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Load Case Preference Patterns based on Parameterized Pareto-Optimal Vehicle Design Concept Optimization

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Abstract

Classical Topology Optimization (TO) methods aim to optimize the distribution of material within a design space for one given objective function and constraints. However, in the vehicle design process, there are many different load cases and several different objectives. Among them maximizing stiffness of components for regular working conditions, and maximizing energy absorption in exceptional loading conditions, for instance in crash events, are important. Recently, the Scaled Energy Weighting Hybrid Cellular Automata (SEW-HCA) [1], [2] method was adopted in LS-TaSC™. The SEW-HCA is a practical multidisciplinary TO approach for devising concept structures based on the intuitive choice of preferences leading to the desired trade-off between crash performance and stiffness. In this paper, we propose an integration of the SEW-LS-TaSC method into LS-OPT® to perform a design of experiments (DOE) on the load case preference parameters. The integration into LS-OPT® results in a convenient user interface that facilitates application in an industrial development process with non-expert users. This integration enables quick studies on many different concept designs based on preference samples generated by the DOE. The results from the sensitivity analysis provide data for a better understanding of the influence of load case preferences on the design space. By comparing the performance of structures obtained for different load case preferences, the user will be able to find a desired trade-off solution within the concurrent optimization runs. For further development, the proposed LS-OPT® workflow can potentially include 1) NVH load cases as additional discipline and 2) optimizations of other topology optimization hyperparameters for further concept exploration.

1 Introduction

During the last years, the design process in the automotive industry has been changing very dynamically. In particular, due to the rising material costs, stringent CO_2 emission targets and a strong competition on the market, the car companies have to substantially shorten the production cycles to widen the spectrum of vehicles as well as to develop and manufacture in a more efficient way [3]. In order to achieve these goals, numerical simulation and optimization methods have to be used. In the context of the early phases of the product development process, Topology Optimization (TO) is one of the most promising approaches for providing the designers with novel structural concepts.

TO is a mathematical method used to optimize the material layout within a defined design space, for a given set of boundary conditions like loads or supports. With the rising complexity of the cars, these methods have to take into account different, very often conflicting performance goals, coming from various disciplines, including structural statics, vehicle dynamics, crashworthiness or NVH (noise, vibration, harshness). In some cases, e.g. for structural statics or vibration problems, very efficient gradient-based TO methods exist [4][5][6][7] and are widely used across different industries. In contrast, design for crashworthiness poses severe difficulties due to complexity of the crash phenomena, which prohibits efficient computation of analytical gradient information and requires development of alternative methods [8][9][10][11][12][13][14][15]. One of the approaches very successful in optimization for both crash and statics is the Hybrid Cellular Automata [12], which is a numerically efficient method mimicking the bone remodeling process. An algorithm inspired by HCA was implemented in LS-TaSC™ [16][17][18] and further developed, showing a great potential to solve real-world TO problems [1].

Although the development of TO methods for each of the above mentioned disciplines is very active, relatively little research was done on multidisciplinary TO, which is crucial for the development of the

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future vehicle concepts. One of the first approaches addressing concurrent TO for static and crash loads was the Scaled Energy Weighting – Hybrid Cellular Automata (SEW-HCA) method [[2], which has been successfully used in the optimization of the real-world BIW structures [2], taking into account several static and crash load cases. SEW-HCA allows for exploration of the solutions balancing conflicting optimization objectives like minimum compliance to safeguard the cabin and protect the passengers, and maximum energy absorption by structures in extreme events such as a crash. The SEW-HCA method has been successfully applied in the past [19],[20], to generate concept designs of complex structures.

In case of the Multidisciplinary Design Optimization (MDO) [21], a single solution optimizing all of the objectives simultaneously usually does not exist. As a consequence, one is interested in finding a set of solutions, called Pareto front, where each design can be improved in one of the objectives only by decreasing the performance in the other ones. Since each of the solutions on the Pareto front is equally good, the designers have to make the choice which design to use based on their individual preferences. As a result, the ability to explore different options, compare the design concepts and analyze trade-offs between the relevant design criteria becomes crucial for the overall process.

In the current paper, we demonstrate the extension of the SEW-HCA by using the recent advancements in the LS-TaSC™. To distinguish between the methods, we refer to the latter as SEW-LS-TaSC. In order to explore different design concepts, we present a workflow created in LS-OPT® 5.2.1, which uses SEW-LS-TaSC implemented in LS-TaSC™ 4.0. Such an integration allows the user to use the capabilities of LS-OPT® to perform Design of Experiments (DOE) on the preferences determining the weight or importance of each load case. As a result, different design concepts are devised and the solutions reflecting the best preferences of the designer can be easily selected. Various trade-off solutions, compromising stiffness and energy absorption, can be explored using an intuitive graphical user interface of LS-OPT®. The implementation of the workflow is very straightforward and allows the designers for an efficient utilization of the multidisciplinary TO methods in industrial scenarios. The workflow presented in the paper can be easily extended by adding more load cases or by integrating new disciplines, e.g. NVH.

