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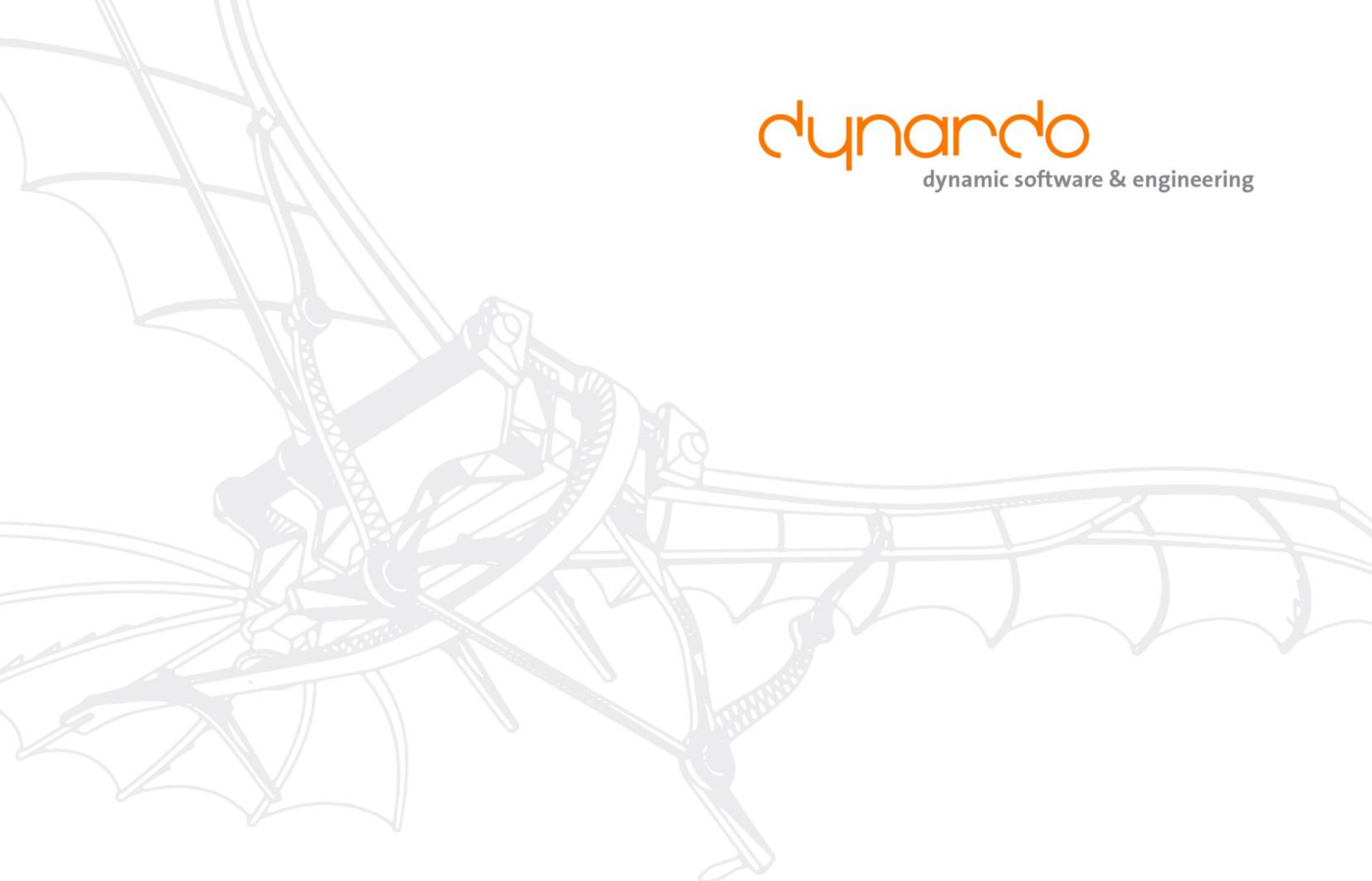

Lectures

Combining Robustness Evaluation with current automotive MDO application

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Combining Robustness Evaluation with current automotive MDO application

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Abstract

Numerical simulation is nowadays established in almost every discipline of the product development process in automotive industry. Much effort has been and will be spent to improve both simulation models and analysis software. The existence of easy to use optimization tools has introduced multidisciplinary design optimization (MDO) to the virtual product and process development. Typically the task MDO is used if load cases like stiffness evaluation, NVH and passive safety are optimized at the same time. First steps have been taken to apply these optimization methods to multidisciplinary problem definitions. However, engineers tend to mistake black-box optimization with a panacea that, applied to a starting design, inevitably delivers a significant improvement.

