APPLICATION EXAMPLES OF OPTIMIZATION AND RELIABILITY STUDIES IN AUTOMOTIVE INDUSTRY

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THEME

Optimization and Robustness

KEYWORDS

Robustness, Stochastic Analysis, Monte Carlo Simulation, Meta Models, Design of Experiments, Reliability based Optimization, Successive Response Surface Scheme

SUMMARY

The aim of this paper is to summarize several optimization and robustness applications, which have been performed over the past years in automotive industry with LS-OPT. The examples include Multi-Objective Optimization (MOO), Multi-Load Case Optimization and Reliability Based Design Optimization (RBDO). In addition, user-friendly visualization of optimization and stochastic results is demonstrated.

The approach for all the optimization and robustness studies is based on the usage of Meta-Models. This is inevitable for very long and costly solver runs, which is usually the case for crashworthiness and for metal forming applications as well. The challenging task is to establish methodologies, which require as few as possible solver calls.

1: Introduction

In this paper three industrial applications dealing with multi-load case, multi-objective and reliability based optimization are presented. The examples are performed in cooperation with Daimler AG, AUDI AG and Alcan Ltd. The used software for optimization is exclusively LS-OPT. In addition, for these projects the program D-SPEX is used, which interfaces with LS-OPT as an advanced optimization and stochastic post-processor. D-SPEX has been developed by DYNAmore in cooperation with AUDI.

An outstanding capability of LS-OPT is the available meta-models for optimization as well as for Monte Carlo and reliability analysis. For very expensive simulations meta-models are applied to preserve the practical applicability of the optimization. The number of required FE-simulations is reduced significantly. Meta-models are established on the basis of interpolation points. Apart from polynomials, non-linear approximation schemes, such as Neural Networks can be applied (Stander et al. [5], Liebscher et al. [7]), in order to evaluate meta-models that might be suitable to replace the expensive FE-simulation within an optimization or stochastic analysis.

2: Example - Optimization of an Adaptive Restraint System for Several Front Crash Load Cases

For this example we would like to express acknowledgement to Marcel van den Hove and Dr. Bernd Mlekusch (AUDI AG, Germany).

Load Cases

The ideal restraint system decelerates the occupant as fast as possible on a constant acceleration level. Different masses of the occupants and thus different load cases mean for an ideal deceleration behaviour, that the restraint system must be adapted to the required force levels (F = ma). With the today's state of technology it is possible to identify the load case and the different types of occupants. This means, system parameters of the restraint system, such as trigger time for seat-belt, airbag and steering column might be adapted to specific load cases.

For the optimization problem presented in this Section, 4 different front-crash load cases (FMVSS208) are taken into account:

- H305a: Hybrid III 5th female dummy; 56km/h - belted
- H305p: Hybrid III 5th female dummy; 40km/h - not belted
- H350a: Hybrid III 50th male dummy; 56km/h - belted
- H350p: Hybrid III 50th male dummy; 40km/h - not belted

FE-models for Hybrid-III 5th female and Hybrid III 50th dummy male from FTSS are used. In Figure 1 the FE-Model with a belted Hybrid III 50th male dummy is shown. It represents the load case H350a.

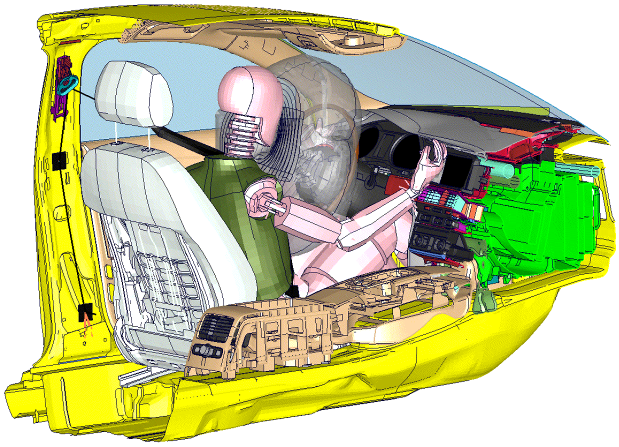

Figure 1: FE-Element crash model with a belted Hybrid III 50th male dummy

Multi-Load Case Optimization Problem

Goal of the optimization is to adapt the adjustments of the restraint system in order to optimize the occupant safety performance for all four load cases H305a, H305p, H350a and H350p simultaneously.

Design Variables

Some system parameters as for example time to fire (TTF) of the airbag might be set individually for each load case. Due to different identification technologies the restraint system can recognize a specific load case and assign an associated TTF-value. Other system parameters such as vent hole diameter of the airbag can of course not be adapted individually to the different load cases. Thus, these parameters have to be set globally. After each iteration of the SRSM, in LS-OPT the variables are updated to ensure a unique intermediate design for the multiple disciplines (load cases).

Objective

The objective of the optimization is to minimize the thorax acceleration in terms of the a3ms-criteria described in [12]. This is applied to all four solver cases with respect to a multi-objective function with equal weights.

