Optimization of Lightweight Vehicle Components for Crashworthiness Using Solution Spaces

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Abstract. In this work, we investigate the potential of using the solution space as constraint in an optimization problem of newly developed components: we propose a workflow to find the best compromise between the mass of a component and its crashworthiness. We provide a link between the solution space methodology - a systems engineering method for crashworthiness - and the shell thicknesses of newly developed components to better exploit the potential of the method itself. To do so, we use the Efficient Global Optimization (EGO) algorithms, constrained by the output of the solution space method - force intervals. By optimizing all components involved in a frontal impact we understand the limitations of the proposed workflow: despite the solution space method providing a guideline to develop all components independently, this is not always possible. We show to what extent one can use the solution space as a constraint in an optimization problem, hence, quickly finding the best compromise between independent development, mass reduction and crashworthiness.

Keywords: Lightweight optimization · Solution space · Crashworthy design · Efficient global optimization

1 Introduction

Designing new cars is a challenging process, driven by multiple objectives of often conflicting needs; for example, the necessity of reducing the total mass to reduce fuel consumption challenges the safety of the vehicle. Instead of solving these conflicts from a general perspective, a common practice is to cascade the different requirements on a component level and find a solution in a simpler setup. When assembling the entire vehicle, the solutions provided in the simpler cases manage to overcome the general conflicts. For an overview of methods to cascade requirements refer to [1]. We want to re-design the front of the Honda

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Accord [2] to find better designs of the components in the front of the car that is lighter and also crashworthy. To do this, we pick the solution space method for cascading the results and individually find an optimal compromise.

The solution space methodology was introduced to help the development in the early stage design and to allow each component to be developed independently of each other [3]. Nowadays it is more and more common to constrain an optimization problem with the solution space. This allows for optimizing multiple components in parallel while fulfilling all general requirements. Most of these applications involve linear problems: designing the drivetrain of a new electric vehicle [4,5], or engineering a robotic arm [6].

The success of these applications inspired us to attempt a similar scheme for designing new crashworthy and lightweight components. This involves using the methodology for a non-linear problem. Despite the developments in the solution space methodology for crashworthiness [7,8], the non-linearity of the problem has limited the practical applications. An early example can be found in [9]. However, it is limited. In it, only one component is optimized and both the objective and the constraints are oriented to fulfil only the solution space. Therefore, understanding from it whether or not the methodology can handle the problems of the development for crash and solve the conflicts originating from opposing requirements is difficult. In this work, we better explore this field of application by re-designing all the components of the Honda Accord [2] that dissipate most of the energy in a crash. This reveals to us the capabilities of applying the solution space method for optimizing crash components under conflicting requirements.

The paper is structured to first introduce in Sect. 2 the solution space methodology and, in Sect. 3, the algorithm chosen to perform the optimization. In Sect. 4, we present how we define our optimization problem. Finally, in Sect. 5, we showcase the results and reflect on them.

2 Defining the Solution Space

To use the solution space to constrain an optimization problem, we first need to compute the space itself. In literature, two different methods are available: the direct [7] and the indirect method [9]. We work with the direct method. More specifically, we follow the steps of the example presented in [10].

The direct method requires a simplified model that captures the loadcase and the requirements of crashworthiness. To set up the necessary model we use the Deformation Space Method described in [11]. The Deformation Space Model we consider—corresponding to the Honda Accord of 2013 [2]—is composed of 7 components divided into two loadpaths, as shown in Fig. 1. The loadpaths are divided into a total of 31 sections, each one of a fixed deformation length. Each component can, therefore, deform the length pre-defined in the Deformation Space Model.

The second element needed to compute the solution space is the definition of crashworthiness. In our case, we borrow the definition provided by NHTSA [12]:

- The vehicle must absorb a minimum quantity of energy corresponding to its kinetic energy at the speed of 56 km/h;
- The vehicle must decelerate at a maximum rate of 300 m/s^2;
- The components must deform in a specific order, from the front to the back.

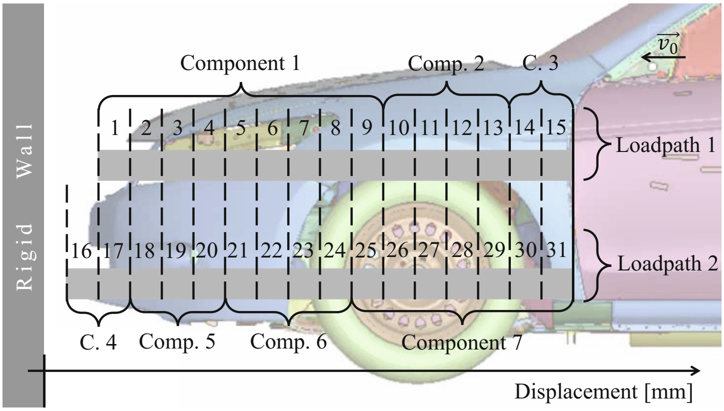

Fig. 1. Geometry Space Model computed according to the method presented in [11]

With both the Deformation Space Model and the crashworthiness definition we compute the solution space. Since the details are available in [10], we present in Fig. 2 only the final results. In this figure, the white area represents the solution space, whereas the grey area represents the space where the solution is not crashworthy.