The paper is organized as follows: In section 2, we describe the SEW method. In section 3, we present the implementation of the workflow to automate the SEW-LS-TaSC method in commercial LSTC software. Section 4 illustrates a case study using a beam model, along with results and discussions. Section 5 provides the conclusion of the paper.

2 Topology Optimization based on Load Case Preference

The work presented in this paper is further development of the SEW-HCA optimization algorithm [1] for more convenient industrial application and extended parameter design concept and performance studies. The SEW method allows solving for multiple objectives like minimum compliance and energy absorption concurrently for various load cases. The SEW method is briefly discussed below.

2.1 Scaled Energy Weighting

In TO, the target is to find the optimal material distribution within a two or three-dimensional design space or design domain. The density of each finite element of the discretized design domain is an optimization variable, i.e. the optimization assigns a density variable that controls the material properties within the element. In such density-based topology optimization algorithms a power law approach according to the well-known SIMP approach [5] is applied:

$$E_i(\rho_i) = \rho_i^p E_0, \tag{1}$$

where $\rho_i \in [0,1]$, is the density of element i, E_0 is the Young's modulus of the full material and p is a penalization exponent (in this case the default value of 3 is assigned) and $i = 1 \ldots N$ are the indices of the elements. In typical mathematical optimization approaches the densities are iteratively updated based on the sensitivities of the objective function with respect to the densities, hence gradients are used by a mathematical optimizer. Other approaches such as the Hybrid Cellular Automata (HCA) approach have the capability to address certain types of crashworthiness TO problems. They use heuristic material distribution based on field variables aiming for uniform energy distribution and a control based update-rule.

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The Scaled Energy Weighting was developed originally for the Hybrid Cellular Automata algorithm to balance the energy field variables of multiple crash and static load cases (SEW-HCA) [1, 2]. For the kind of problem addressed by SEW-HCA the field variables are usually the strain or internal energy densities of the elements. However the SEW approach is independent of the concrete optimizer use. In the following S_{il} may represent design update information such as field variables or mathematical sensitivities of element *i* and load case *l* depending on the optimizer. This update information is combined for all elements before the update by the optimizer as proposed in [1]:

$$S_i = \sum_{l=1}^{L} w_l S_{il} = \sum_{l=1}^{L} \rho_l \frac{1}{S_l} S_{il}, \tag{2}$$

with the number of load cases L, a weight w_l for each load case. For intuition, the SEW approach refactors the weight w_l in a user-defined preference factor p_l and a scaling factor S_l. This refactoring enables to separate the task of scaling each of the load cases to the same level from the task of expressing how important the load case is for the user, hence the preference factor.

In the previous work where typically the compliance subject to static loads or the energy absorption subject to crash loads were optimized by SEW, good results were obtained for the following scaling factor:

$$S_l = \frac{w_l}{w_{min}}, \tag{3}$$

where $w_l = \Sigma^N_{i=1} S_{il}$ is the work of the structure obtained from the analysis of the load cases within the initial iteration of the TO. Except for the constant factor w_{min} (which is irrelevant for typical optimizers) this is equivalent to an L1 norm on the update variables. Such a scaling applied to gradients is also part of the projected sub-gradient (PSG) optimization method available in LS-TaSC 4.0 as described in equation (9) in [22]. Hence the central idea of the SEW method is available as part of the provided PSG algorithm in LS-TaSC 4.0 and can be readily applied. An additional improvement is that the scaling in the available method happens every iteration and could potentially achieve the most stringent balance of the load cases.

3 Integration of LS-TaSC© 4.0 with SEW-LS-TaSC & LS-OPT® 5.2.1

The following setup describes the SEW-LS-TaSC setup for a two load case example. A multi-stage setup was used in LS-OPT 5.2.1 with one stage for the LS-TaSC simulations and the second stage for running LS-DYNA simulations on the optimized design(s). The LS-OPT performs a DOE on the preference parameters before running the optimization simulations. The LS-OPT setup is shown in the Figure 1 below. The scaling of the preference parameters occur within LS-TaSC 4.0 using the PSG method described briefly in the previous section.

