SENSITIVITY ANALYSIS FOR EFFICIENT PARAMETERIZATIONS OF AUTOMOTIVE COMPOSITE STRUCTURES FOR CRASH

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Abstract
A significant challenge in structural optimization of vehicle architectures for crash is handling of the typically large number of quantities defining the input and system parameters. The use of advanced composites materials increases this challenge by introducing more parameters and complex failure behavior. This paper introduces a novel design workflow that can help reduce the problem complexity for composite vehicle structures and provide for a more efficient design workflow. First a computationally efficient prognosis method is introduced to smooth the design space and reduce the number of required samples. Second a sensitivity analysis using the Sobol decomposition is introduced to provide a parameter importance hierarchy. Results show a reduction of 71.12% of required samples at the same time achieving a better quality design space. The sensitivity analysis results in a reduction of 22 to 8 parameters.

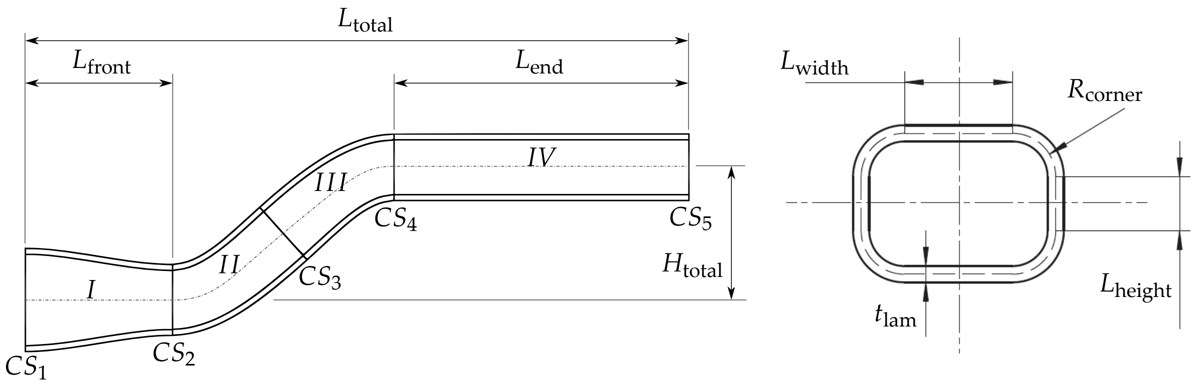
1. Introduction

Due to environmental considerations and stringent emission legislation, vehicle emissions are becoming increasingly important. Vehicles need to get more economical by using less fuel and weight reduction of the vehicle structure, also called body in white (BIW), is one way of achieving this. Another important function of the BIW is to absorb the energy of the impact during a crash. Because occupant safety is regarded as one of the most important vehicle design drivers, it is extensively tested and assessed based on rules defined by various independent institutions world wide, such as the NHTSA and UNECE, two major test programs are the Euro- and USNCAP. Currently it is common to use sheet metals for BIW and crash absorbing vehicle architectures in the automotive industry. Because sheet metal components have been used in the automotive industry for more than 100 years, design methodologies, optimization workflows and concept development are focused around the use of metallic (sub)structures. Their isotropic nature, extensive material databases and thoroughly researched elastic, plastic and failure behavior make it a well understood material to design with [1]. The increasing need for weight reduction and the importance of crash performance drive the research into new materials for vehicle design such as composite materials, specifically advanced carbon fiber reinforced plastics (CFRP). CFRP in automotive structures show great promise; composites have been shown to be lightweight, more robust and may have superior crash performance [2]. CFRP that is being used today in sub-structure component testing show typical specific energy absorption (SEA) values between 60 to 70 kJ/kg [3], which is two to three times higher than obtained by metals. The high SEA, specific strength and stiffness of advanced composites could have a significant influence on the overall weight reduction in automotive structures. Metallic impact structures in vehicles absorb energy by plastic deformation, work hardening and heat losses. The main energy absorption mechanic in composite structures is by undergoing fragmentation in the impact zone, thus deforming and removing the material. Indeed, the large differences in material properties and failure behavior between metals and composites may require a significant redesign of vehicle architectures. Replacing components in existing architectures with composite parts may not use the full potential of advanced composites [1]. Consequently, novel methods in optimization strategy are needed to integrate advanced composite materials in automotive design. Furthermore, due to the brittle nature of CFRP, the structural stability of a composite structure during crash is important if stable progressive crushing in the crash front is required. If the structure shows global buckling or fails in a different location than in the crush front, the energy absorbing characteristics may be significantly reduced, reducing the energy absorption of the structure. The division between stable crushing and sudden global structural failure creates a highly discontinuous design space, which is difficult to handle for both optimization methods and approximation techniques such as response surface modeling (RSM). This paper aims to introduce a design methodology for advanced composite structures optimization for crash. A parametric front longitudinal structure (S-rail) model is developed, presented and used to validate the proposed design methodology. The methodology is built into a design workflow, which is used to perform a parameter sensitivity study to determine the critical design parameters. Together with the proposed method for structural stability prognosis, the methodology increases the computational efficiency by significantly reducing the design space without losing valuable design flexibility.