Constraints

Four different, typical dummy responses for each load case are evaluated:

- HIC15 - Head Injury Criteria for 15ms, evaluation see [12]
- Femur Forces (left/right)
- Thorax Acceleration
- Thorax Intrusion

These responses are considered as constraints in order to not exceed 80% of the maximal value required by regulations. The starting design does violate some of these constraints significantly.

Results

As optimization method the successive response surface scheme (SRSM) is applied. Detailed description of the methodology is available in Stander et al. [5]. Since the simulation time of a single occupant safety run is rather time consuming, fast convergence of the algorithm is important. In order to achieve for design exploration a meta-model with a reasonable global approximation, simulation points in sparse regions are added and a neural network is fitted to all points.

The approach can be summarized as follows:

- Constrained optimization using SRSM
- Augment points within global design space using Space Filling DOE
- Create Meta-Models (Neural Network) for design exploration

Optimization using SRSM with Linear Polynomials

For the baseline design the constraints are heavily violated. The main goal of the optimization is to find a feasible design, which satisfies the constraints of all four load cases. SRSM is applied with linear polynomials by zooming into local regions of interest until it converges to an optimum, see Figure 2.

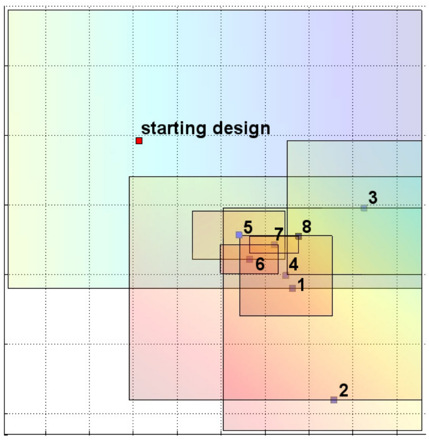

Figure 2: Deployment of the optimum in the SRSM-optimization process with respect to the two variables FAB-VENT and SBA-VENT

In Figure 3 (left) the optimization history of the constraint violation is shown. The values of the max constraint violations for the eight iterations do not always refer to the same constraint criteria. Small changes of the parameter values can lead to a significant change in the responses and thus swap the maximum violated constraint. This is for example the case when the airbag is too soft and the head of the dummy strike through onto the steering wheel. In this case, the HIC15 response is almost like a discontinuous function. This effect can be seen in iteration 4 and 6 in the optimization history plot of the maximum constraint violation (Figure 3, left), where the HIC15 value cause a very large maximum constraint violation. Such effects are a challenging task for an optimization algorithm. In the 8th iteration the constraint violation drops down to zero and minimization of the multi-objective function is performed subsequently.

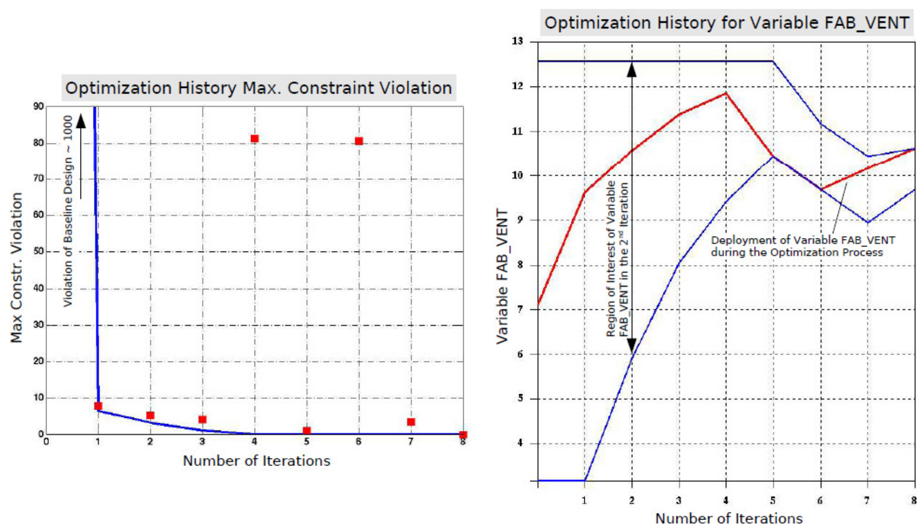

Figure 3: Left: Optimization history of maximum constraint violation. In Iteration 0 (baseline design) the violation is approx. 1000, after 8 iterations the maximum constraint violation is equal to zero. This means, all the constraints listed in 3.2.3 are for each load case fulfilled. Right:As an example the deployment of the variable FAB-VENT is shown during the successive response surface scheme.

For the displayed optimization results in Figure 3 adaptive variables for the steering wheel are not considered. This means, in total there are only 9 design variables for the four load cases, 5 variables for the active load cases H305a and H350a, 2 variables for the passive load cases H305p and H350p and 2 global variables for all load cases. In total 272 crash simulations for all four load cases are performed within the 8 iterations. Within previous studies for the same problem an evolutionary algorithm has been tested. For this, approx. 30-40% more simulations had been necessary to achieve a similar result.