Numerous real-world applications especially in case of passive safety have shown the necessity to incorporate stochastic analysis for evaluating the robustness of designs as well as the robustness of the numerical model. Here the robustness of the design against scattering material values, loading or test conditions as well as the robustness of the numerical models (the amount of numerical noise) is investigated. Especially in cases of high amount of “numerical noise” the use of simulation results for optimization purposes may lead to very pure optimization performance or useless optimization results. Therefore ensuring a high degree of determination for those result values, which are important for objective functions or constraints, is necessary.

The paper gives a brief summary of robustness evaluation using stochastic analysis and multidisciplinary optimization methods. They will be characterized from a practical point of view and the combination of both will be emphasized. The benefit of robustness evaluation and sensitivity analysis to the optimization of a frontal impact simulation model will be shown exemplarily.

Keywords: stochastic analysis, robustness evaluation, multidisciplinary design optimization (MDO)

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1 Introduction

Virtual product and process development has become an essential part in automotive engineering. High fidelity simulation models and analyses have been developed in order to improve simulation results for a better mapping of reality to numerical simulation. Along with this development there has been a growing demand for CAE-based optimization methodologies. First experiences with optimization algorithms where mostly gained from methodically studies on single components or sub-structures.
The existence of easy to use optimization tools has introduced multidisciplinary design optimization (MDO) to the virtual product and process development [Duddeck, 2005]. This meets the requirements of the short product development cycles, where an integrated optimization across multiple disciplines concurrently becomes unavoidable. The following disciplines could be part of an MDO:

- Passive safety
- Noise, vibration, harshness (NVH)
- Stiffness and vehicle dynamics
- Process simulation
- Cost
- …

The combination of disciplines and the high fidelity simulation models on the one hand and the available time slot for an MDO in the product development process on the other may be conflicting objectives. Therefore MDO requires both high performance computing (HPC) and the collaboration and communication between teams of different disciplines.
While optimization has already become an integral part in numerical simulation, the evaluation of design robustness, the reliable function within admissible boundaries, increasingly comes into focus. Numerous real-world applications have shown the necessity to incorporate robustness evaluations to numerical simulation. For single disciplines like NVH [Will, Möller, Bauer, 2004] or passive safety [Will, Baldauf, 2006], robustness evaluations have been successfully integrated in the product development process and are performed at predefined milestones. Here the robustness of the design against scattering material values, loading or test conditions as well as the robustness of the numerical models (the amount of numerical noise) is investigated. Especially in cases of high amount of "numerical noise" the use of simulation results for optimization purposes may lead to very pure optimization performance or useless optimization results. Therefore ensuring a high degree of determination for those result values, which are important for objective functions or constraints, is necessary.
Consecutively it will be shown how the methodology of robustness evaluation can be incorporated into MDO. First a brief summary of robustness evaluation using stochastic analysis and multidisciplinary optimization methods is given. They will be characterized from a practical point of view and the combination of both will be emphasized. The benefit of robustness evaluation and sensitivity analysis to the optimization of a frontal impact simulation model will be shown exemplarily.

2 Methods for Stochastic Analysis and Optimization

One fundamental difference between optimization and robustness evaluation is that optimization is performed within a user defined design space, but robustness has to be performed in a naturally given space of scattering variables. While optimization parameters are usually characterized by lower and upper bounds, definition of stochastic variables includes distribution and correlation information. So the design space of an optimization problem represents all possible design realizations. Restrictions can be considered by formulating constraints regarding both design parameters or result values and one or multiple objectives can be specified. Differently from this pure deterministic concept, the design space of a stochastic problem represents expected scatter around an initial design. The differences and particular features of the methods shall be outlined in the following subsections.

2.1 Sensitivity Analysis

A sensitivity analysis is recommended as a preliminary of optimization tasks. Sensitivity analysis is used to scan the design space by varying design optimization parameters within upper and lower bounds. Either systematic sampling methods (koshal linear / quadratic, D-optimal, full factorial, central composite, …), so called Design of Experiment (DoE) schemes can be applied to generate designs, or stochastic sampling methods (Plain Monte Carlo, Latin Hypercube Sampling) can be used. Stochastic sampling methods are recommended for most engineering problems with multiple parameters in order to apply statistic post-processing. For keeping the number of design evaluation small, Latin Hypercube Sampling is the stochastic sampling method of choice. The following results are obtained by a global sensitivity analysis:

- Global sensitivities (which optimization parameter influences which response?) by correlation analysis
- Estimation of variation of the responses based on the defined design space
- Identification of important input parameters and possible reduction of the design space dimension for optimization
- Better understanding of the optimization problem, detecting optimization potential and extracting start designs for optimization

How this is done successfully for a frontal impact model is described in the following chapter.