2. S-rail design and parameterization

The design problem addressed in this paper is a parametric tubular structure with a single S-shaped bend, see Figure 1, and represents a simplified vehicle S-rail, which is divided in four sections and five cross-sections. The initial design is chosen such that it resembles an actual S-rail taken from a current vehicle architecture.

The structure has initial setup parameters and design variable parameters. The initial setup parameters are: $W_{\text{end}} = 0$, $H_{\text{end}} = 180$ mm, $CS_{2\_X} = 200$ mm and $CS_{4\_X} = 400$ mm. They influence the structure's fixed design or basis, namely: W_{total}, H_{total}, L_{front} and L_{end} respectively. L_{total} remains unchanged and is set in the SFE CONCEPT [4] model. The dimensions of L_{front} and L_{end} can be changed by moving cross-sections CS_2 and CS_4 respectively. H_{total} and W_{total} control the vertical and horizontal position of the straight end section. Cross-section CS_3 is mapped to the bend so that it will be centered between CS_2 and CS_4 and rotated such that it follows the S-shaped bend in the structure. A 3rd order Bézier curve is used to shape the curved sections, making sure that the structure will stay smooth with the correct tangents at all cross-sections. Cross-sections CS_i are parametrized such that the dimensions L_{width} and L_{height} can be changed symmetrically with respect to their symmetry axis. The corner radius R_{corner} remains



(a) *side view of the S-rail.* **(b)** *cross-section view of the S-rail.*

Figure 1. Problem description; parametrized tubular structure with single S-shaped bend.

unchanged. Obviously the total height and width of the cross-sections CS_i is calculated by $2R + L$.
In this research a CFRP composite was used, which was thoroughly tested to obtain accurate crush data. This CFRP was then implemented in an user material, called VUMAT, for Abaqus/explicit (v6.12). The user material incorporates 26 parameters in total, which define the elastic, plastic and failure behavior of the composite material. This material model is designed for plane-stress elements, in our research three and four node conventional reduced integration shell elements are used (S3R and S4R).

Lamination Parameters (LP) were used to parameterize the composite material properties [5]. Only balanced and symmetric laminates were used, with available ply orientations constrained to ±45°, 0° and 90°. The S-bend was divided in 4 material sections by creating 5 cross-sections. Each cross-section could change its dimension uniformly and symmetrically about the center y and z axis, created by relating the 8 corner coordinate dimensional variables in the yz-plane to two influence points. This results in two geometrical parameters per cross-section. In each material section the material is allowed to change uniformly. Material parameters that are allowed to change within each section are Lamination Parameters (LP) V_{iA} with $i = 1, 3$ and laminate thickness t.

3. Design workflow and DOE

The design workflow was built in Noesis Optimus (v10.13). Optimus allows for the linking of different programs, such as Abaqus/Explicit, in a graphical user environment. A set of 26 parameters controls the S-rail geometry and material specifications, 22 parameters were selected as design variables, see Section 2. An overview of the workflow is presented in Figure 2.

The responses that were calculated are the intrusion of the barrier into the S-bend structure, δ_{max}, the critical buckling force corresponding to the first buckling mode, P_{crit}, and the total S-rail weight M_{rail}. The S-rail weight can be directly calculated from the parameters, i.e. $M = M(\mathbf{\Phi})$ where $\mathbf{\Phi}$ equals the set of available parameters.

To create a sufficiently large and diverse data set, a Monte Carlo design of experiments (DOE) was set up to collect 600 samples. The lamination parameters have a feasible domain which should not be violated. To ensure that the DOE picked samples within these bounds, dependent constraints were be set on the LP bounds. The method of enforcing these bounds should not interfere with the uniform random sampling distribution, or false correlations might occur. Therefor each time the Monte Carlo DOE picks a sample outside the feasible domain, the sample is disregarded and a new sample is tried in its place.

