

CUSTOMER STORY // AUTOMOTIVE ENGINEERING

## ROBUST AUTOMOTIVE SUSPENSION DESIGN USING MULTI-OBJECTIVE OPTIMIZATION

A Robust Design Optimization (RDO) approach with optiSlang is used to implement further improvements in car suspension design with respect to model transferability and a wide spectrum of load variations.

### Introduction

For decades, automotive experts have gained a profound level of knowledge in the field of conventional suspension design leading to a high degree of maturity of current car suspensions. To carry out further improvements, it is inevitable to increase complexity by introducing more sophisticated designs. In parallel, the needs with respect to robustness are dramatically increasing due to a still growing number of derivatives on the one hand and a wider spectrum of wheel load variations by introducing electric batteries for plug-in and pure electrically driven cars on the other hand. Under these circumstances, optimal solutions are hard to find by human search. Computer-based optimization used in the digital phase of suspension development may help to improve insight into the system and to implement better designs. Besides optimizing individual car suspensions, however, it is also desirable to ensure consistent ride and handling behavior for a whole car segment including different engines, extra equipment, plug-in batteries and customer loading. Thus, a suspension system should be designed so that it can be used in several derivatives such as sedans, station wagons, coupes, etc. This may be achieved by using RDO as it will be shown by an approach based on optiSlang.

### Robust Design Optimization

Generally, RDO is an optimization performed under consideration of uncertainties. Typical tasks are to optimize a given objective while fulfilling constraints with a specified safety margin or minimizing the variance of responses with respect to uncertainties.

Because robustness measures (variances and mean values) are used in the presented optimization loop, the procedure is considered as an integrated variance based RDO. For each design generated by the optimization algorithm, mean value and variance need to be estimated. Because this procedure needs a vast amount of CPU-time for expensive direct function evaluations, an efficient design evaluation process using an adaptive Response Surface approach is needed if time-consuming simulations are involved.

### Adaptive Response Surface Based RDO

As mentioned above, the Response Surface Method (RSM) offers an opportunity to minimize the amount of CPU-time needed for the RDO process. Here, an aRSM based multi-objective RDO is used and explained in the following.

The goal is to optimize a system in terms of minimizing mean and variance of an objective function with a given set of design parameters between some upper and lower bounds and with normally distributed stochastic variables representing uncertainties. The solution process consists of two parts: an initial sampling and the main RDO loop consisting of different process steps, see Figure 1.