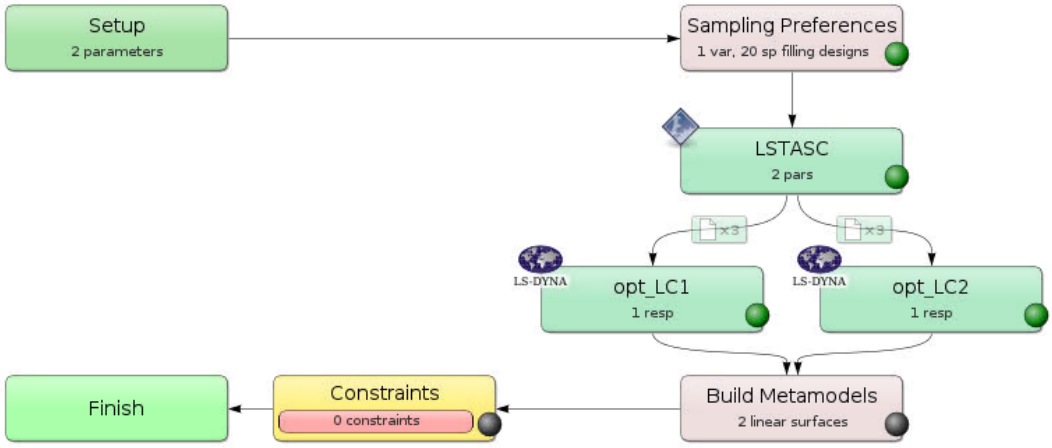

Fig.1: LS-OPT setup for SEW-LS-TaSC workflow

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The LS-OPT setup consists of a DOE task with an LS-TaSC stage to run TO for different load case weights, and lower LS-DYNA stages, *opt_LC1* and *opt_LC2* (as shown in Figure 1), to run final LS-DYNA analysis of the optimized designs generated in LS-TaSC. Since LS-TaSC is not available as a solver package in LS-OPT v5.2.1, a user-defined solver type is used.

In this paper, full factorial design is used to sample user-preferences and weights, for the two load cases. These factorial designs are transferred to the LS-TaSC simulations. "Global variables" (load case weights) defined in LS-TaSC input file are read as design parameters for LS-OPT and constraints defined in LS-TaSC are directly extracted as LS-OPT parameters. The implementation of this step is illustrated in Figure 2. Finally, the responses extracted from the optimized topology designs of the two load cases can be visualized as a Pareto front in two-dimensional space, with user-preferences being the variables.

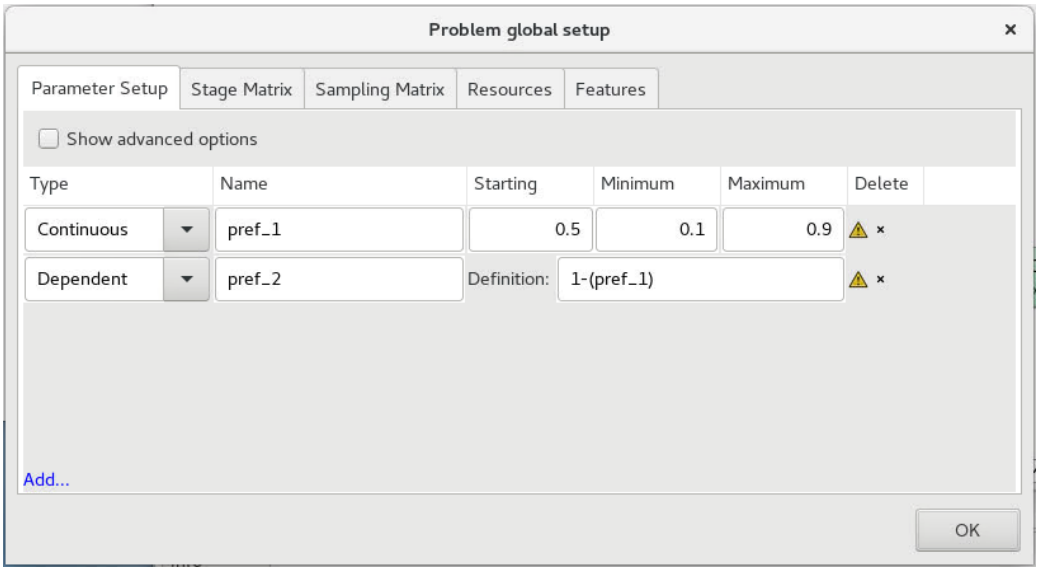

Fig.2: Parameters Setup in LS-OPT

4 Case Study on Cantilever Beam

In this paper, the method described to utilize the SEW-LS-TaSC method in LS-OPT® is demonstrated using a beam model. The beam model, optimized for two conflicting objectives (minimum compliance and maximum energy absorption) in two load cases, is discussed in detail below. The finite element model is developed in LS-DYNA® keyword format. The static load case is analyzed using the implicit solver while the load case for energy absorption is solved using the explicit solver in LS-DYNA®. The material model used in this analysis is a piecewise linear elastic-plastic material.