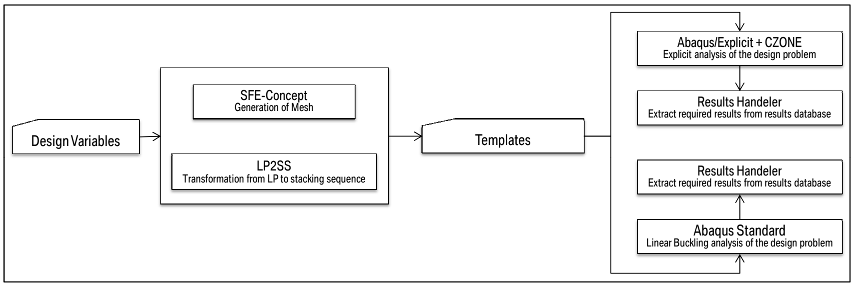


Figure 2. Flow diagram of the workflow used in this research.

4. Structural stability prognosis method

As explained earlier, a large percentage of the design space shows S-rail designs which do not support stable crushing as the main method for energy absorption. These designs are deemed structurally unstable. This research introduces a prognosis methodology that aims to assess the design space with less computational intensive implicit FE methods. The method works by filtering the DOE before computationally expensive responses are determined. This leaves a DOE in which the samples are predicted to produce stable S-rail designs. This filtered DOE is then parsed to the Abaqus/Explicit + CZONE [6] analysis methods for evaluation, reducing the computational costs. As a result the designs that are left should show a significantly higher percentage of structurally stable designs, effectively smoothing the design space.

The prognosis on structural stability is based on the observation that buckling is often the start of local structural collapse away from the crush front. Buckling weakens the structure locally whereas the stresses are not reduced, resulting in collapse and eventually local failure of the laminate. It is stipulated that a relatively simple linear buckling analysis can serve as a guess for the impact force threshold at which the structure becomes unstable. Prognosis is done by comparing the analytically derived crushing force in cross-sections 4 and 5 with the critical buckling load. For the buckling analysis the same model, mesh, boundary conditions and material parameters are used as in the explicit calculation. A unit perturbation force is applied at the center of cross-section 5 in the x-direction to simulate the force resulting from contact with the barrier. The first buckling mode is taken as the critical buckling load. To validate the method, both the Abaqus/Explicit + CZONE and the Abaqus/Standard buckling analysis are run in parallel, see Section 3. The results from the explicit analysis serve as a validation of the proposed prognosis method, i.e. actual structural stability is assessed by evaluating the force / displacement diagrams of each experiment. The structural stability is predicted with the following calculation:

$$P_{\text{crit}} > \max\left[F^4_{\text{crush}}, F^5_{\text{crush}}\right] \quad \rightarrow \quad \text{Stable} \tag{1}$$

The crush forces F^i_{crush} are calculated by deriving the cross-sectional area as a function of the parameters: CS_{i_Y}, CS_{i_Z}. Then the maximum crushing stress, σ_{crush}, of the material is used to calculate a conservative value for the crush force in that section. σ_{crush} is predetermined by coupon experiments. For a thorough explanation of crush-stresses in CZONE, see [6]. Depending on the parameters, either cross-section 4 or 5 may provide the highest crush force, therefor both are derived, see equation (2).

$$A(CS_{i\_Y}, CS_{i\_Z}) \cdot \sigma_{\text{crush}} = F^{i}_{\text{crush}}, \quad i = 4, 5 \tag{2}$$

4.1. Results

Table 1. Validation results of the prognosis method.

Total DOE	599
Validated stable designs	173 (28.88%)
Soft stability	26
Predicted stable designs	123
correctly predicted	103 (83.74%)
Valid stable designs neglected	70 (40.46%)

The results of the prognosis validation are shown in Table 1. They show that initially 173 designs (28.88%) of the 599 experiments showed stable crushing. Of these, 26 designs showed soft stability, which means that stable crushing occurred up to Section 3, after which the stiffness of section 3 caused structural failure. Therefore soft crushing is not considered to be a prediction failure. After prognosis 123 design are deemed structurally stable, which is a reduction in the number of DOE of 71.12%. Furthermore, 103 designs after filtering are validated structurally stable. Meaning that the filtered DOE has 83.74% stable designs. Consequently showing great improvement over the 28.88% stable designs in the far larger 599 sample DOE set. The results prove the buckling prognosis method to be promising. It should be noted however, that after filtering 70 stable designs are neglected, this is equal to 40.46% of all stable designs. As a consequence the engineer should make a trade-off between the loss of valid designs over increased computational efficiency and smoother design space.