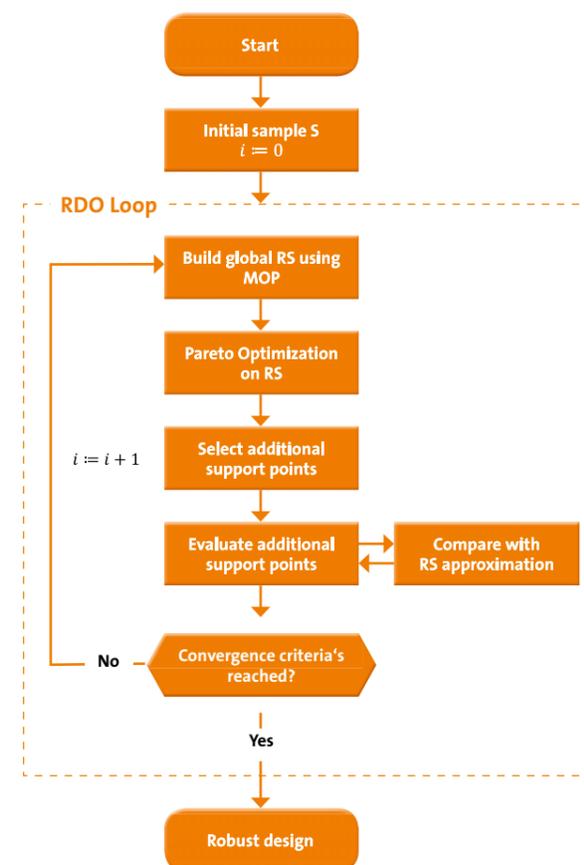


Fig. 1: Flow chart of the adaptive response surface based RDO

In the first step, a predefined number of design points are generated in the design space of the optimization. For every point in the optimization space, a sampling within the space of uncertainties is done. To avoid purely distributed inputs, particularly for a small amount of samples, advanced Latin Hypercube Sampling (aLHS) is used for initial and uncertainty sampling. The resulting set of sample points in the design space of optimization acts as a set of support points for generating response surfaces for mean and variance estimation. These robustness measures are evaluated by solving the sampling in uncertainty space of every support point. In the first step of the main RDO loop, response surfaces are built up from the actual set of support points and associated response values. To build up the response surface, the Metamodel of Optimized Prognosis (MOP) is used. Briefly said, MOP is an automatic approach which searches for the best subspace of important optimization parameters and the best response surface approximation

for a given dataset with respect to a specific validation method. For the developed process, parameter filtering is disabled and the MOP is only used for metamodeling. Polynomial least squares approximation, moving least squares and ordinary Kriging have been currently implemented in optiSlang. After generating the response surface, the optimization problem is solved on the response surface. A global evolutionary optimization algorithm based on the Strength Pareto Evolutionary Algorithm (SPEA2) is used. The algorithm generates a Pareto-front of optimal compromises between low mean value and low variance dominating the remaining designs. The result of the optimization is a set of non-dominated compromise designs and a remaining set of dominated designs.

In the next step, proper sample points for the adaption of the response surfaces have to be selected, which is briefly explained in the following. At first, minimum distances between non-dominated designs and all points of the actual set of support points are calculated. The design with the maximum distance is then chosen as a new potential RS support point and removed from the set of non-dominated designs. In order to prevent the selection of new support points lying too close to others or being even identical to an already existing support point, a characteristic distance criterion is introduced which needs to be fulfilled. If the characteristic distance criterion cannot be satisfied by enough Pareto optimal designs, the set of non-dominated designs is extended by the set of dominated designs, forcing the algorithm to globally update the meta-model. This process repeats itself until a predefined number of new support points are found. After updating the set of support points, design evaluation is performed for all new support points. Based on the new set, response surfaces are updated and the RDO loop in Figure 1 repeats itself until a maximum number of iterations or a convergence criterion is fulfilled.

To check for convergence, approximation quality of the new support points is assessed in the criterion space, meaning that the relative differences between objective values gained from response surfaces and originally evaluated values are assessed: if this error rate is smaller than a predefined error tolerance, the algorithm is assumed to be converged and the RDO procedure finishes.

### Implementation in optiSlang

The proposed process is implemented in the commercial optimization tool optiSlang by combining the described algorithms with existing process nodes out of the optiSlang library. The implementation of the RDO process in optiSlang is shown in Figure 2 (see next page), where the different process nodes are numbered and will be explained in the following.

The first node in the blue box (1) in Figure 2 (see next page) is a sensitivity node used for initial sampling. Here, a predefined number of sample points are generated and evalu-

