TCs section view: (a) TC1, (b) TC2.

the optimization of the boundaries between the two materials (ABS and Polyurethane Foam). Since the volume fraction parameter influences both the computational cost and the necessity for post-processing operations, the future works pertain to the definition of an automated procedure to properly select this key parameter and the process for achieving the optimized CAD model, possibly considering a further shape optimization. It will be considered a criterion to avoid closed volumes filled with the other material. In addition, it will be possible to consider also Lattice Structures for intermediate densities. Moreover, to analyze a real scenario of the seat TC, the future steps of this study will include the reduction of the accelerations for passengers, the random solicitations from the road, and the complete model of the seat.

References:

[1] Ahmad, A.; Bici, M.; Campana, F.: Guidelines for Topology Optimization as Concept Design Tool and Their Application for the Mechanical Design of the Inner Frame to Support an Ancient Bronze Statue. Applied Sciences, 11(17), 7834, 2021. ISSN 2076-3417. http://doi.org/10.3390/app11177834.

[2] Belluomo, L.; Bici, M.; Campana, F.: A Generative Design Method for Cultural Heritage Applications: Design of Supporting Structures for Artefacts. Computer-Aided Design and Applications, 663–681, 2022. ISSN 16864360. http://doi.org/10.14733/cadaps.2023.663-681.

[3] Bici, M.; Brischetto, S.; Campana, F.; Ferro, C.G.; Seclì, C.; Varetti, S.; Maggiore, P.; Mazza, A.: Development of a multifunctional panel for aerospace use through SLM additive manufacturing. Procedia CIRP, 67, 215–220, 2018. ISSN 22128271. http://doi.org/10.1016/j.procir.2017.12.202.

[4] Bici, M.; Broggiato, G.B.; Campana, F.: Topological Optimization in Concept Design: starting approach and a validation case study. In Advances on Mechanics, Design Engineering and Manufacturing, 289–299. Springer International Publishing, Cham, 2017. ISBN 9783319457802 9783319457819. http://doi.org/10.1007/978-3-319-45781-9_30.

[5] Ferreira, K.; Anwer, N.; Mehdi-Souzani, C.: Characterization of L-PBF lattice structures geometric defects. Procedia CIRP, 100, 846–851, 2021. ISSN 22128271. http://doi.org/10.1016/j.procir.2021.05.033.

[6] Li, Q.; Tong, M.; Jia, M.; Yang, J.: Towards Low Carbon: A Lightweight Design of Automotive Brake Hub. Sustainability, 14(22), 15122, 2022. ISSN 2071-1050. http://doi.org/10.3390/su142215122.

[7] Sigmund, O.; Maute, K.: Topology optimization approaches: A comparative review. Structural and Multidisciplinary Optimization, 48(6), 1031–1055, 2013. ISSN 1615-147X, 1615-1488. http://doi.org/10.1007/s00158-013-0978-6.

[8] Zhang, C.; Li, Z.: A Review of Lightweight Design for Space Mirror Core Structure: Tradition and Future. Machines, 10(11), 1066, 2022. ISSN 2075-1702. http://doi.org/10.3390/machines10111066.

[9] Zhu, J.; Zhou, H.; Wang, C.; Zhou, L.; Yuan, S.; Zhang, W.: A review of topology optimization for additive manufacturing: Status and challenges. Chinese Journal of Aeronautics, 34(1), 91–110, 2021. ISSN 10009361. http://doi.org/10.1016/j.cja.2020.09.020.