4.1 Model Setup

The beam model is setup as a simply supported beam problem with two load cases. Figure 3 shows the constraints used for setting up the model used in the paper. The design space of the beam model contains 12,000 voxel elements as shown in Figure 4. A target mass fraction of 0.3 is set along with a move limit of 0.1. The results obtained from the optimization run can be used as a starting point for further design development process.



Fig.3: Simply Supported Beam

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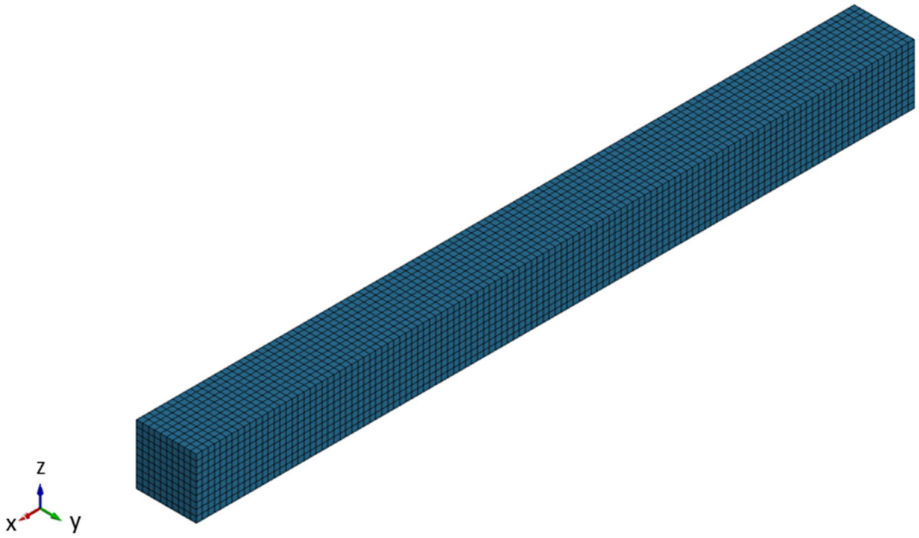

Fig.4: Voxelized Beam Model

The first load case is a dynamic crash scenario shown in Figure 5, in which the optimization objective is to maximize the energy absorption from the indenter. The cylindrical indenter is forced into the beam, along the z-direction, to create significant deformation. The motion of the indenter is defined as a linear motion with a constant velocity, until a displacement of 100mm is reached. This is applied within LS-DYNA using the *BOUNDARY_PRESCRIBED_MOTION* card. In the second load case, a point static load of 1000N is applied in the y-direction as shown in Figure 6. The optimization objective for this case is to minimize compliance.

