Evaluation of optimization algorithms for crash and NVH problems

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Abstract

The purpose of the studies presented here was to establish a standard optimization strategy for crash and NVH (i.e. noise, vibration, and harshness) problems. Crash simulation is a CPU consuming task, the optimization for this type of problems requires efficient strategies. The approaches should be rather general, which is inevitable for their integration into the standard design process. Monte-Carlo-search strategies, evolutionary and genetic algorithms, kriging, simulated annealing, and some methods based on regression analysis were tested. Mono- and multi-criteria optimization problems were considered. Finally, a standard strategy for optimizing is proposed and tested on a real MDO problem with five crash load cases, statics and dynamics with a finite element model of about 800,000 elements.

Keywords: Multi-disciplinary optimization; Crashworthiness; NVH; Evolutionary algorithms; Genetic algorithms; Simulated annealing; Kriging

1. Introduction

Recently, special focus was laid in the automotive industry on the simultaneous optimization of crashworthiness, dynamic, and static functionality of car bodies, e.g. [1,2,3,4,5]. Several test cases of crashworthiness were accounted for and several load cases in static and dynamic analysis were considered. These sometimes called multi-disciplinary optimization (MDO) problems were mostly solved by stochastic optimization strategies because of their inherent nonlinearity. In general, gradient-based methods are not adequate for this type of problem because parallel computing for crash simulation does not deliver correct gradient data due to numerical noise originating from parallel computing. Nevertheless, stochastic optimization requires a large number of simulations. Thus, effectivity is crucial for the algorithms. In the literature, several types of algorithms were already discussed, e.g. Monte-Carlo-search strategies, response surface methodology, evolutionary computing strategies, kriging, and space mapping. The methods based on meta modeling are advantageous as long as the meta models can represent the real physical problem. As some studies have shown in the preliminary stages of the negotiations presented here, this is valid only for some of the crash load cases. In particular, the highly non-linear character of the frontal impact is difficult to be approximated by simple meta models.

1.1. Four benchmarks for crash and NVH optimization

In this paper, the results of the evaluation of optimization algorithms effectuated at the research center of BMW in Munich are presented. Four particular examples for benchmarking the algorithms were defined. As a first test case, a really multi-disciplinary example of a full car frontal impact together with linear analysis of statics and dynamics was defined. This size optimization problem had 63 independent parameters (sheet thicknesses) and was initially infeasible. Secondly, a side impact problem with 10 independent variables was considered, where special focus was laid on multi-criteria optimization. As a third example, a model was taken with an industrial model size (137 independent parameters) for which the NVH (noise, vibration, and harshness) functionalities were optimized. Finally, the examples were accomplished by a shape optimization problem. The first three benchmarks are depicted in Fig. 1. The shape optimization example is presented in an additional paper, cf. [6].

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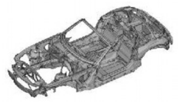
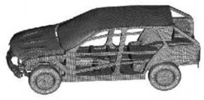
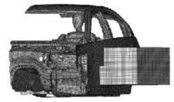
NVH: statics / dynamics	
MDO: crash / NVH	
crash (substructure)	

Fig. 1. Three of the four benchmark examples.

1.2. *Validation for a real full car multi-disciplinary optimization*

As a final validation example, a vehicle from the actual design process was chosen. The model taken for optimization consists of about 800,000 elements. Frontal impact, side impact, and rear impact were regarded as well as two low speed assurance cases. The computation time on 8 processors varied between 5 and 10 hours. In addition, statics and dynamics were computed. In all load cases, several constraints, e.g. intrusion, frequencies, and rigidities, were defined.

1.3. *Optimization algorithms*

For all four benchmark examples, several optimization algorithms with several parameter constellations were tested. Evolutionary algorithms, genetic algorithms, simulated annealing, and a kriging method combined with an evolutionary strategy were chosen, cf. for example [7]. The aim of this study was not to find the optimum after an infinite number of computations but to find sufficient improvement in a certain time, which is realizable in standard car design processes. Thus, the number of allowed variants per optimization was limited to a few hundred. Computations of crashworthiness are CPU devouring tasks; heuristic studies for optimization, sensitivity or robustness analysis demand even more resources. For the algorithms, it is hence required that they rapidly find a feasible area and that they advance there sufficiently fast. The final convergence is of no real importance. The strategy has to be robust and fault-tolerant because in the industrial context some network failures occur as well as hardware errors, which should not render the optimization result questionable. Special checking and monitoring facilities were realized in the framework of the benchmarks presented here.