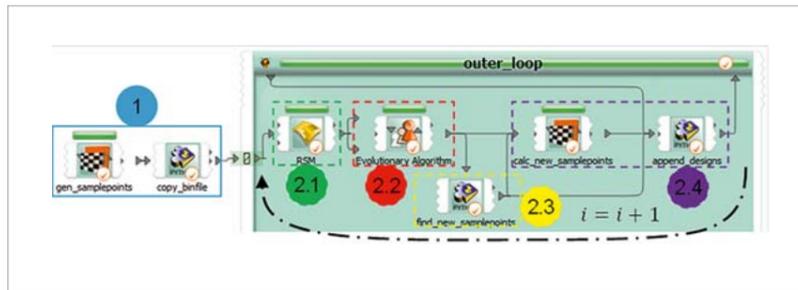


Fig. 2: Implementation of the proposed method in optiSLang

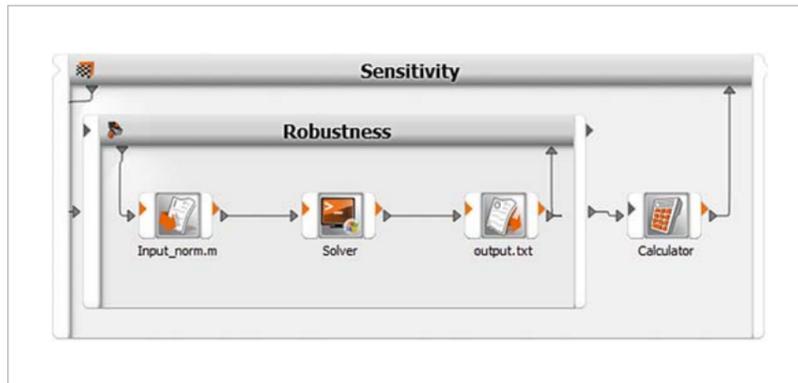


Fig. 3: Sensitivity analysis with nested robustness analysis

ated to be used as support points later. In order to determine robustness measures, a nested robustness analysis is performed for each design generated by the sensitivity node as shown in Figure 3.

The results are stored in a single file which is relocated to a specified folder by the second node. This is done by a simple script written in Python-code which can be directly executed in optiSLang by using the Python integration node.

In the first step of the main RDO loop (see the green dashed box 2.1), response surfaces are built up from the actual set of support points by using the MOP node. To get the set of actual support points, the MOP node reads the file mentioned above that is stored in a standardized location. Again, as explained for the sensitivity node, the MOP node is only used for metamodeling, meaning that filters and post processing are deactivated. After generating the metamodels, the multi-objective optimization problem is solved on the response surfaces via the EA node shown in the red dashed box (2.2). In the next step, proper sample points for the adaption of the response surfaces are selected, which is done by a script executed in the Python node in the yellow dashed box (2.3). Evaluation of the new support points and check for convergence is done by the nodes in the purple dashed box (2.4). The first node, a sensitivity node, acts similarly to the node used for initial sampling in the blue box (1). Here, the chosen points are evaluated by using the nested robustness analysis. The last node then appends the evaluated designs to the set

of support points. It checks for convergence and stores the new set of support points to the standardized location as mentioned above. Now, the next iteration is performed starting with the metamodeling of the MOP node. This process repeats itself until one of the stop criteria defined above is fulfilled.

### Application to Suspension Design

The proposed method is applied to Robust Design Optimization of a suspension of a full vehicle model. The vehicle, a luxury passenger car, is modeled as a multibody system (MBS) with 112 rigid bodies and 111 degrees of freedom (DOF). Model components are suspension links, wheel carriers, bushings, spherical joints, springs, dampers, wheels, tires, steering system, as well as subframe at the rear axle and the main body. Two different comfort oriented load cases are investigated. The main goal is to find a bushing setup

which has the best robust performance with respect to the specific objectives and uncertainties. The uncertainties shall emulate different car derivatives which have the same track width, wheelbase and kinematic hard points, but different mass and size.

#### Design Goal

Design goal is to minimize the oscillation intensities of two typical driving maneuvers. The first load case is called axle tramp which is a coupled oscillation between wheel and axle appearing while a car is accelerating or braking. In this article, only the axle tramp during braking is investigated. Depending on axle kinematics, the wheel moves backwards and upwards due to the applied braking force which leads to a loss of road contact and, thus, a reduction of the friction force on the tire. This, however, lets the wheel swing back gaining more road contact again. Repetition results in the oscillation are illustrated in Figure 4. The most sensitive parameters for this scenario are the tire mass and stiffness as well as the bushing stiffness and damping where a certain amount of damping should be realized in particular.

To get a reproducible axle tramp behavior in the simulation, an initial vertical force impulse is applied to the rear wheels while the car is braking. The resulting longitudinal and vertical accelerations of the rear wheels in the time-domain are squared, integrated, normalized to a reference car and chosen e.g. as characteristic response criterion  $f_2$  to be minimized, see Figure 5.

In the second load case, the vehicle is driving with constant speed on a straight road while a single step-shaped roadway excitation occurs at the rear axle. Here, the acceleration of the driver's seat in the opposite driving direction is investigated in the time-domain and transformed to criteria  $f_5$  similarly to  $f_2$ , which should be minimized, see Figure 6.

The first acceleration peak can especially be recognized by passengers and, therefore, is of particular interest. To minimize the seat acceleration in the x-direction, the axles should provide enough longitudinal compliance and little damping.