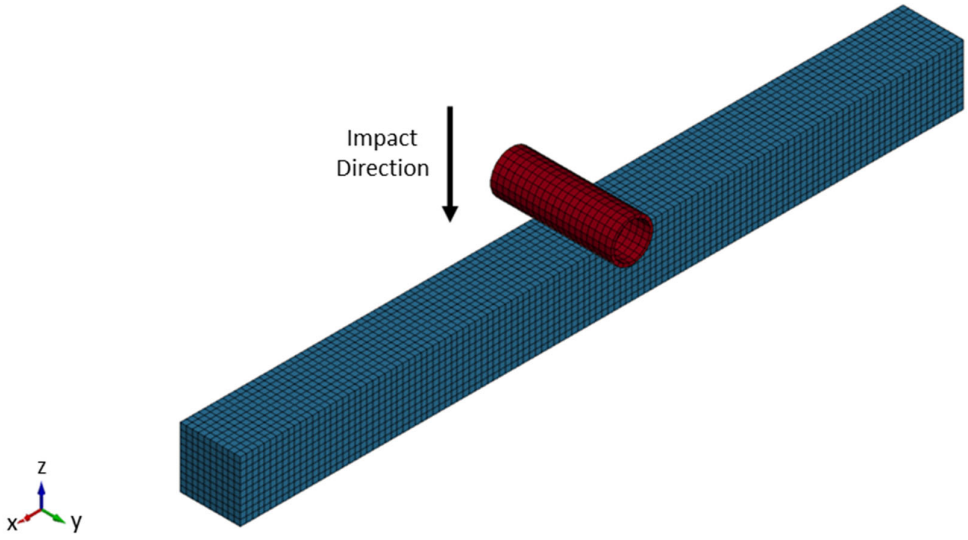

Fig.5: Dynamic Load Case Setup

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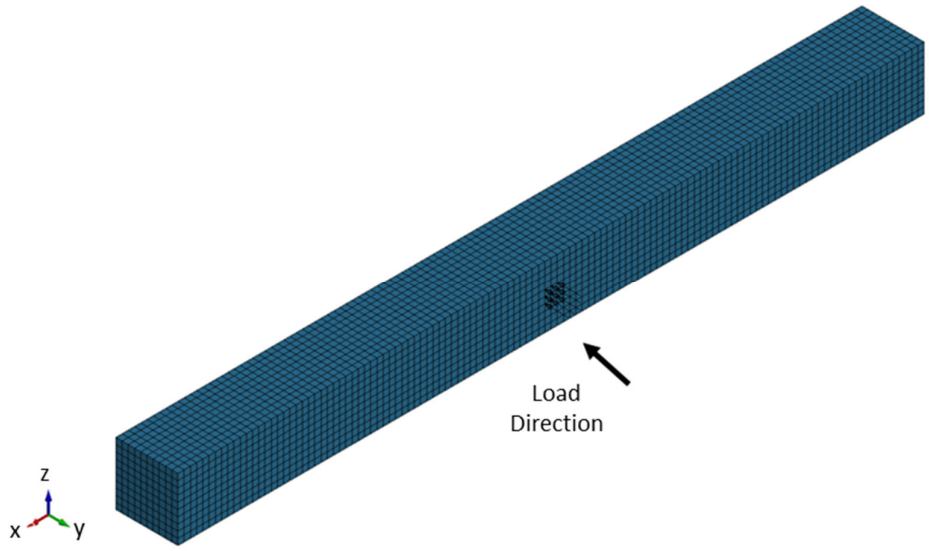

Fig.6: Static Load Case Setup

4.2 Simulation Results

The TO procedure is run for a total number of 20 sampling points and 30 iterations in each LS-TaSC optimization. Figures 7 and 8 shows the results obtained when the preference parameters are skewed towards one of the load cases. For example, in Figure 7 the preference for crash load case is 0.9 and for static is 0.1; the other way round in figure 8 (i.e. 0.9 for static and 0.1 for crash).

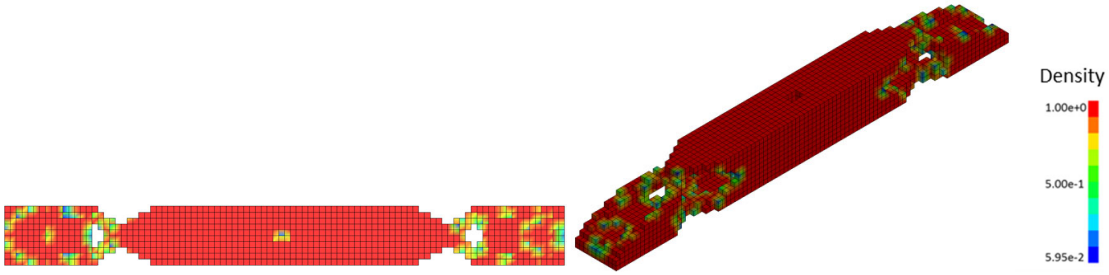

Fig.7: Topology Optimization Result for Crash Load Case Dominant Preference (L -> R: Top View, Isometric View)

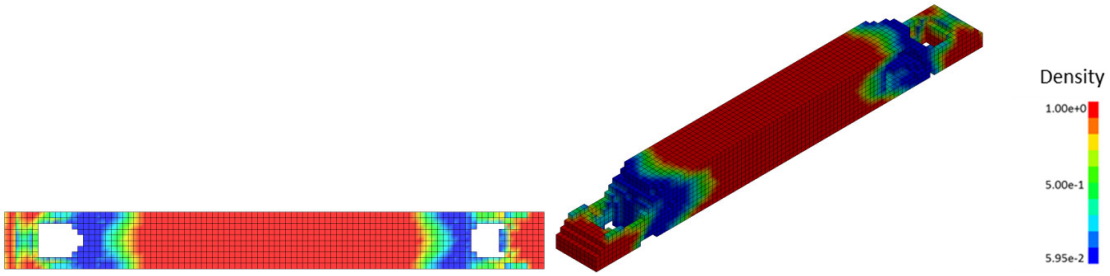

Fig.8: Topology Optimization Result for Static Load Case Dominant Preference (L -> R: Top View, Isometric View)

The effect of preference parameters on the load cases can also be seen in Figures 9 and 10. In Figure 9 the internal energy for the crash load case:

a. In the crash dominant scenario, the internal energy is higher since the preference is set at 0.9. This requires the beam to absorb maximum internal energy
b. While in the static dominant scenario, the energy absorption is lower due to the fact that the preference parameter for the crash case is 0.1.