2. Benchmark 1 – MDO

2.1. *Crash and NVH simulations*

For the first benchmark example, a frontal impact offset crash (Euro-NCAP) with an impact velocity of 64 km/h was defined. The finite element model consists of ca. 150,000 elements. For computation, up to four hours were needed. This small example was chosen to enable multiple repeated optimizations. A larger example would have limited the number of repeated optimizations to a very low number leading to non-significant comparisons between the algorithms. The frontal impact is highly non-linear; a first test with meta modeling showed that finding a valid approximation is not evident in this case. Thus, pure stochastic algorithms were tested in this example and no regression models, response surface models or comparable approaches were applied. The computation time of the linear analysis for statics and dynamics is negligible with respect to that for the crash analysis. A total NASTRAN computation for one of these load cases actually takes about 10–30 minutes. Particular attention should be paid to the mode-tracking algorithm (an algorithm which identifies eigen modes of new designs on the basis of eigen forms of the initial design), which may fail when the original design is altered too strongly.

2.2. *Optimization*

The car design process limits the time available for optimization to maximal two weeks, cf. [8]. In most cases, the time window open for the changes taken from an optimization is even smaller. Thus, a strategy is required which can give the intermediate status and which is flexible enough to be adapted to the process requirements. For the studies presented here, the total number of variants was hence limited to 280. The objective of this MDO example was to minimize the mass while respecting additional boundary conditions on footwell intrusion, A-pillar displacement, dynamic frequencies, and static stiffnesses. The original design – already pre-optimized during the standard design process – was nevertheless infeasible; the boundary conditions of the frontal impact were violated slightly.

2.3. *Performance*

The results of the optimizations obtained by the different algorithms are given in Table 1. Here, the mean amelioration was evaluated over several optimizations. The performance is highly dependent on the particular tuning of the algorithms. The results are obtained after evaluating the best configurations of the particular approach. In total, it can be stated that for problems

Table 1
Results for the first benchmark (MDO)

Algorithm	Mean amelioration
Monte-Carlo-search	$\Delta m = -14.6\,\mathrm{kg}$
Kriging	$\Delta m = -9.3\,\mathrm{kg}$
Simulated annealing	$\Delta m = -10.1\,\mathrm{kg}$
Genetic algorithms	$\Delta m = -12.2\,\mathrm{kg}$
Evolutionary algorithms	$\Delta m = -15.5\,\mathrm{kg}$

similar to benchmark no. 1 evolutionary algorithms perform best. Monte-Carlo-search strategies can be regarded as the simplest evolutionary algorithms without adaptivity. Thus they perform quite well. If a higher number of variants can be generated, the advantage of the evolutionary algorithm with respect to the Monte-Carlo-search becomes more and more visible.

3. Benchmark 2 – substructure for side-impact analysis

3.1. Mono- and multi-criteria optimizations

For the second benchmark, a submodel was chosen with about 340,000 elements. Design parameters are the thicknesses of the parts in the B-pillar. The mono-criteria optimization led to results similar to the first benchmark. For multi-criteria optimization (two objectives: mass and lateral displacement of the structure), the evolutionary algorithm, which performed best in the mono-criteria examples, was tested against a meta modeling strategy based on regression analysis. The physics of the side impact is more straightforward than that of the frontal impact. Thus, the meta modeling was successful and performed better than the evolutionary optimization. Both succeeded in establishing a Pareto-front.

4. Benchmark 3 – NVH simulation

4.1 Full car FE-model

This benchmark was defined to test the optimization algorithms for a standard full car FE-model for NVH analysis. An additional goal was to check the mode-tracking procedure which finally failed in about 1.5% of all computations. The mode-tracking was based on an MAC value (modal assurance criterion) comparison. Here, constraints with respect to the first three eigen modes of the structure and static bending and torsion forms were imposed; the objective was to minimize the mass.

4.2 Optimization

The optimization results are comparable to those of Section 2. Mono- and multi-criteria optimizations were effectuated. Genetic algorithms, simulated annealing, and kriging performed poorly compared to response surface and evolutionary strategies.