For each of the altogether five response criteria, mean value as well as variance are calculated, normalized with respect to a reference car and partly summed up to finally achieve two objectives for each load case. The different needs of both load cases regarding stiffness and damping should lead to compromised bushing setups forming a Pareto-front. These tradeoffs are hard to find by human search which is why the proposed computer based optimization procedure is used.

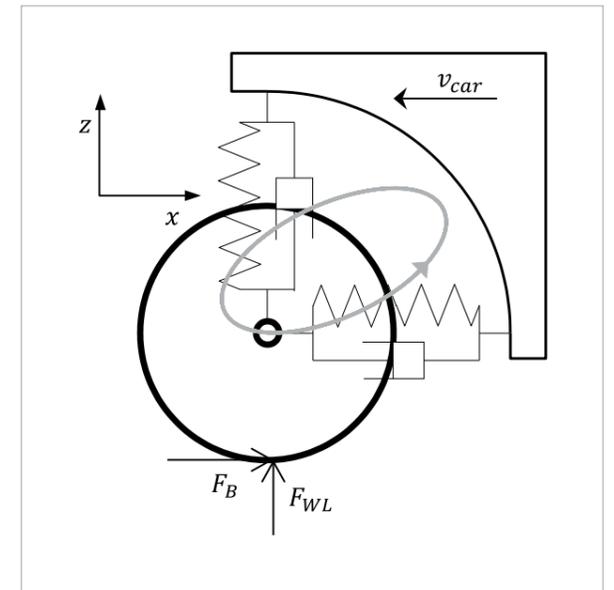


Fig. 4: Schematic tire movement during tramp oscillation

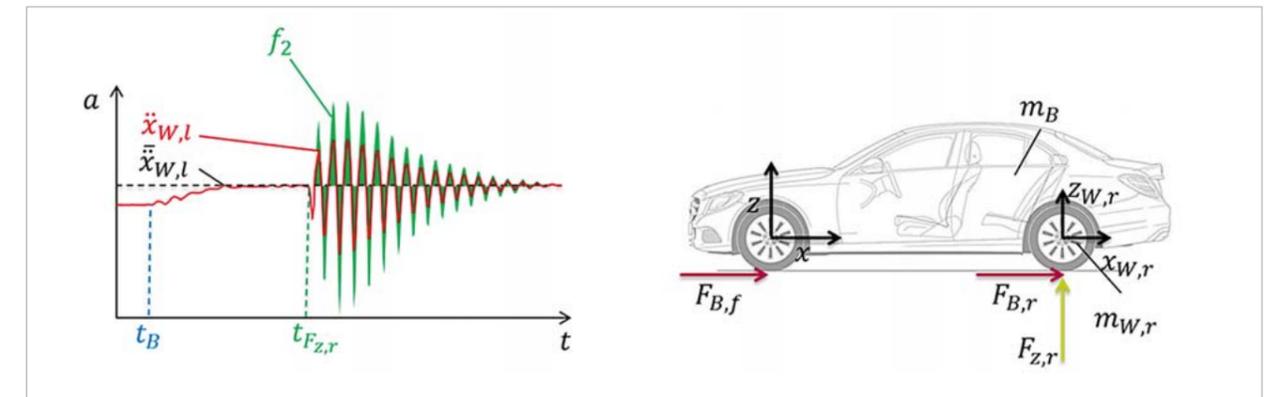


Fig. 5: Schematic representation of one of the axle tramp responses (green curve) for the rear left wheel acceleration in x-direction (red curve)