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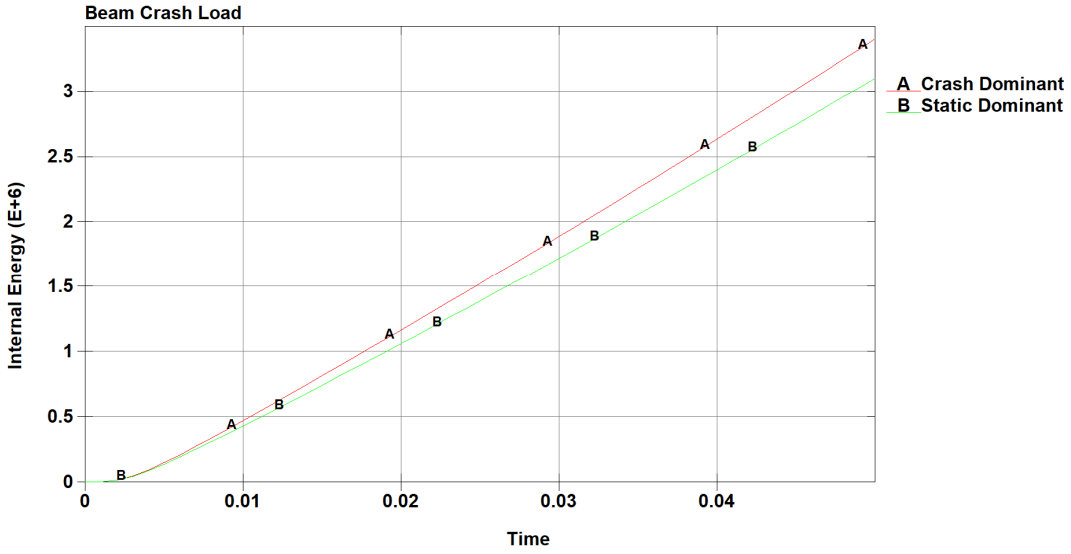

Fig.9: Overall Internal Energy (N/mm²) of the Beam for Crash Load Case

Similar results are also shown for the static load case in Figure 10. As observed in the figure, the internal energy for the static dominant case is lower, since the objective in this case is to minimize compliance (internal energy being directly proportional to the compliance).

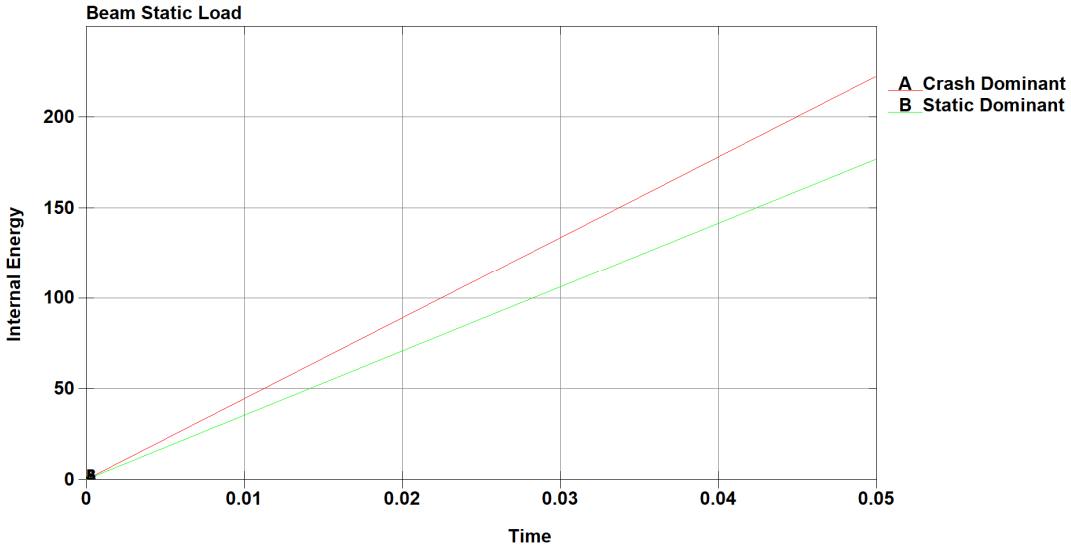

Fig.10: Overall Internal Energy (N/mm²) of the Beam for Static Load Case

4.2.1 Sample Results based on Pareto Front

The in-built capability of LS-OPT® to perform DOE and produce Pareto front makes it easier to analyze the results obtained for various preference values. Figure 11 shows a sample Pareto front obtained for the two load cases considered in the case study. Each square in the Pareto front corresponds to a particular set of preference values for each load case, generated using the DOE method (full-factorial) in LS-OPT. Selecting the data point within an acceptable range of internal energies, would give the desired conceptual design. The integration into LS-OPT® results in a convenient user interface that facilitates application in an industrial development process with non-expert users. This integration enables quick studies on many different concept designs based on preference samples generated by the DOE. The results from the sensitivity analysis provide data for a better understanding of the influence of load case preferences on the design space. By comparing the performance of structures obtained for different load case preferences, the user will be able to find a desired trade-off solution within the concurrent optimization runs. The resulting Pareto front also

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provides a balanced distribution of solutions. It also helps the designer pick the optimal starting design since the results do not cluster in certain regions.