5. Full MDO validation example

The benchmarks have indicated that an evolutionary algorithm performs best for the type of problems discussed here. Thus, an optimization problem (cf. Fig. 2) with five crash load cases, statics and dynamics with a finite element model of about 800,000 elements is solved in a real industrial context. Figure 3 gives the result in comparison to the performance of a simple Monte-Carlo search. It can clearly be stated that the evolutionary algorithm is by far more effective. In the predefined time frame of 12 days the evolutionary optimization reduced the mass of the model by about 13.5 kg while the Monte-Carlo approach came to a reduction of 11.6 kg. The

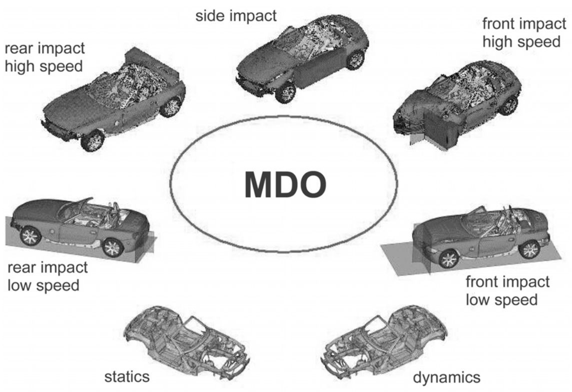


Fig. 2. Large MDO – example for crash and NVH.

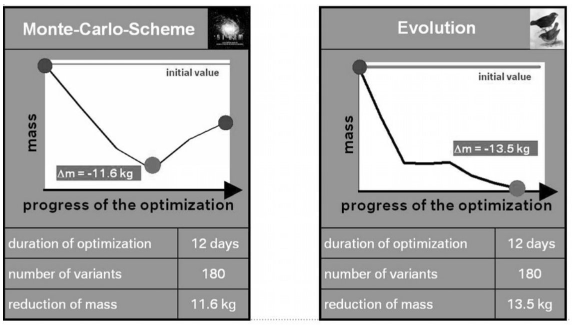


Fig. 3. Performance of the Monte-Carlo-search strategy and the evolutionary algorithm for the large MDO example.

optimization has been stopped not because the algorithm had converged to an optimum but because of the time limit defined by the goal to introduce the results into the real production development process.

6. Conclusions

The four benchmarks defined for testing optimization algorithms with respect to their usability in a real industrial context for optimization of crashworthiness and NVH-performance have clearly shown that evolutionary algorithms perform best. They lead to a rapid, controlled, and repeatable amelioration of the design. Crucial for this is the insertion of the initial engineering knowledge of the model. In general, the initial design is already pre-optimized before an automatic optimization is started. Thus, the algorithm should generate a sufficient number of variants around the initial design to ensure that the information is not lost during optimization.

References

[1] Blumhardt R. Numerical optimization of crashworthiness of vehicle structures and components (in German). PhD thesis. Aachen: Shaker, 2002.

[2] Duddeck F, Heiserer D, Lescheticky J. Stochastic methods for optimization of crash and NVH problems. In: KJ Bathe, editor, Computational Fluid and Solid Mechanics. Oxford: Elsevier Science, 2003.

[3] Forsberg J. Simulation-based crashworthiness design – Accuracy aspects of structural optimization using response surfaces. PhD thesis, Linköping Studies in Sci and Tech, 2002.

[4] Redhe M. On vehicle crashworthiness design using structural optimization. PhD thesis, Linköping Studies in Sci. and Tech., 2004.

[5] Stander N, Roux W, Giger M, Redhe M, Fedorova N, Haarhoff J. Crashworthiness optimization in LS-OPT: case studies in metamodeling and random search techniques. In: Proc of the 4th European LS-DYNA Users Conference, Ulm, Germany, 2003.

[6] Volz K, Duddeck F. Crash optimization of car bodies in the concept stage of vehicle development. In: KJ Bathe, editor, Computational Fluid and Solid Mechanics. Oxford: Elsevier Science, 2005 (submitted).

[7] Bäck T. Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms. Oxford University Press Inc, USA, 1996.

[8] Lescheticky J, Duddeck F, Willmes L, Girona S. Efficient product development of car bodies using multi-disciplinary optimization (in German). In: Numerical Analysis and Simulation, VDI-Conference, Würzburg, Germany, 2004.