2.2 Multidisciplinary Optimization

Multidisciplinary design optimization is a methodology for improving design of engineering systems including multiple disciplines concurrently. The design space is searched for solutions which have a minimum objective value and fulfill all constraints. Due to the high non-linearity of problem definitions and analysis tools with significant solver noise, not all optimization methods are suitable for solving MDO problems. The optimizer should be able to:

- Handle noisy solver responses

- Process multiple designs parallel for taking advantage of HPC infrastructures
- Handle failed designs

Therefore two categories of algorithms are recommended for MDO: Evolutionary algorithms (Genetic algorithms, Evolution strategies) and Response surface methods.

2.2.1 Evolutionary Algorithms

Evolutionary algorithms (EA) are stochastic search methods which try to mimic processes of biological evolution like adaption, selection and variation. Within an EA a population of artificial individuals, each representing a possible solution, search the design space for gradually finding better solutions and detecting or approximating optima.
The optimization starts with the random initialization of the first population. Alternatively existing knowledge about good solutions can be incorporated by specifying a start population. After initialization the actual iteration loop starts, where every loop represents a generation. Genetic operators like selection, crossover and mutation are applied to generate offspring individuals. A replacement scheme is used to form the next generation. The iteration continues until a stopping criterion is fulfilled. Figure 1 illustrates the general flow of an evolutionary algorithm.

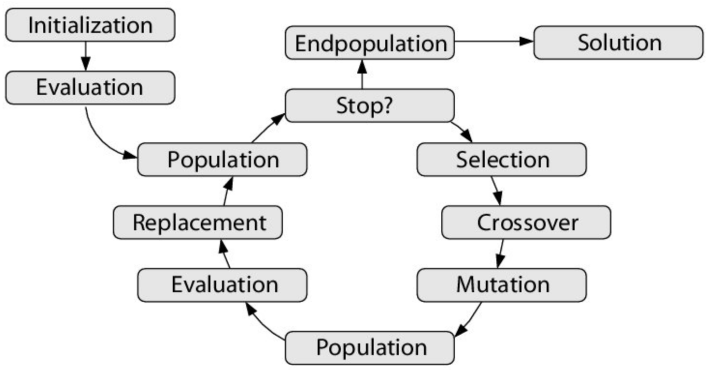


Figure 1: General flowchart of an evolutionary algorithm

Two main variants of an EA have been established: genetic algorithms (GA) and evolution strategies (ES). The main difference between both algorithms is the way variation is introduced to the population. Recombination of genes using crossover operators represents the main variation within genetic algorithms, while for evolution strategies (adaptive) mutation introduces variation to the population.
GA is a suitable method for globally searching the design space if there is only little a priori knowledge about the problem. For improving pre-optimized designs respectively evolution of best practice designs, ES are recommended. Both strategies can handle different types of variables (continuous, discrete and binary) and a large quantity of them (up to many thousands).

2.2.2 Response Surface Methods

The response surface methodology (RSM) is used to approximate responses in a multi-dimensional space. For calculating the response surface, a surrogate model of the real response, both appropriate approximation functions and support points are necessary. Design of experiment schemes are applied to generate optimal support points for the approximation function. Gradient-based optimization methods or EA can be used for finding optima of the surrogate model.

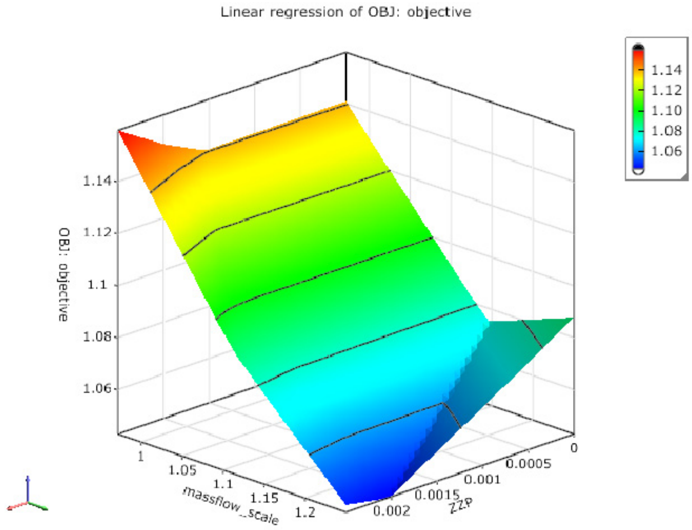


Figure 2: Response surface of an objective function based on the linear approximation of responses

The quality of results depends on the accuracy of the approximation, which is influenced by the number of support points, the kind of approximation function used and the design space itself. The accuracy of the approximation increases if the range of the approximated sub region is decreased. This principle is used for the adaptive response surface method (ARSM) where the approximation of responses is calculated for a sub region of the design space. By adaptively zooming and shifting this sub region, the quality of the approximation is gradually increased.