Summary and Conclusions for the Restraint System Optimization Example

The successive response surface scheme has been applied successfully to the optimization of an adaptive restraint system considering several front crash load cases at AUDI. Starting from a highly infeasible design, after eight iterations a feasible solution was established by the meaning of satisfying all constraints for all load cases. With the optimization a combination of parameters for the adaptive restraint system has been found, which results for the FE-simulations in response values significantly lower than the pre-defined requirements. In total nine design variables have been considered. However, not all variables are used in each load case, some of them are fully shared and some are partially shared. For this type of optimization problem the SRSM is a suitable and effective methodology. Among system optimization it might be useful to have a mathematical approximation model (meta-model) in order to explore relationships between variables and responses. This has been performed for the considered restraint system problem using a feed-forward neural network approximation.

3: Example – Reliability Based Design Optimization for a Metal Forming Application

For this example we would like to express acknowledgement for cooperation to Prof. Dr. Karl Roll (Daimler AG, Germany)

Considered Uncertainties in Metal Forming Process

The influence of the random variation of material and manufacturing parameters on the forming process of an automotive deck lid outer panel is investigated in this study. The geometry of the forming die is shown in Figure 4. The material used for this part is the steel grade DCO6 (1.0873), a typical mild steel used for complex outer panels.

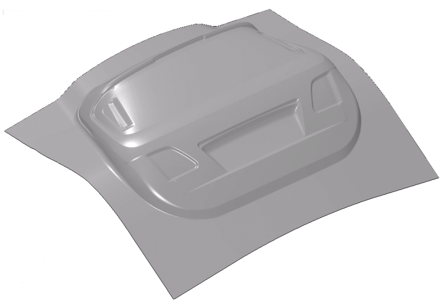

Figure 4: Die geometry of the deck lid forming tool (Courtesy of Daimler AG)

Considered uncertainties regarding material properties are yield stress, hardening properties and anisotropy coefficients. As uncertainties of the manufacturing process friction, draw bead and binder forces and blank thickness due to cold rolling process are taken into account.

Simulation Results of Random Variation of Uncertainties

For this, in total only 21 simulations are performed. The wall clock simulation time on 2 CPUs is about 10h per run. It turned out, that although the baseline run is a feasible design (Figure 5), the perturbations due to the considered uncertainties leads in 15 runs to an infeasible design. The main criteria for the feasibility of the design are the minimum shell thickness after the forming process and the performance with respect to the FLC-diagram. In 15 runs localization occurs and the minimum sheet thickness becomes very low, see Figure 6. Consequently the FLC requirement is also violated (Figure7).

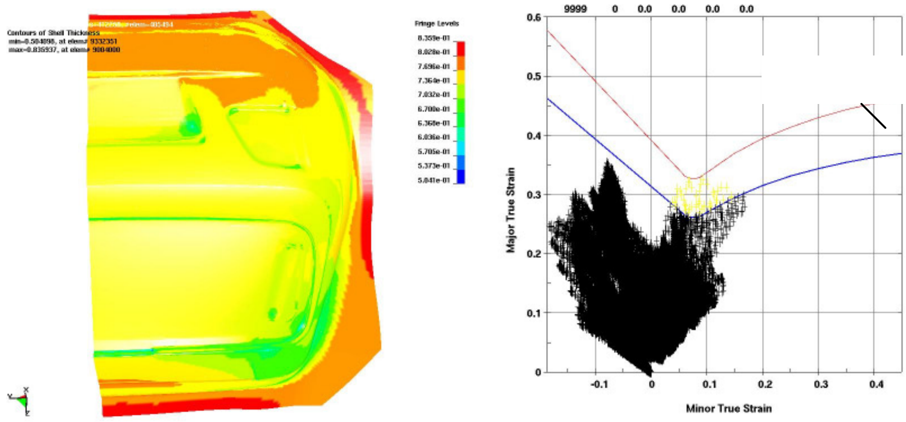

Figure 5: Left - Final shell thickness distribution of the baseline run (min. shell thickness ~0.51mm) Right – FLC-Diagram for the baseline run, no points above the FLC-Curve.

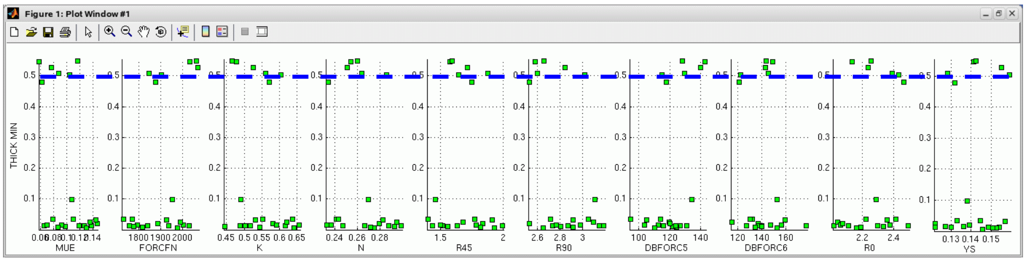

Figure 6: Minimum sheet thickness of the blank (THICK_MIN) vs. considered parameter variations. Initial target value of sheet thickness is 0.8mm, acceptable: > 0.5mm

A similar behaviour is observed for the distance of the strain-ratios to the FLC-Curve. A positive value indicates the maximal perpendicular distance of a point above the FLC-Curve (infeasible), a negative value indicates the minimum distance below the FLC-Curve (feasible), see Figure 7.