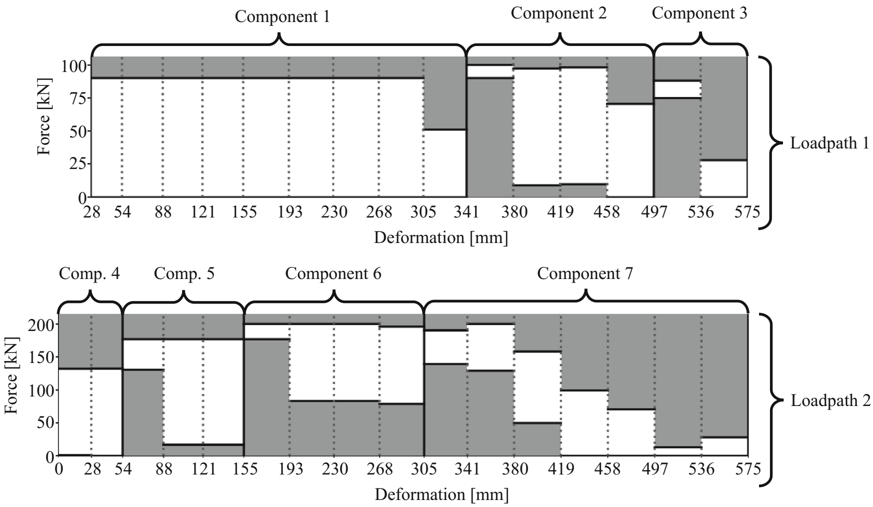

Fig. 2. Solution space computed according to the methodology described in [10]

3 Efficient Global Optimization

As we stated at the beginning, we want to optimize the new components using the constraints from the solution space. Our choice for the optimization algorithm is the Efficient Global Optimization (EGO) one. This approach is ideal when the number of affordable evaluations for the optimization itself is limited. EGO was initially proposed in [13] for constrained and in [14] for unconstrained, single objective optimization. It is a response surface method with adaptive sampling, which is well-suited for the optimization of expensive black-box functions, like finite element simulations. It is designed such that it approximates the response surface and finds the optimum with a low number of sample points. This is possible by identifying promising regions on the response surface and sampling selectively only in these areas. To do so, the algorithm utilizes a Gaussian Process Regression. It takes advantage of the fact that a stochastic process model predicts the response surface and the uncertainty of this prediction. On top of this, an adaptive sampling scheme is used to locate promising regions where to find the minimum of the objective function.

4 Problem Formulation

Let us now look at our optimization problem and how we constrained it with the solution space. In this section, we define an objective function compatible with the solution space methodology, how we are evaluating it, and how to define the constraints.

The solution space is represented on a force-deformation plane in Fig. 2. It is, thus, convenient to relate the objective function to at least the force or the deformation (to explicit the relation to the solution space), and the mass of the component (to find a lightweight component). We use the Specific Energy Absorption (SEA), which is a function of the mass of the component m, the total deformation of the component s, and the force absorbed F:

$$SEA = F \cdot s/m. \tag{1}$$

To evaluate this function we, therefore, need a way to test how much force each component absorbs, how much it deforms, and how much it weighs. If on one hand the weight of the component can be easily retrieved, on the other hand, the force and deformation need to be measured with an experiment. The test of our choice is the drop-tower setup. In this setup, a component is fully locked at one end, meanwhile the other end is crushed by a heavy impactor, as showcased in Fig. 3. We run this experiment in a virtual environment: a finite element simulation. From the simulation, we can measure and plot the force against the deformation. The area under this curve is the numerator of the SEA function.

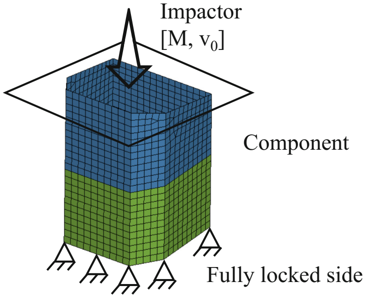

Fig. 3. Example of drop-tower test used to measure the force-deformation curve from the components; in this figure component 4 is represented.