The application of RSM as well as ARSM is limited by the number of design variables. Otherwise the number of support points exceeds practicable limits for optimization problems with many parameters. Because ARSM shows good optimization performance using simple approximation functions (linear approximation) in combination with D-optimal support point sets, the methodology is attractive up to 15 parameters. If sensitivity analysis can be used to reduce the dimension of the optimization problem, ARSM may be a good choice for the pre-optimization of MDO-problems, followed by an evolutionary improvement of the pre-optimized design.

2.3 Robustness Evaluation

The reliable function of a numerical model within admissible boundaries is investigated by robustness evaluation. Scatter of input parameters is considered by assigning distribution and correlation information to the scattering input variables. A basic knowledge of realistic input scatter is necessary for the definition of stochastic analysis. Usually it can be derived from test series results, manufacturer information or experience values.

Possible design realizations are generated by stochastic sampling methods, where Latin Hypercube Sampling is recommended for keeping the number of design evaluations small. Statistic postprocessing is used to estimate variation and probability of responses as well as the correlation between the scattering inputs and the scattering results.
Therefore the sensitivity of input scatter to the variation of responses is identified by linear and quadratic correlation analysis as a result of robustness evaluation. This causality can be quantified by the coefficient of determination, which specifies how much of the response variation can be explained by correlation to the input variables [Will, Bucher, 2006]. Especially the coefficient of determination is a valid measurement for quantifying the rate of numerical noise. If the coefficient of determination based on linear and quadratic correlation hypothesis is still far away from 100% after removing "outliers" and clusters, the amount of numerical noise may be significant. Gained from our experience of the last four years of introducing robustness evaluations to different disciplines, it can be stated that in cases of coefficients of determination less than 80% numerical noise was significant, for coefficients of determination less than 60% numerical noise had a very strong influence to the response values.
Further statistical methods can be applied to the results like principal component analysis (PCA), which identifies the most important mechanisms involving multiple inputs and responses, or the automatic fitting of distribution functions to deterministic histograms for estimating probabilities of exceeding possible limit values.

3 Robustness Evaluation and Optimization of Frontal Impact Simulation Model

The following example is a simplified frontal impact car model consisting of 6181 nodes and 5458 shell, beam and solid elements. The frontal impact of a small car body with a rigid pole is simulated for a 120 ms time interval. The initial vehicle velocity is 100 km/hr. The numerical simulation is done using the explicit analysis tool LS-DYNA. See Figure 3 and 4 for a visualization of the model.

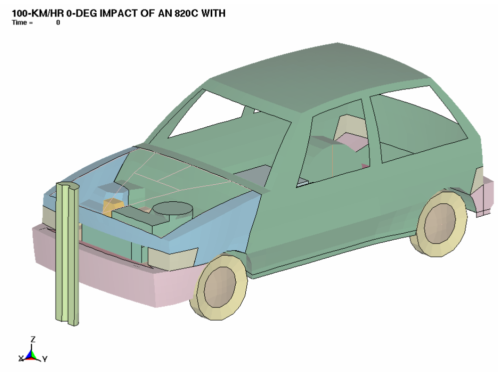


Figure 3: Frontal impact FE-Model with pole

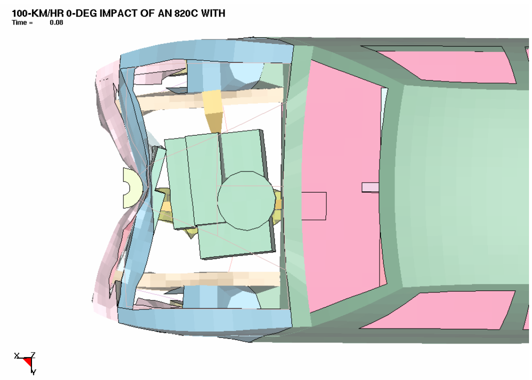


Figure 4: Deformed frontal impact model (view from top)

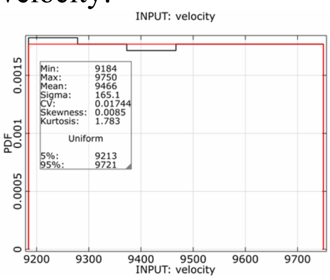
Optimization of the car body regarding mass of the car body will be performed. Possible optimization parameters are the thicknesses of plate and material proper-

ties like yield stress of different parts. Various optimization strategies will be applied to the problem and the results will be compared.
Having the simulation model and the set of parameters, one could think of taking an optimization tool and starting the optimizer. It will be shown in the following subsections that it is essential to verify simulation results by means of robustness evaluation and helpful to prepare the optimization problem in advance in order to obtain useful results from the optimization.