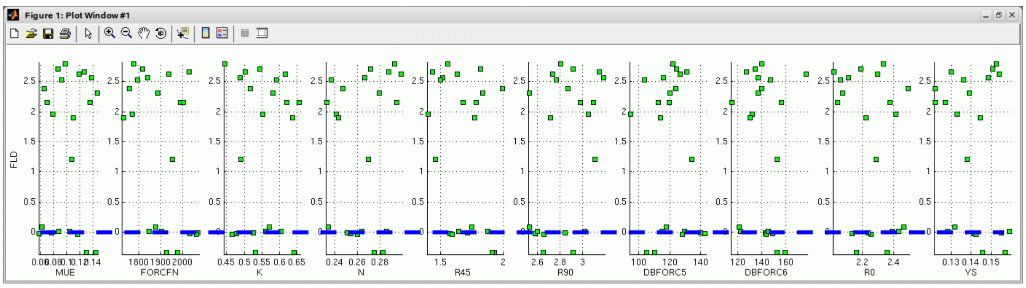

Figure 7: Points indicate the distance to the FLC-Curve, positive: infeasible, negative: feasible

Conclusions after Random Latin Hypercube Simulations

Considering the chosen baseline design, the FE-simulation is very sensitive regarding the assumed variations of the uncertain process parameters. The failure probability is very high and the baseline configuration must be declared as non-robust. Consequently, the next step has to be the improvement and optimization of the robustness of the model. Therefore, reliability based design optimization is investigated. Approach and results are discussed in the next section.

Reliability Based Design Optimization (RBDO)

The methodology of the applied RBDO study is FOSM (First Order Second Moment) in combination with the successive response surface scheme. FOSM is based on the assumption of normal distributed probability density function. The representation of the distribution function is just by the mean and the standard deviation. For the meta-model, which is adapted sequentially through the successive scheme iterations, a neural network approach is used. Details regarding the RBDO approach and the successive response surface scheme with neural networks are discussed in the LS-OPT Users Manual [5].

Definition of the Optimization Problem

Here, the objective of the RBDO is to minimize the failure probability under consideration of the introduced uncertainties. Failure is defined by exceeding a threshold for the minimum shell thickness and for the violation of the FLC-Line. For the RBDO in total 17 variables are considered. Thereof, 10 variables are pure “noise variables” which take into account the uncertainties. To drive the optimization process 7 “control variables” are introduced (see Table 1), simultaneously these variables operate as noise variables with specific probability distributions.

Variable	Description	Distribution ”noise variable”			Range “control variable”	
		Type	mean	std	min	max
DBF1	Draw Bead Force #1	normal	70	5 kN	20 kN	200 kN
DBF2	Draw Bead Force #2	normal	20	5 kN	20 kN	200 kN
DBF3	Draw Bead Force #3	normal	80	5 kN	50 kN	120 kN
DBF4	Draw Bead Force #4	normal	90	5 kN	60 kN	120 kN
DBF5	Draw Bead Force #5	normal	100	5 kN	70 kN	130 kN
DBF6	Draw Bead Force #6	normal	140	5 kN	20 kN	200 kN
FORCFN	Binder Force	normal	1910	50 kN	1400 kN	2400 kN

Table 1: Seven variables are defined as control and noise variables. Control variables drive the optimization process, noise variables are to consider uncertainties.

Meta-Model Based RBDO

For the successive surface scheme 26 runs are performed per iteration. The density of the sampling points increases towards the optimum. The neural network is updated with additional training points after each iteration (see Figure 8).

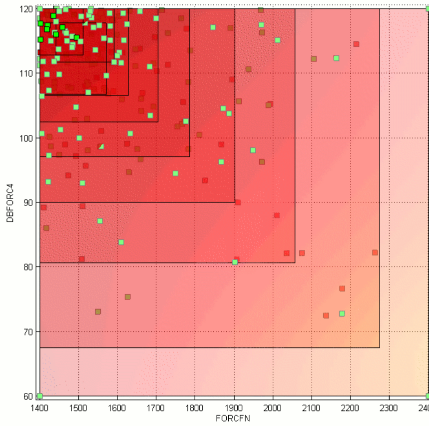

Figure 8: Successive Response SurfaceScheme with Neural Nets after 10 iterations

Optimization History for the Responses THICK_MIN and FLD

Figure 9 shows the optimization history of exceeding the lower bound for the minimum sheet thickness THICK_MIN. The probability of failure drops down from about 55% for the base line design to 3.3515e-4 after 10 iterations. The "computed" value at the optimum is fairly close to the "predicted" value. "Computed" means the simulation value for the optimum parameter combination and "predicted" means the approximated value of the meta-model for this parameter combination.