Lastly, we need to define the constraints linked to the solution space methodology. As it can be seen in Fig. 2, the solution space is defined by an upper force limit F^i_{upper} and a lower force limit F^i_{lower} at each i-th section. We can use them to set a constraint on the force measured during the drop-tower test. To ease the problem, we consider the average absorbed force over the i-th section. On top of this, we need to set an equality constraint on the total deformation length because it is fixed in the Deformation Space Model. The last constraint is on the thicknesses of the walls of the components. These can vary between 0.5 mm and 3.0 mm for manufacturability reasons. Therefore, also the mass of the component is indirectly constrained by these manufacturability limits.

We can finally formulate our optimization problem:

$$\begin{cases} min & f(x) = -SEA \\ \text{s.t.} & g_1(x) = F^i(u_x) - F^i_{upper} \leq 0, \\ & g_2(x) = F^i(u_x) - F^i_{lower} \geq 0, \\ & h_1(x) = u_x - u_x^{target} = 0, \\ & x_L \leq x \leq x_U. \end{cases} \quad (2)$$

where $f(x)$ is the objective function, $g_1(x)$ and $g_2(x)$ are the inequality constraints, $h_1(x)$ is the equality constraint; $F^i(u_x)$ is the average value of the measured force over the i-th section, F^i_{upper} and F^i_{lower} are respectively the upper and lower limit of the solution space in the i-th section, u_x is the measured deformation, and u_x^{target} is the deformation defined in the Deformation Space Model. Lastly, x_L and x_U represent the manufacturability limits imposed on the thicknesses x of the walls

Given the objective function, we can solve this optimization problem per each component in parallel. In other words, we optimize each component independently, thanks to the properties of the solution space method.

5 Results and Discussion

Let us now look at the results so obtained. As shown in the figures below, of the 7 components we optimize only 3 to fulfil the constraints of the computed solution space, see Figs. 4, 7 and 8. These three components are all positioned at the front, while the others are all towards the back. The violations on these other 4 components are, however, not severe, see Figs. 5, 6, 9 and 10.

Consider the solution space formulation. As one can read in [10], the space represented is only the feasible and independent one. Hence, part of the feasible space (i.e. the space where all conditions for crashworthiness are fulfilled) is not represented in the solution space. Since the violations are mild, all components are very likely to be in this feasible space. We, however, still do not have a consistent method to test just for the feasibility of the solution.

Moreover, the fact that the components violating the constraints are towards the rear can be related to the fact that the inter-dependencies between different components are nearly not considered. On one side, the Deformation Space Model captures the influences between different components only if related to the order of deformation. On the other side, the drop-tower test was designed for components at the front (e.g. crashboxes like the one shown in Fig. 3), and not for bigger components like number 7 or 3. It is well known that components like these are affected by the surrounding parts. Nevertheless, for these components, there is still no commonly used test for properly measuring the force-deformation curves. The work in [15] and further developed in [16] attempts to address this problem. They propose a methodology to better represent the conditions under which these bigger components deform. However, the method is still too young for us to use it in the work here presented.

We are not able, as of now, to assess if changing the test would positively benefit the solution found. It is too early to conclude if the violations are due to the test performed or to the independence condition imposed by the solution space methodology.

6 Conclusion

All in all, the development of a new car is a complicated process. The key factor to success is finding proper compromises between opposing requirements. The solution space methodology can help the development to find these tradeoffs. However, the application in the crashworthiness field is still full of difficulties. In this work, we tackle one of these conflicts: we optimize the components at the front of a car to find a lightweight and crashworthy design. To this purpose, we define an objective oriented at reducing the weight of the component, while we use the solution space to constrain the problem and ensure the crashworthiness. The results of this approach are not completely positive: out of 7 components, 3 are successfully optimized inside the solution space. These 3 components are all positioned at the very front of the car. At this point in time, we can say that the solution space methodology can help to develop all components with a limited amount of interactions with the neighboring systems (i.e.: the components at the front).

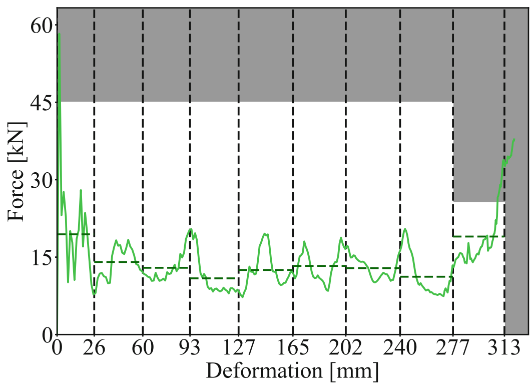

Fig. 4. Force-deformation curve measured from the successfully optimized component 1: in light green the measured signal, in dark green the average value over each section ($F^i(u_x)$).