The bottom most and top most points in the Pareto front (Figure 12) represents the designs with static dominant and crash dominant preferences respectively. The one in the middle is the design obtained for equal preferences to both the load cases. As expected, the optimization algorithm removes material from the inside of the beam, making it less stiffer and more energy absorbent, as the preference moves from static towards crash. This can be seen in the cross-sections of the beams shown in Figure 12.

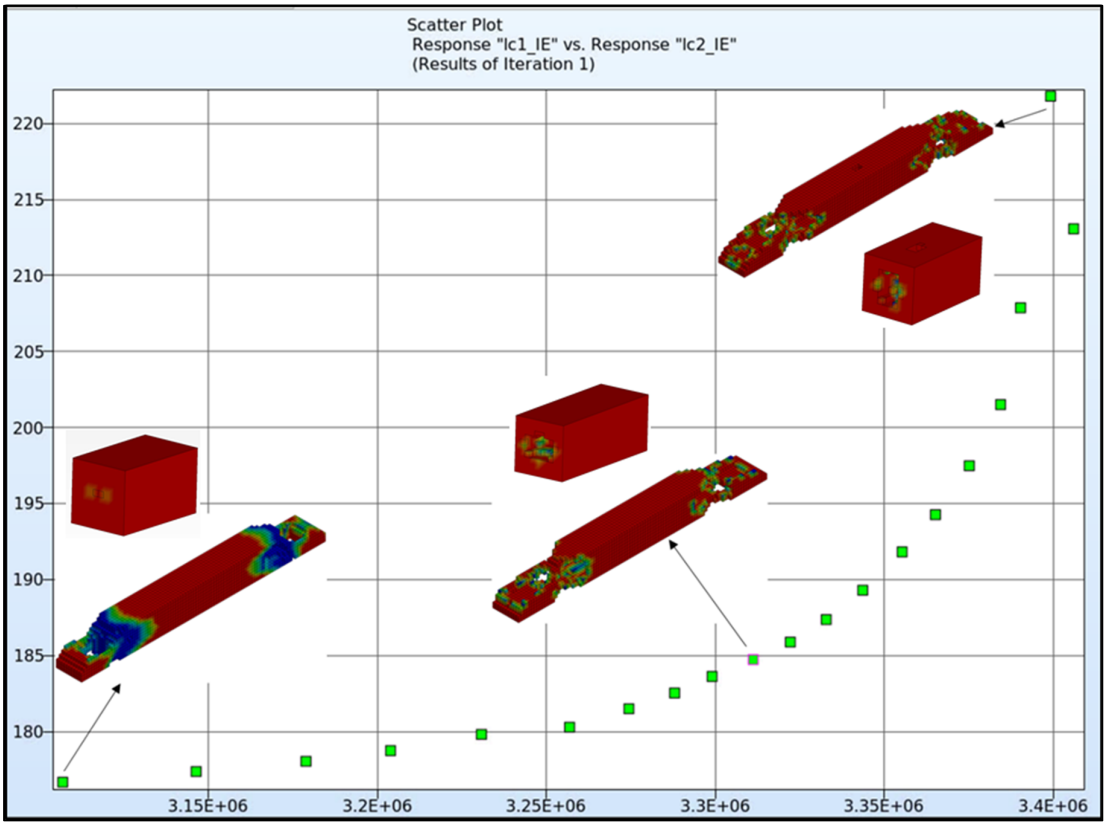

Fig.11: Pareto Front Obtained from the Optimization for both the Load Cases

5 Conclusion/Summary

In this paper, we successfully demonstrated the integration and application of the SEW-LS-TaSC method with LS-OPT®. The integration of SEW-LS-TaSC within LS-OPT® makes it readily accessible to the industry to include such a method into the development process. The approach can easily be extended to a body-in-white (BIW) structure with more than two load cases. Future work includes 1) adding a NVH load case to the workflow for BIW structure and 2) optimizations of other topology optimization hyperparameters for further concept exploration.