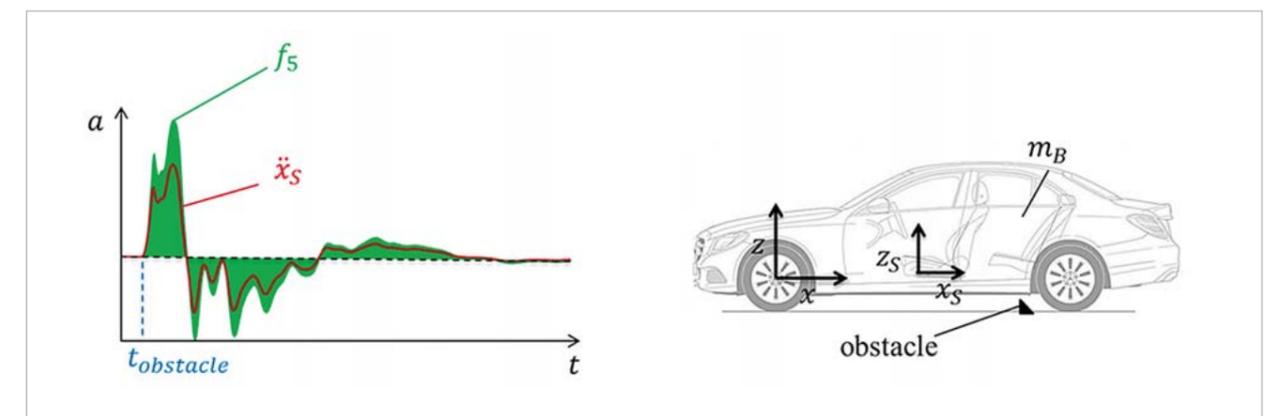


Fig. 6: Schematic representation of the obstacle crossing response (green curve) for the driver's seat acceleration in x-direction (red curve)

#### Design Parameters

The stiffness and damping characteristics of the suspension bushings are chosen as design parameters where the bush-

ings are represented by a Kelvin-Voigt (KV) model as shown in Figure 7 (see next page). This model is limited in terms of approximating real bushing behavior, but it only needs two

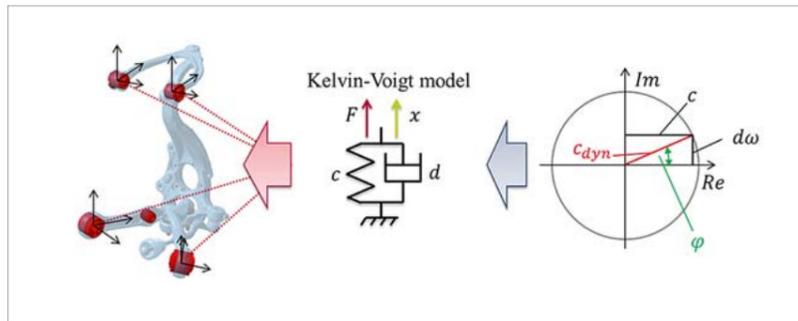


Fig. 7: Schematic bushing parameterization process

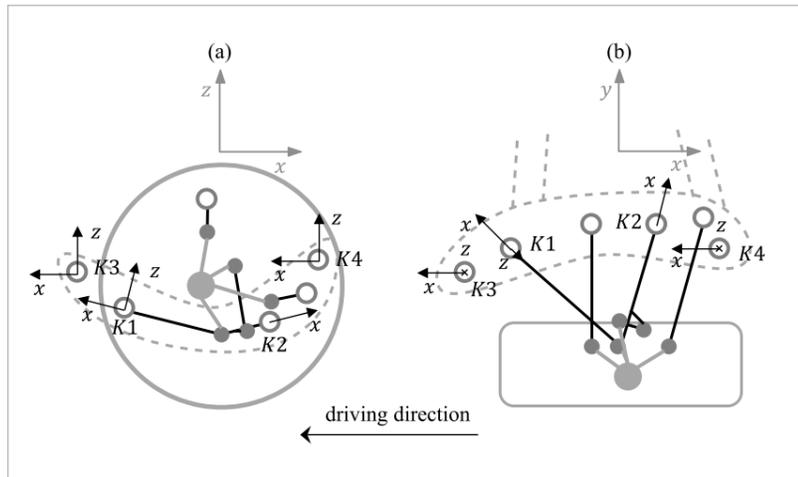


Fig. 8: Side (a) and top view (b) of investigated rear axle with wheel carrier (grey), linkages (black), bushings (white circles) and subframe (gray dashed)