5. Sensitivity analysis

A large challenge in structural optimization of vehicle architectures is handling the typically large number of quantities defining the input and system parameters. This is normally handled by selection of only few parameters that define the system. Another approach to simplify such problems is to identify a hierarchy among the parameters and focus only on those inputs that have the largest influence on the system response. Such a method is presented next.

Global sensitivity analysis of complex numerical models can be performed by calculating variance-based importance measures of the input variables, in this research the Sobol indices are used. The Sobol decomposition method emphasis the global nature of the results, meaning that the Sobol indices show the relative importance of the individual input parameters over their entire domain. This is in contrast with the more commonly used point sensitivity analysis that is provided by the classical gradient sensitivity analysis. The global nature of the Sobal decomposition makes it a powerful tool for sensitivity analysis and can provide guidance in model reduction. An explanation of the derivation of the Sobol indices is given in [7].

A support vector machine (SVM) [8] based response surface was used to provide a model for the numerical integration required to determine the Sobol indices. SVM proved to provide the best correlation with our DOE after evaluation of different RSM techniques. For clarity, the results will be discussed per data set.

The parameter sensitivity analysis is done in three parts. First the complete sample set of the DOE is analyzed, called set 1 - *all*, secondly the filtered set is used, called set 2 - *predicted*. Finally, by analyzing the explicit simulation results, a set is collected with designs that show progressive crush behavior to absorb all energy of the impact without structural instabilities, called set 3 - *stable*. For the first set a Pearson correlation and Sobol Analysis is done, for the remaining sets only the Sobol indices are calculated.

Set 1, All

The Pearson coefficients between inputs and outputs showed an overall low correlation. An exception are the correlations between thicknesses t_1 and t_2 and both Buckling and Intrusion. They are very similar and significantly high, see Table 2. This suggests that both intrusion and buckling are equally correlated with t_1 and t_2. This may support the notion that there is a quantifiable relation between global buckling and intrusion. The maximum intrusion is dependent on the global structural stability, i.e. the intrusion is high if the structure can not support the required crush behavior. Therefor a relation between buckling and intrusion could represent a relation between buckling and structural instability.

Table 2. Pearson coefficients between section thickness, buckling load and intrusion.

	t_{S1}	t_{S1}
Buckling load	0.389	0.380
Intrusion	0.383	0.394

Figure 3 shows the derived Sobol indices for the intrusion response. It can clearly be seen that the indices for both section thicknesses t_1 and t_2 are prominent. This corresponds to the conclusion drawn from the Pearson correlation coefficients from Table 2. Thicknesses t_1 and t_2 are important for the structural rigidity in material sections 1 and 2. They directly influence the buckling resistance by increasing the structural bending stiffness and laminate membrane stiffness. Furthermore the Lamination parameters V_{1_S1} and V_{1_S2} are third and fourth ranked in the Sobol hierarchy. Lamination parameter V_1 is the LP that has a large influence on the amount of either 90 or 0 degree ply orientation in the laminate layup, resulting in a large influence on the principal stiffness directions as well. That in turn has a significant influence on the structural bending stiffness in those material sections. Indeed, the Sobol indices show that the parameters influencing the back part of the S-rail structure are the most influential. It can be concluded that for set 1 the design is driven by structural stability and that the parameters, t_1, t_2, V_{1_S1} and V_{1_S2} have the highest influence on that stability.
Figure 3 also shows the derived Sobol indices for the S-rail mass response. The parameter influential hierarchy is as expected and trivial. Material section 4 is the largest and therefore thickness t_4 shows the largest influence on the mass. It can also be seen that the cross-sectional dimensions have a significant smaller influence on the mass than the section thicknesses. Obviously the LP's do not have an influence on the mass and are therefore not present in the graph.