3.1 Verification of simulation results by means of Robustness Evaluation

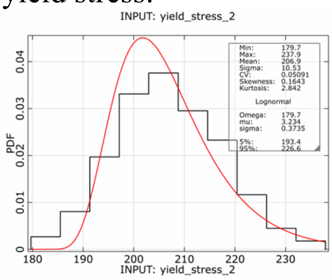
Before starting any optimization, the quality of simulation results of the reference model regarding the quantity of “numerical noise” has to be verified. The system response is analyzed regarding a realistic amount of input scatter, which represents real-world uncertainties of material and test conditions and is incorporated into the model by defining stochastic variables with distribution information. The table below contains examples of assumptions for input scatter and associated distribution functions for different model parameters.

velocity:



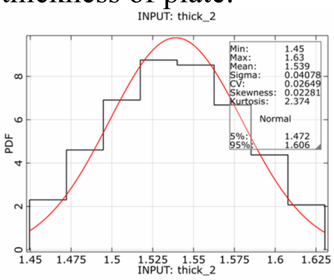
- uniform distribution
- ± 3%

yield stress:



- lognormal distribution
- CoV 5%

thickness of plate:



- truncated normal
- ± 6% / 2σ bounds

For the simplecar example 25 parameters were defined: impact velocity, yield stress of 12 different parts and the corresponding thickness of plate. Output values are energies, forces, displacements and accelerations (36 in total). Latin Hypercube Sampling is used for generating 200 design realizations. The stochastic analysis is performed using optiSLang, whose statistic postprocessing provides the following results:

- Linear and quadratic correlations
- Principal components of the linear correlation structure
- Variation and distribution of responses
- Coefficients of determination

The first evaluation of robustness revealed a high variation of many responses. Not all of them could be explained sufficiently by correlation to the input variables. This could be identified by low coefficients of determination. Numerical problems concerning hourglass energy were determined by visualizing the array of curves of all designs evaluated and all considered responses. Designs with hourglass problems could be identified and were excluded from further evaluation (see Fig. 5 and 6).

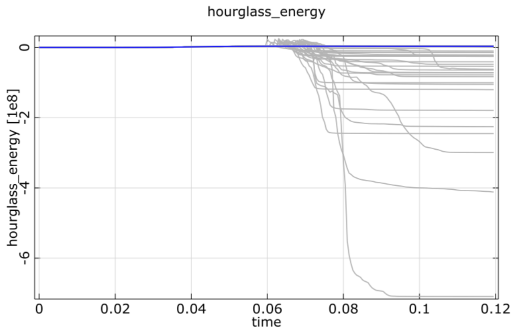


Figure 5: Hourglass energy time series of all designs evaluated and reference run (blue)

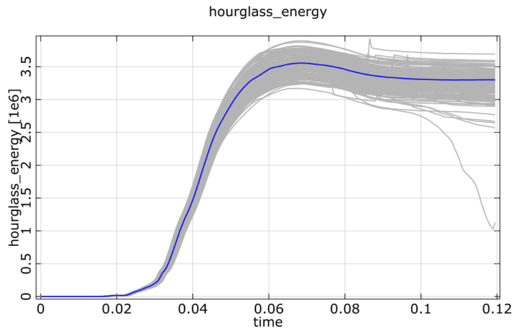


Figure 6: Hourglass energy time series of the reduced set of designs and reference run (blue)

By removing designs with hourglass problems the coefficients of determination of responses could be improved and a set of responses could be designated for the formulation of optimization constraints. A coefficient of determination of 80% can be recommended as threshold value for using responses in objectives and constraints of the following optimization procedure. Especially the variation of relative displacements of the engine could be determined to a high degree. Fig. 7-10 illustrate the improvement of determination for a single response.