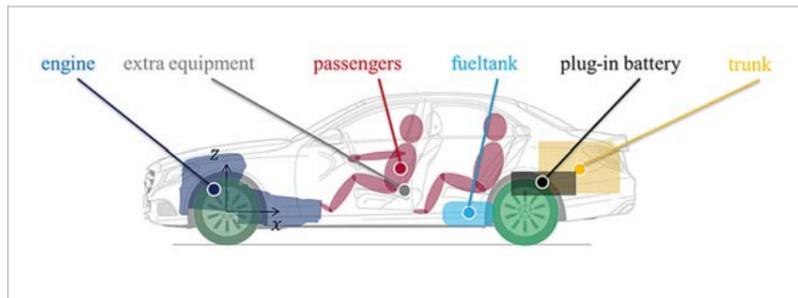


Fig. 9: Sources of uncertainties and representation within the MBD model

parameters which is efficient. The main drawback of the model is the incapability of reproducing the real amplitude and frequency dependencies of rubber material used for vehicle bushings. To overcome this lack of approximation quality, the KV model is parametrized to match the real bushing behavior only for a specific excitation frequency. This has been possible since the two considered load cases, i.e. axle tramp and free vibration after obstacle crossing, have well defined excitation frequencies. Briefly said, dynamic stiffness  $c_{dyn}$  and loss angle  $\varphi$  are calculated from design variables and converted to specific model parameters  $c$  and  $d$ , see Figure 7. In total, the vehicle model has 10 bushings where here only

translational bushing characteristics are changed.  $c_{dyn}$  and  $\varphi$  for each coordinate direction of each bushing accumulates up to 60 parameters that may be considered. To minimize the amount of design parameters, a sensitivity analysis was performed resulting in only 11 important parameters which are varied between predefined bounds. The associated bushings and their individual coordinate systems  $K1$  to  $K4$  are visualized in Figure 8.

### Uncertainties

A passenger car underlies several uncertainties. In this article, the scatter of mass properties of loading and bodies is investigated according to Figure 9. More precisely, the variation of passenger numbers, fuel level, boot loading, extra equipment, engine and battery type are taken into account where positions are assumed to be given. Due to the lack of statistics for the masses described above, they are assumed to be normally distributed within given ranges and independent. For sampling purposes, a truncated standard normal distribution is used for each parameter and generated with aLHS for predefined bounds.

### Optimization Results

The RDO is performed subjected to design objectives, normalized design parameters and uncertainties. For the evaluation of robustness measures, a sample size of 20 is used for uncertainties. The initial set contains 30 support points. In each iteration, 5 new support points are added to improve the RS. The SPEA2 performs an optimization on the RS with a maximum of 150 generations using 20 new individuals in each generation. The RDO procedure is limited to 40 adaptations of the RS resulting in a maximum of  $(30+40 \times 5) \times 20 = 4600$  original design evaluations. While running 10 simulations in parallel, the overall RDO took 6 days and 9 hours until it converged after only 38 adaptation iterations. The evaluated support points are shown in Figure 10.

It is clearly visible that all criteria improve simultaneously resulting in a rather narrow Pareto-front which indicates that mean objectives are not as contradicting as assumed. Nevertheless, both criteria could be enhanced with respect

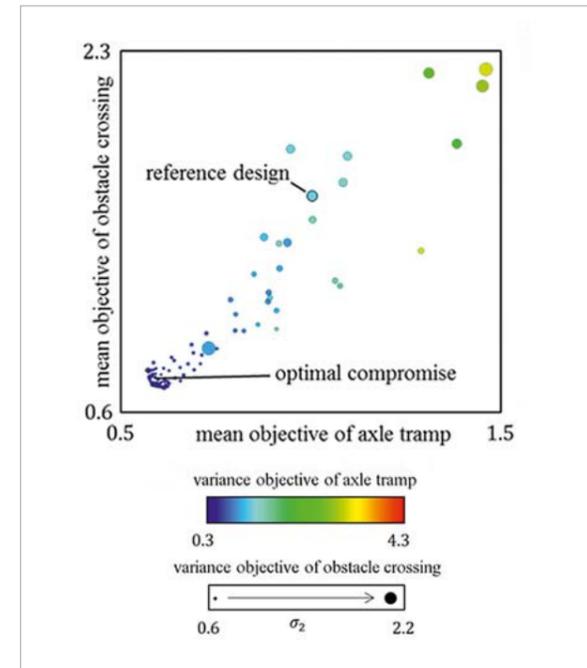


Fig. 10: 4D-Pareto plot of support points

to the reference vehicle setup and also the robustness seemed to be improved. For better visualization of the improvement, histograms of two specific objectives of a Pareto-optimal design lying on the knee of the front are shown in Figure 12. They have been compared to the reference setup. It can be easily observed that mean value and variance are both significantly improved. The corresponding accel-