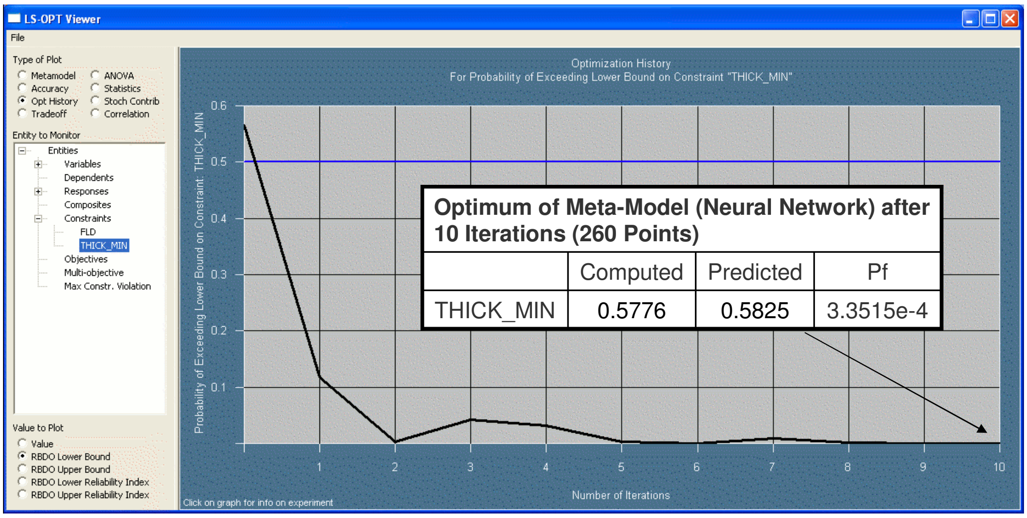

Figure 9: Optimization history of the probability of exceeding the bound for THICK_MIN

Figure 10 shows the optimization history of exceeding the upper bound for the FLD criterion. Finally the probability of failure could be reduced to 0.01191. This means, approximately 1 of 100 designs will exceed the FLC-line.

Verification of Optimum with Direct Monte Carlo Simulations

The failure probabilities displayed in Figure 9 and Figure 10 are estimated by the use of a Meta-Model. This means, the Monte Carlo evaluations are performed by the functional analysis of the meta-model.

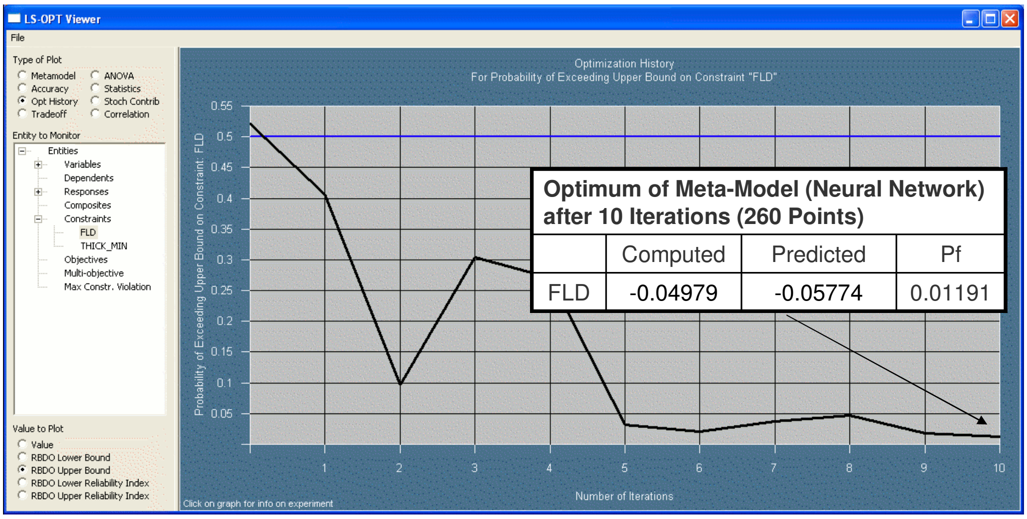

Figure 10: Optimization history of the probability of exceeding the bound for the FLD-criterion

The number of Monte Carlo evaluations on the meta-model is in LS-OPT by default 100000, but of course there is an unknown approximation error of the meta-model. In order to verify the failure probability determined on the meta-model, 160 additional direct Monte Carlo simulations are applied. The mean values for the parameters are taken from the optimal design and the variance is applied according to the considered uncertainties. Table 2 shows that the failure probabilities estimated by the use of meta-models are in the same order of magnitude as for the direct Monte Carlo simulation. Within the 160 Monte Carlo simulations no constraint violation could be observed, see Figure 11. The estimated failure probability in Table 2 is evaluated by the assumption of normal distributed responses THICK_MIN and FLD.

Failure Probability Meta-Model vs. direct Monte Carlo (normal distribution assumed)		
	Pf – Meta Model	Pf - Direct MC
THICK_MIN	3.35e-4	0.59e-4
FLD	0.0119	0.0103

Table 2: Comparison of the failure probability Pf determined by the usage of Meta-Models and by the conventional Monte Carlo approach.