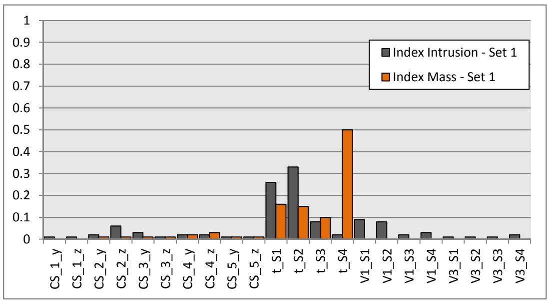


Figure 3. Total Sobol indices with respect to the total deformation response, δ_{max}, and the S-rail mass response, M_{rail}. Based on the samples from set 1.

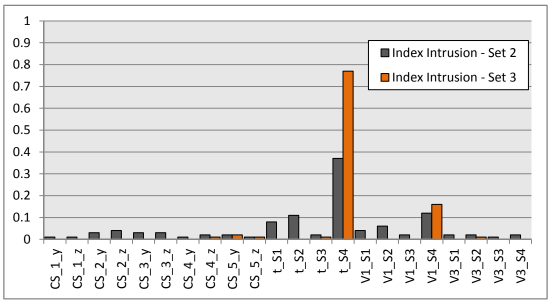


Figure 4. Total Sobol indices with respect to the total deformation response, δ_{max}. Based on the samples from set 2 and 3.

It may be concluded that the Sobol indices for the mass response serve as a verification of the method. For the next data sets, only the intrusion response will be discussed.

Set 2, Predicted

The indices for set 2 in Figure 4 show a different hierarchy than with set 1. The Sobol indices point to section thickness t_4 as the most influential parameter on the intrusion response. When the structure shows stable crushing, the intrusion is determined by the crush resistance material section 4 is providing. The thickness t_4 has a significant influence on this crush resistance. Second in the hierarchy is LP V_{1_S4}, supporting the fact crush resistance is driving the intrusion value in this data set. Although these results may seem trivial, they prove that the buckling prognosis tool sufficiently reduced the design space to a structurally stable region. It was successful in smoothing the stability driven design space from the initial set 1. It should be noted that thicknesses t_1 and t_2 with their respective LP's V_{1_S1} and V_{1_S2} still have a significant presence in the Sobol indices. This shows that a part of the design space is stability driven.

Set 3, Stable

Figure 4 also shows the indices for set 3. A similar hierarchy compared to set 2 is shown, for the same reasons as with set 2. The difference is all structural unstable design were removed manually, leaving a fully stable design space. Consequently the indices that drive crush resistance in section 4 are further increased, whereas the others are almost zero. These results support the theory as discussed for the results from set 2, as they are an extreme of the Sobol indices for set 2.

Results

Looking at the results from the Sobol indices for sets 1 and 2 for the intrusion and mass response, a top 6 of the Sobol indices are made, see Table 3.
It can be seen from Table 3 that there are eight independent parameters. These eight parameters were determined to drive the intrusion response for both set 1 and 2 and the overall mass response. This means a reduction of 22 to 8 design variable parameters. Is it should be noted that the sum of Sobol indices for set 2 is relative low, but a value of 0.78 means that still about 78% of the behavior is captured with the six parameters that are chosen for this set.

Table 3. Top 6 in the parameter hierarchy for set 1 and 2 and corresponding Sobol indices for the intrusion and mass response.

nr.	Intrusion Set 1	value	Intrusion Set 2	value	Mass Set 1	value
1	t_2	0.33	t_4	0.37	t_4	0.50
2	t_1	0.26	V_{1_S4}	0.12	t_1	0.16
3	V_{1_S1}	0.9	t_2	0.11	t_2	0.15
4	V_{1_S2}	0.8	t_1	0.08	t_3	0.10
5	t_3	0.8	V_{1_S2}	0.06		
6	CS_{2_Z}	0.6	CS_{2_Z}	0.04		
Total		0.9		0.78		0.91

6. Conclusion

The proposed structural stability prognosis method has been developed, using a numerically inexpensive buckling analysis. The tool showed significant improvement of design space quality. It successfully predicts the structural stability with only a small margin of error. The sensitivity analysis has supported the validity of the prognosis method. Furthermore, using Sobol indices, a hierarchy in importance of the design parameters has been established. By using these results, the set of design parameters was reduced from 22 to 8, resulting in a significant reduction of the design space. Indeed, the careful selection of parameters based on the design workflow presented here together with the prognosis method may prove to be an efficient method for solving composite structure crash optimization problems.

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