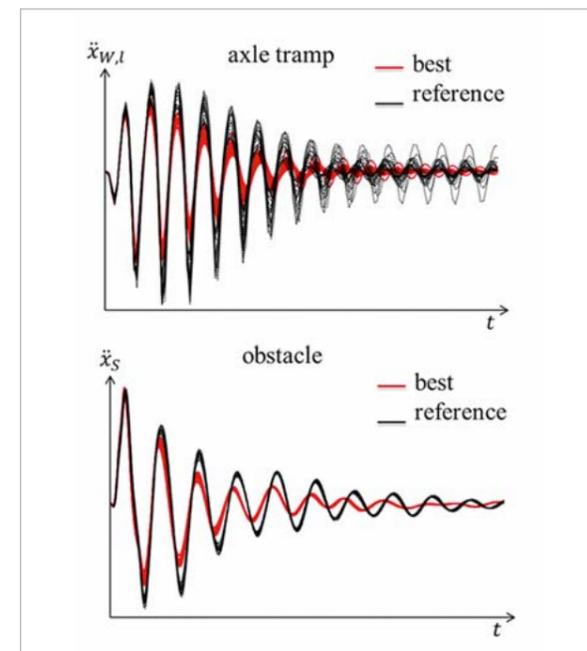
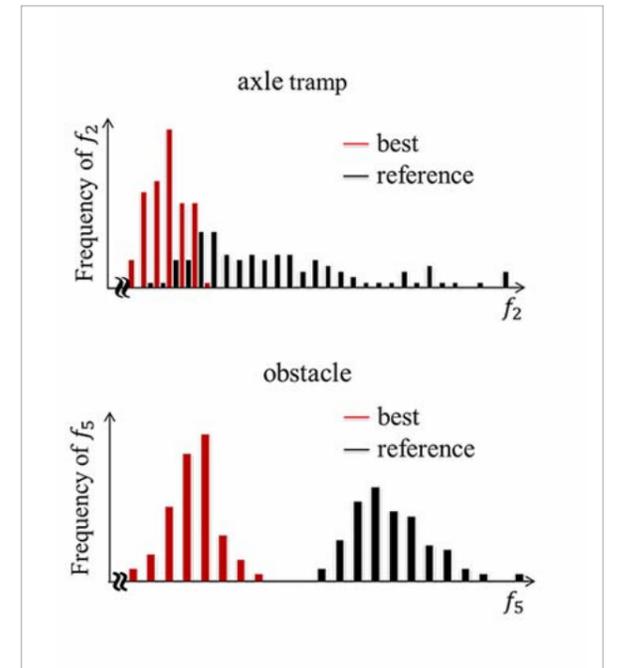


Figure 11: Time plots of tire acceleration during tramp oscillation (top) and driver's seat acceleration after obstacle crossing (bottom) of optimal design (red) and reference design (black)

Fig. 12: Frequency plot of objectives  $f_2$  (top) and  $f_5$  (bottom) for optimal compromise design (red) and reference design (black)

erations determine  $f_2$  and  $f_5$  as the acceleration of the left tire during tramp (Figure 11 top) and the driver's seat after obstacle crossing (Figure 11 bottom) in x-direction. They confirm the histogram information in Figure 12 in the time-domain. The large scatter in tire oscillation of the reference car during axle tramp can especially be observed.

### Conclusions

The article demonstrates an efficient multi-objective robust design optimization procedure. The implementation of an adaptive response surface modeling strategy significantly reduces computational effort compared to direct optimization. This is proven by optimizing a simple test function. An application of the proposed method to vehicle suspension design by using multibody system simulations and optiS-Lang is successfully performed. The optimization is done in terms of minimizing predefined accelerations measured throughout the load cases, which are axle tramp and single step-shaped roadway excitation for a given range of bushing stiffnesses as well as damping parameters under presence of scattering vehicle masses. Although both load cases need contrary bushing characteristics, optimal compromise designs could be found where mean value and variance of the vehicles dynamical behavior are significantly improved compared to a reference design.

**Authors //** P. T. Ubben, J. Haug (Daimler AG) / D. Bestle (Brandenburgische Technische Universität Cottbus-Senftenberg)  
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