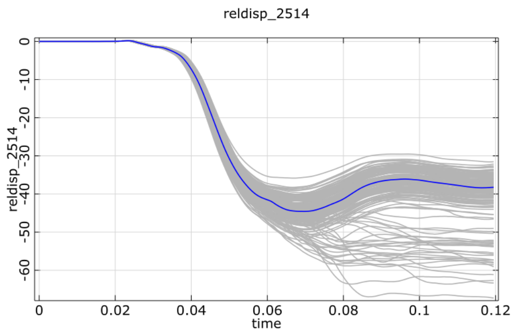


Figure 7: Relative displacement of the engine time series of all designs evaluated and reference run (blue)

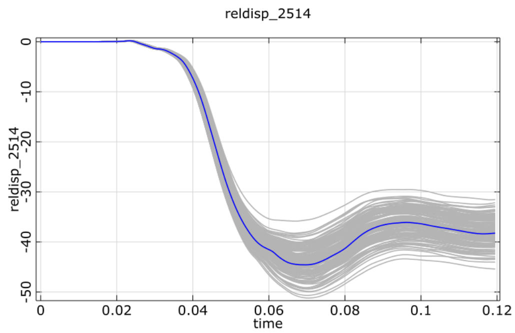


Figure 8: Relative displacement of the engine time series of the reduced set of designs and reference run (blue)

The reason of numerical instabilities could be identified and the quality of simulation results could be improved as a result of robustness evaluation. The visualization of time series was helpful to determine instabilities of the model, which is always recommended, if responses are extracted as peak values of time series. To avoid the identified hourglass problems for the following optimization, a criterion was formulated for automatically removing designs with hourglass problems. Alternatively the meshing of critical parts could have been improved, but we wanted to use the public model without modifications.

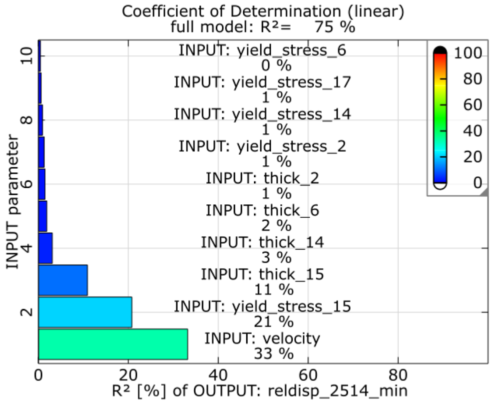


Figure 9: Coefficient of determination of the relative displacement of the engine considering all designs evaluated

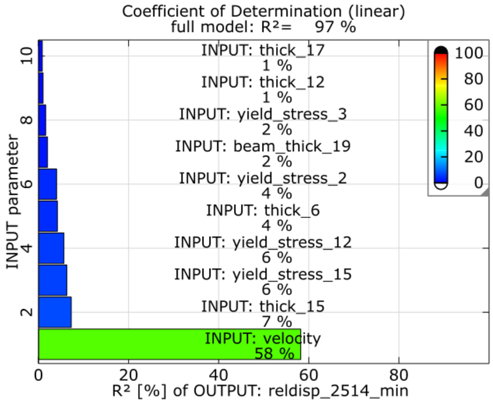


Figure 10: Coefficient of determination of the relative displacement of the engine based on the reduced set of designs

3.2 Preparation of the optimization problem

After robustness evaluation was used to verify prognosis quality of simulation results, sensitivity analysis will be applied for the preparation and formulation of the optimization problem. Possible optimization parameters are varied within upper and lower bounds of the design space. Note that this design space significantly differs from the space of stochastic parameters used for robustness evaluation. Instead of admissible or expected scatter, the parameter range for sensitivity analysis is chosen according to manufacturing restrictions or physical limits.

For this example 24 optimization parameters were defined: yield stress of 12 parts of the car body (140 … 200 N/mm²) and corresponding thicknesses of plate d (0.5d … 2d). It is obvious that the impact velocity is not considered, because it is not adjustable for this problem definition. The analyzed responses are maximum hourglass energy, relative displacements of the engine and the mass of the car body. Additionally a cost function based on the material property and mass of parts is evaluated. Global sensitivities of the responses due to the variation of optimization parameters are analyzed.

The 200 design realizations for the sensitivity analysis were generated again by Latin Hypercube Sampling. The most important input parameters, which influence the variation of responses, could be identified. Fig. 11 and 12 illustrate the results for the mass of the car body, showing both the histogram of the response and the linear coefficients of correlation regarding input parameters.