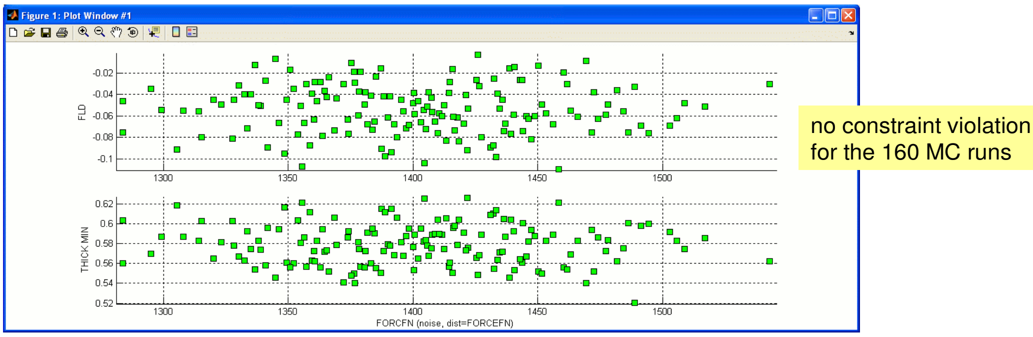

Figure 11: Green colour of the points indicate feasible designs

Summary and Conclusions of the Metal Forming Study

For the metal forming study considering the chosen baseline design, the FE-simulation is very sensitive regarding the assumed variations of the uncertain process parameters. Frequently violation of the FLC requirements and under-run of the minimum sheet thickness appear. This represents a high probability of failure P_f. Thus, the design is referred as non reliable. Furthermore, it is considered as non robust due to assumed random variation of the input parameters (material properties, manufacturing process parameters) and their strong effects on the results. In order to establish a feasible design the problem is reformulated in view of the reliability-based design concept. The objective of the RBDO is to minimize the probability of failure P_f and thus to maximize the reliability of the design. The limit state function $g(\mathbf{x})$ is formulated with respect to the failure criteria minimum shell thickness and distance of the strain-ratios to the FLC-Curve. The reliability-based design optimization is investigated using LS-OPT. Due to the fact that the computational cost of the metal forming simulation is quite high, a meta-model based approach is applied. Utilizing RBDO leads to a design, which has a significantly improved failure probability. The verification of the optimum design by conventional Monte Carlo simulations justify the use of meta-models for reliability investigations for metal forming applications, at least for P_f values not less than 0.01.

4: Example – Multi-Objective Optimization of a Crash Management System

For this example we would like to express acknowledgement to Martin Feuerstein (Alcan Ltd., Germany).

This study describes the design of a bumper in a given constructed space. Two load cases are considered and the objectives are to remove the impact energy by plastic deformation of the bumper and to reduce the mass of the bumper. The given constraints are a maximal force level of the barrier contact force for the AZT crash repair test and that the bumper has an extruded section. The idea is to use the ANSA Morphing Tool to modify the geometry from a starting design, and to modify some sheet thicknesses using LS-OPT.

Load Cases

Two load cases are considered, the AZT crash repair test and the RCAR test.

AZT Crash Repair Test

The AZT barrier has a mass of 1000kg, it impacts the vehicle with a velocity of 16 km/h and an impact angle of 10°, see Figure 12.

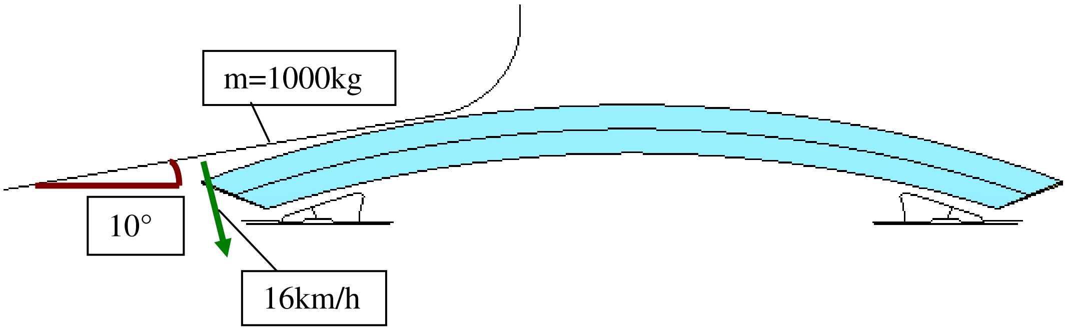

Figure 12: AZT repair crash test

RCAR Test

For the RCAR test, the vehicle impacts the barrier with a velocity of 10km/h, see Figure 13.