6 References

[1] N. Aulig, E. Nutwell, S. Menzel, and D. Detwiler, “Preference-based Topology Optimization of Body-in-white Structures for Crash and Static Loads,” in *14th International LS-DYNA Users Conference*, 2016.

[2] N. Aulig, E. Nutwell, S. Menzel, and D. Detwiler, “Preference-Based Topology Optimization for Vehicle Concept Design with Concurrent Static and Crash Load Cases,” *Struct. Multidiscip. Optim.*, vol. 57, pp. 251–266, 2017.

[3] F. Duddeck, “Multidisciplinary optimization of car bodies,” *Struct. Multidiscip. Optim.*, vol. 35, no. 4, pp. 375–389, 2008.

[4] M. P. Bendsøe and O. Sigmund, *Topology optimization by distribution of isotropic material*. 2013.

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[5] M. P. Bendsoe, “Optimal Shape Design as a Material Distribution Problem,” *Struct. Optim.*, vol. 1, no. 4, pp. 193–202, 1989.
[6] M. P. Bendsøe and N. Kikuchi, “Generating Optimal Topologies in Structural Design using a Homogenization Method,” *Comput. Methods Appl. Mech. Eng.*, vol. 71, no. 2, pp. 197–224, 1988.
[7] G. Allaire, F. Jouve, and A.-M. Toader, “Structural Optimization using Sensitivity Analysis and a Level-Set Method,” *J. Comput. Phys.*, vol. 194, no. 1, pp. 363–393, 2004.
[8] M. Cavazzuti, A. Baldini, E. Bertocchi, D. Costi, E. Torricelli, and P. Moruzzi, “High Performance Automotive Chassis Design: A Topology Optimization based Approach,” *Struct. Multidiscip. Optim.*, vol. 44, no. 1, pp. 45–56, 2011.
[9] G.-J. Park, “Technical Overview of the Equivalent Static Loads method for Non-Linear Static Response Structural Optimization,” *Struct. Multidiscip. Optim.*, vol. 43, no. 3, pp. 319–337, 2011.
[10] C. B. W. Pedersen, “Topology Optimization Design of Crushed 2D-Frames for Desired Energy Absorption History,” *Struct. Multidiscip. Optim.*, vol. 25, no. 5–6, pp. 368–382, 2003.
[11] C. Ortmann and A. Schumacher, “Graph and Heuristic based Topology Optimization of Crash Loaded Structures,” *Struct. Multidiscip. Optim.*, vol. 47, no. 6, pp. 839–854, 2013.
[12] N. M. Patel, “Crashworthiness Design using Topology Optimization,” University of Notre Dame, 2007.
[13] N. Aulig, “Generic Topology Optimization Based on Local State Features,” Technische Universitaet Darmstadt, VDI Verlag, Germany, 2017.
[14] M. Bujny, N. Aulig, M. Olhofer, and F. Duddeck, “Identification of Optimal Topologies for Crashworthiness with the Evolutionary Level Set Method,” *Int. J. Crashworthiness*, vol. 23, no. 4, pp. 395–416, 2018.
[15] E. Raponi, M. Bujny, M. Olhofer, N. Aulig, S. Boria, and F. Duddeck, “Kriging-Assisted Topology Optimization of Crash Structures,” *Comput. Methods Appl. Mech. Eng.*, vol. 348, no. 1, pp. 730–752, 2019.
[16] T. Goel, W. Roux, and N. Stander, “A Topology Optimization Tool for LS-Dyna users: LS-OPT/Topology,” in *7th European LS-DYNA Conference*, 2009.
[17] W. Roux, “Topology Design using LS-TaSC™ Version 2 and LS-DYNA®,” in *8th European LS-DYNA Users Conference*, 2011.
[18] Livemore Software Technology Corporation, “The LS-TaSC Software, Topology and Shape Computations Using the LS-Dyna Software, User’s Manual - Version 3.0,” 2013. [Online]. Available: www.lspoptsupport.com.
[19] N. Aulig, S. Ramnath, E. Nutwell, and K. Horner, “Design Space Dependent Preferences of Multi-Disciplinary Body-in-White Concept Optimization,” in *15th International LS-DYNA Users Conference*, 2018.
[20] S. Ramnath, E. Nutwell, N. Aulig, and K. Horner, “Detail Design Evaluation of Extruded Sections on BIW,” in *15th International LS-DYNA Users Conference*, 2018.
[21] J. Sobieszczanski-Sobieski, “Multidisciplinary Design Optimization: an Emerging, New Engineering Discipline,” *Adv. Struct. Optim.*, vol. 25, pp. 483–496, 1995.
[22] W. Roux, G. Yi, and I. Gandikota, “Implementation of the Projected Subgradient Method in LS-TaSC™,” in *15th International LS-DYNA Users Conference*, 2018.

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