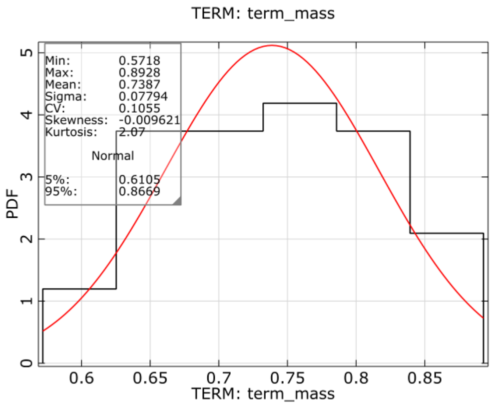


Figure 11: Histogram of the output term: mass of the car body

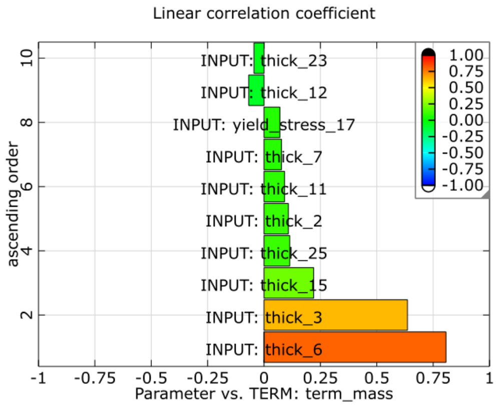


Figure 12: Linear coefficients of correlation of the mass of the car body regarding input parameters

The dimension of the optimization problem could be reduced to 10 important variables. This reduces the number of required support points for one ARSM iteration from 38 (for 24 parameters, D-optimal, linear approximation) to 17 (for 10 parameters, D-optimal, linear approximation).
As a further result of the sensitivity analysis the potential for the optimization was analyzed. Constraints for the relative displacements of the engine were formulated based on the analysis of variation and visualization of response time series. For other examples it can also become necessary to shift or modify parameter ranges in order to meet the desired response range.

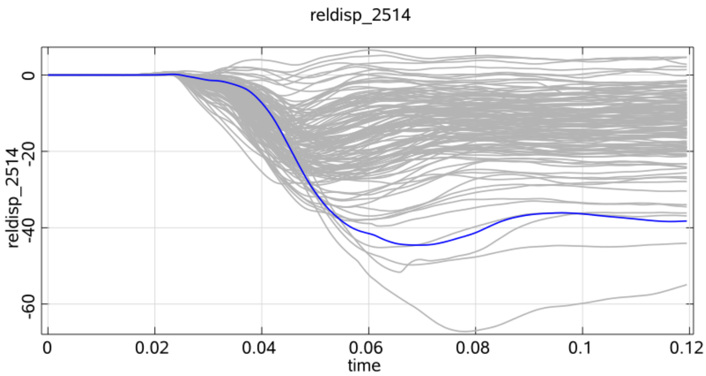


Figure 13: Time series of the relative displacement of the engine with reference run (blue) from sensitivity analysis

3.3 Comparison of different optimization strategies

After a comprehensive preparation of the optimization problem, different optimization methods were applied to the example. For the evolutionary algorithm with global search characteristic a problem definition consisting of all 24 optimization parameters was used: yield stress of 12 parts of the car body (140 … 200 N/mm²) and corresponding thicknesses of plate d (0.5d … 2d). The reduced set of the most important parameters, as obtained by sensitivity analysis, was used for the ARSM optimization. The considered objective is the mass of the car body. Additionally 5 inequality constraints for the relative displacements of the engine were formulated. For all optimization runs the number of design evaluations was limited to a

feasible quantity. The settings used for the different optimization algorithms are listed in Tab. 1 and Tab. 2. The results of the different optimization methods regarding the mass of the car body are compared in Tab. 3.
Both optimization methods applied provided a significant improvement of the reference model. They were able to handle failed designs resulting from numerical instabilities and to smooth numerical noise. The best result was obtained by the ARSM optimization, but note that for this method a modified problem definition was used, considering only 10 parameters. For the full parameter set 586 design evaluations would have been necessary. Furthermore it should be mentioned that all results were obtained using optiSLang default settings or presets for the algorithmic parameters.

EA parameter	**Value**
Population size	10
Number of offspring individuals	10
Number of generations	20
Parent selection method	stochastic universal sampling
Crossover method	uniform crossover
Crossover probability	0.5
Mutation rate	0.2
Mutation standard deviation	0.1 (start), 0.01 (end)
Adaptive mutation	no

Table 1: Evolutionary algorithm settings for global search strategy

ARSM parameter	**Value**
Approximation method	linear
Sampling method	D-optimal
Start range in % of global range	50
Optimization method on RS	GA & NLPQL
Number of iterations	15