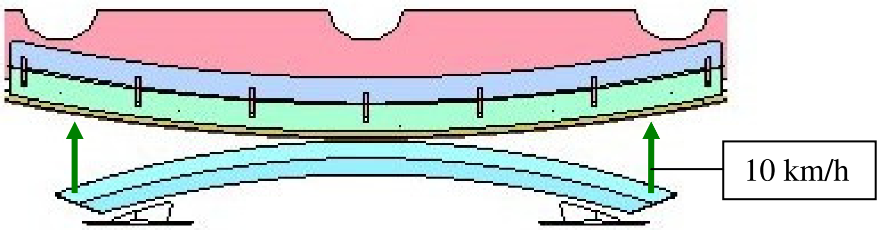

Figure 13: RCAR test

Optimization Problem

Shape Optimization using ANSA's Morphing Tool

As a starting geometry, a shape with constant cross section in the given constructed space is selected to obtain an extruded profile. This geometry is modified during the optimization using ANSA's Morphing Tool. Four morphing parameters are defined to modify the shape of the bumper. The morphing boxes and parameters are defined such that the constant cross section of the bumper is preserved. As an additional geometrical restriction is given that the back part of the bumper keeps its height. Some resulting shapes are presented in Figure 14. For the definition of the morphing boxes and the optimization task in ANSA, we refer to [14].

Design Variables

The bumper is subdivided into five parts. In addition, to the morphing parameters, the sheet thicknesses of these five parts are defined as design variables. Hence we get 9 design variables in total.

Objectives

(1) To optimize the energy absorption by plastic deformation of the bumper for the AZT crash repair test, the contact force between the barrier and the vehicle should be as near as possible to the maximal force level. Hence the sum of squares error between the calculated force curve and a target curve with a constant value, which is the given maximal force level, is considered, see Figure 15.

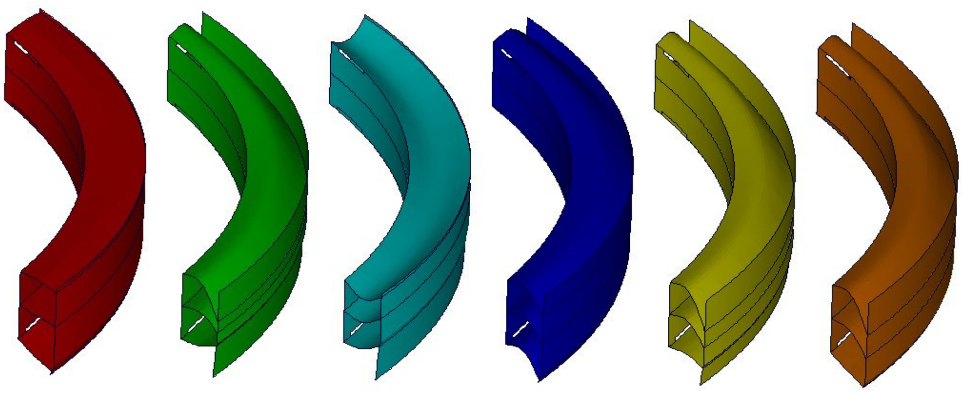

Figure 14: Shapes resulting from ANSA morphing

(2) For the load case RCAR, the maximal intrusion of the bumper is important. The intrusion is defined as the difference of the displacement of the center of mass of the vehicle and a node at the inner edge of the bumper.

(3) The last objective considered is to minimize the total mass of the bumper.

For an optimization that leads to one single result, a weighted sum of all objectives is optimized. If the objectives are conflicting, the result strongly depends on the selected weights. LS-OPT offers in addition the possibility to compute multiple Pareto optimal solutions on a selected meta model.

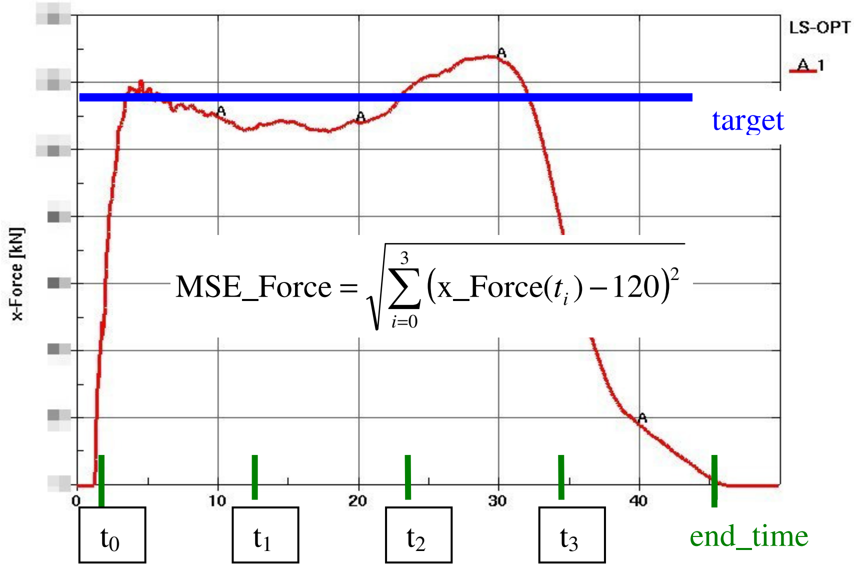

Figure 15: Objective MSE_Force to maximize energy absorbtion

Optimization Results

Figure 16 displays the results of the optimization of a weighted sum of the three objectives. The weights are selected so, that the objective values are normalized with respect to the starting design results. Thus all objectives are treated equally. The optimized force curve and the intrusion improved compared to the starting design, but the mass of the optimal run is too high. That is a typical effect with conflicting objectives. Hence we look at the set of Pareto optimal solutions calculated on the meta-model to select a solution that suits better to the application.