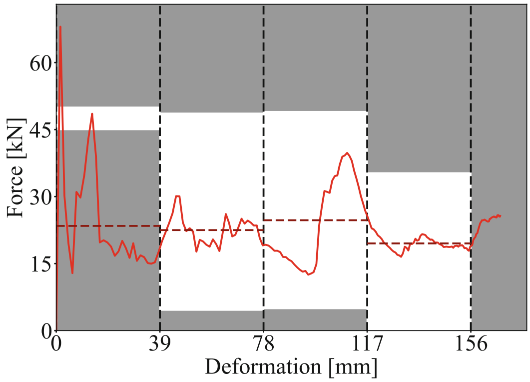

Fig. 5. Force-deformation curve measured from the failed optimized component 2: in light red the measured signal, in dark red the average value over each section ($F^i(u_x)$).

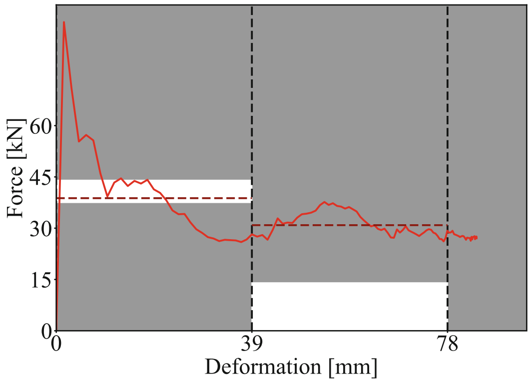

Fig. 6. Force-deformation curve measured from the failed optimized component 3: in light red the measured signal, in dark red the average value over each section ($F^i(u_x)$).

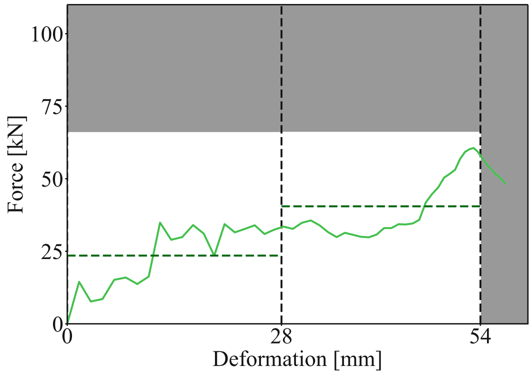

Fig. 7. Force-deformation curve measured from the successfully optimized component 4: in light green the measured signal, in dark green the average value over each section ($F^i(u_x)$).

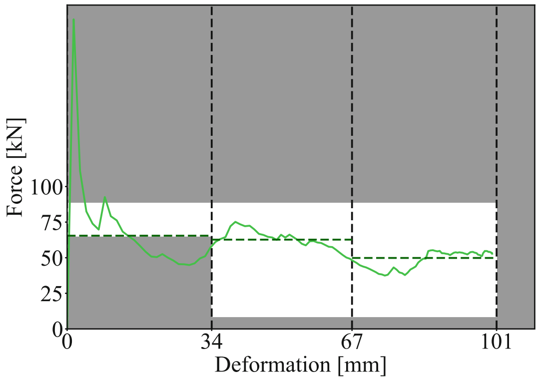

Fig. 8. Force-deformation curve measured from the successfully optimized component 5: in light green the measured signal, in dark green the average value over each section ($F^i(u_x)$).

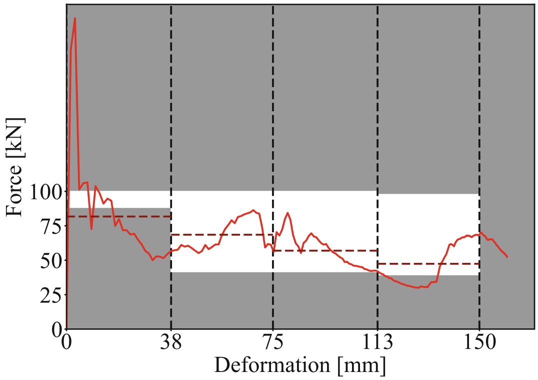

Fig. 9. Force-deformation curve measured from the failed optimized component 6: in light red the measured signal, in dark red the average value over each section ($F^i(u_x)$).

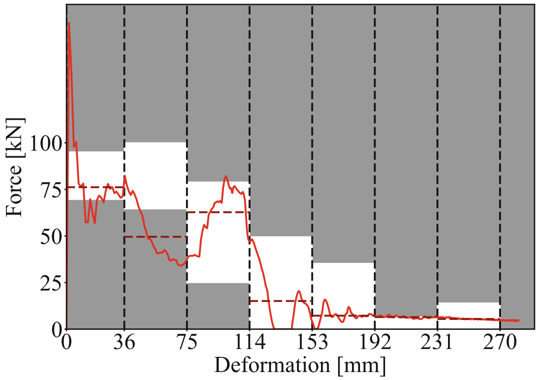

Fig. 10. Force-deformation curve measured from the failed optimized component 7: in light red the measured signal, in dark red the average value over each section ($F^i(u_x)$).

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