Table 2: Algorithm settings of the ARSM optimization

Optimization method	Number of design evaluations	Total mass of the car body [kg]	Relative mass reduction
Reference run	-	656.78	
Evolutionary Algorithm (global search)	200	558.58	15 %
Adaptive Response Surface Method (ARSM)	271	**535.38**	**18.5 %**
Stochastic Design Search using LHS (Sensitivity analysis)	200	575.88	12 %

Table 3: Comparison of results of different optimization methods

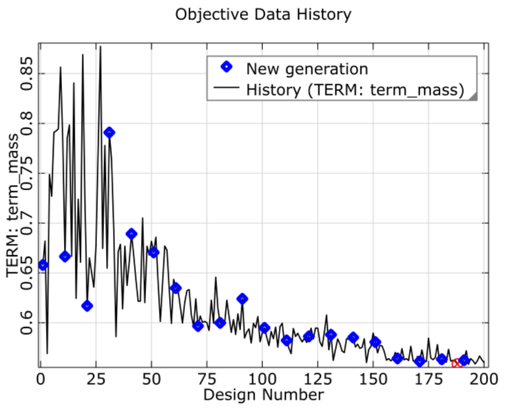


Figure 14: History of the total mass of the car body as result of the EA optimization

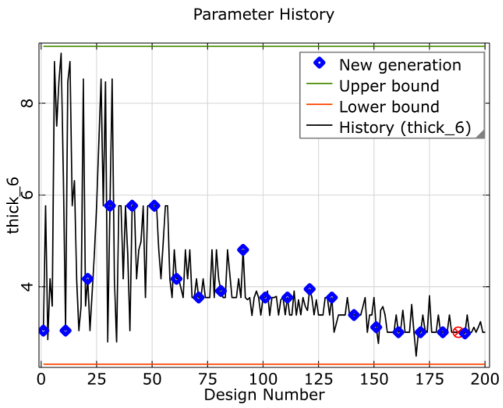


Figure 15: Corresponding history of the optimization parameter thickness_6

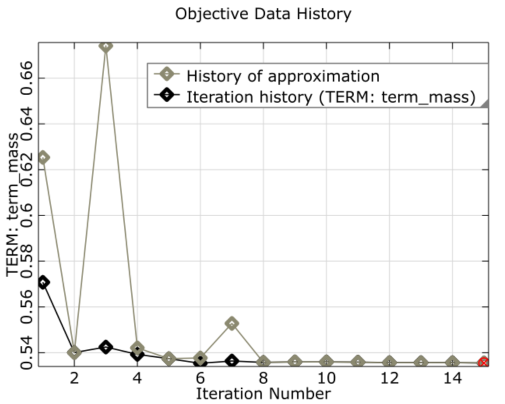


Figure 16: History of the total mass of the car body as result of the ARSM optimization

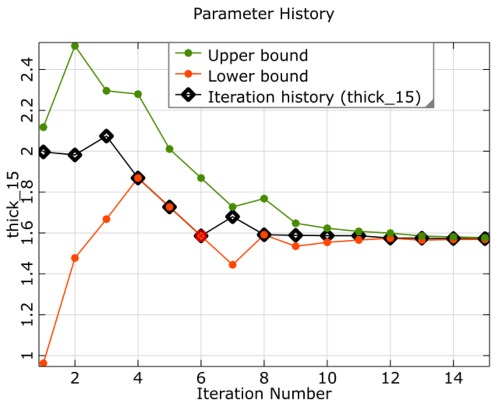


Figure 17: Corresponding history of the optimization parameter thickness_15

4 Conclusions

The benefit of robustness evaluation and sensitivity analysis to the optimization of a frontal impact simulation model could be shown exemplarily. First robustness evaluation was used to verify prognosis quality of simulation results and to identify model instabilities. The coefficients of determination, a measure of how much variation can be explained, could be increased significantly for all responses used in the following optimization. It was recommended, only to consider highly determined responses (coefficient of determination > 80 %) within an optimization.
Sensitivity analysis was used to prepare the optimization problem by globally searching the design space of optimization parameters for global sensitivities to the responses. An identification of the most important optimization parameters and a reduction of the dimension of the problem were the results of this analysis.
Finally different optimization methods were compared regarding efficiency and performance. Both tested algorithms were suitable for solving the optimization problem. The choice of the method rather depends on the number of optimization parameters. The results show that for optimizing a well prepared problem formulation no specialist knowledge about the algorithm is needed, as all results were obtained with default algorithmic settings.
In a second phase of the project we will benchmark further optimization algorithms without introducing pre-optimized designs or best practice designs. In a third phase we will test the optimization algorithms introducing pre-optimized or best practice designs, in our case extracted from the sensitivity study or from ARSM optimization. The complete benchmark will be published soon at www.dynardo.de.

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