Pareto Optimal Solutions

If the user adopts the successive response surface methodology, LS-OPT offers the possibility to compute a set of Pareto optimal solutions at the same time. The meta-models are used to evaluate designs to determine the Pareto optimal solutions. Using meta-models reduces the computational cost of identifying the Pareto optimal set, but the accuracy of the resulting solution depends on the quality of the meta-models. In this example radial basis function networks are used to approximate the responses. In order to aid the engineer in understanding different trade-offs, the optimization post-processing tool D-SPEX provides dedicated features to visualize Pareto optimal solutions, an example is given in Figure 17.

As an additional dimension, a variable, response or composite can be selected to colour the points. To visualize the relation between objectives and variables, responses or composites, it is also possible to plot objectives against variables, responses or composites in any combination, see Witowski et al. [11].

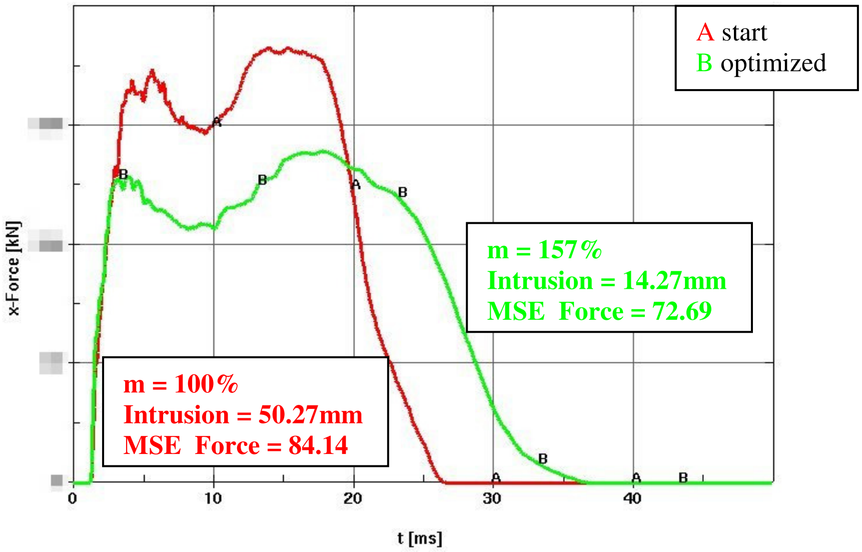

Figure 16: Force curve starting design vs. force curve optimized design

Summary and Conclusions of the Multi-Objective Example

The example shows a multi-objective optimization of a crash management system using LS-OPT. Two different load cases and three objectives are considered. To realize shape variations, ANSA's Morphing Tool is used, that provides easy coupling with LS-OPT. In addition, sheet thicknesses of five parts of the bumper are considered as design variables. In total, 9 design variables are introduced. For the multi objective optimization, the conversion to a single-objective optimization is not sufficient hence the calculation of Pareto optimal solutions is necessary. These solutions are calculated meta-model based to keep the computational costs (number of solver calls) within an acceptable range.

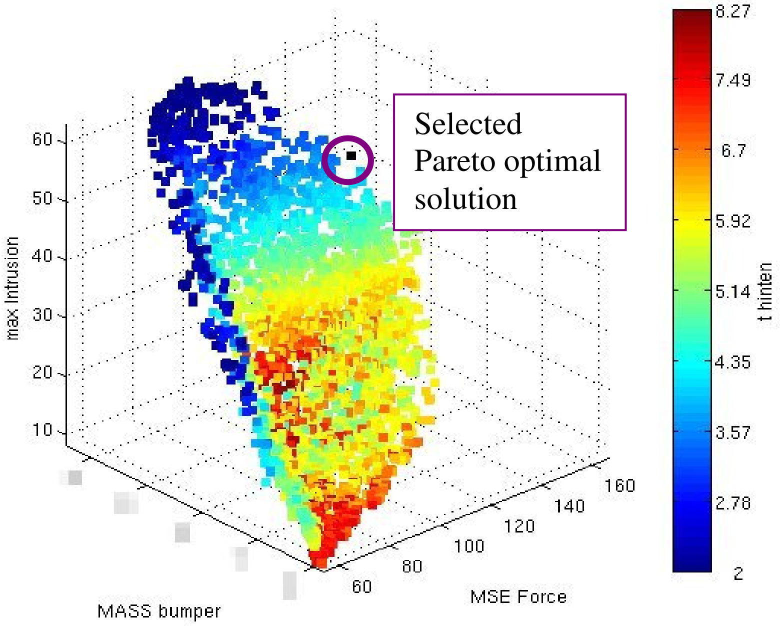

Figure 17: Pareto optimal solutions calculated on the meta-model for the considered three objectives

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