Use of Data Reduction Methods for Robust Optimization

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Abstract

Data reduction methods like principle component analysis, singular value decomposition and independent component analysis methods allow analyzing huge sets of data. Applied to simulation results they allow the characterization of major trends in the variation of these results.
For the public Chevrolet Silverado example all thicknesses are initially varied independent of each other among a number of simulation results and its correlations are computed to the variation of the behavior of the firewall. The behavior of the firewall is approximated using data reduction methods. It turns out, that the variation of the firewall can be characterized by one basic deformation mode. The thickness variation of a part may show strong or weak correlation to the behavior of this deformation mode. In several steps now, the sensitivity analysis is repeated using only those parts for thickness variation, which had a strong correlation in the previous step.
Finally it turns out, that the thicknesses of the longitudinal rails as well as certain bifurcation behavior of the longitudinal are responsible for this variation mode of the firewall.

Background

Since the past few years the overall awareness of variability and scatter for CAE predictions is steadily increasing. Giving the fact that variability is inherent in nature it is also a major task to master it during product- and in this case especially vehicle-development. As a matter of fact in car industry for many load cases there is only provision for a single performance confirmation test to verify the CAE model. As such a test is influenced by a series of potential variability sources like e.g. production tolerances and crash test parameter settings, the chance to run into unpredictable crash results rises. In case of unforeseen results this usually leads to expensive and inefficient design changes, at a late vehicle development phase.

To counteract the above mentioned the CAE model should already have a robust design which is not sensitive to small variations and still delivers predictable results. Thus before applying design optimizations, the overall robustness of the model needs to be ensured.

Taking a deeper look into the complex event of a car crash many reasons can be discovered why small variations actually lead to a big spread among the results. Just to mention a few, consider parts kinking in one direction or the other or parts passing each other instead of hooking up. As a consequence one approach to generate a robust design is to find these events (often referenced to as bifurcations) and derive design suggestions that can handle the variations and still deliver a deterministic crash behavior.

One way to achieve this is mainly based on Principle Component Analysis methods and standard statistics, which are both applied in the example case of the Chevrolet Silverado from the NCAC and described below.

PCA Analysis for crash simulation results

Given the fact that for a robustness analysis as described in this manuscript a set of 30 or more simulation runs is analyzed, the use of a dimensional reduction method is beneficial. In our case the Principal Component Analysis is used to easier extract the essence of the crash behavior for sets of simulations.

Principal Component Analysis for crash results [1]

According to [2], principle component analysis (PCA) was introduced by Pearson in the context of biological phenomena [3] and by Karhunen in the context of stochastic processes [4].

In [5], PCA was applied to full crash simulation results. Let $(p,)$ be the displacement of simulation run i out of n simulation runs at node p and time t. If $\bar{X}$ (p,t) is the mean of all simulation runs, the covariance matrix C can be defined as

$$C := [c_{ij}]_{1\leq i,j\leq n} \quad \text{and} \quad c_{ij} :=< X_i - \bar{X}, X_j - \bar{X} >_2$$

The eigenvectors v_i of C form a new basis (principle components) and the λ_i (square roots of the eigenvalues of C) provide a measure for the importance of each component.

If this method is applied to crash simulation results, n^2 scalar products between the simulations runs of length $3 * \#P * \#T$ have to be computed ($\#P$ number of points, $\#T$ number of time steps.)

From

$$\hat{X}(a) := \sum_{i=1}^{n} a_i X_i \quad ,$$

follows that

$$\lambda_i = \left\|\hat{X}(v)\right\|_2 \quad .$$

The $\hat{X}(v_i)$ show the major trends of the differences between the simulation results. The coefficients of the eigenvectors v_i correspond to the contribution of $\hat{X}(v_i)$ to $X_i - \bar{X}_i$ and can be used for cluster analysis and correlation with input parameters. If input parameters have been changed between the different simulation runs, the correlation analysis will indicate how certain trends can be avoided or increased by changing these inputs (e.g. thicknesses of parts) (c.f.[1], Chapter 2.4] for the properties of PCA analysis in general).

Principle Component Analysis is a mathematical method which determines mathematical trends in contrast to physical trends. To be more specific: λ, the square of the maximal eigenvalue of C, can be determined by

$$\lambda = \left(max_v \left\|\bar{X}(v)\right\| \middle| \|v\| = 1\right)$$

and therefore will be in general a mixture out of several physical effects, like buckling.

Difference PCA [1]

Instead of considering the whole simulation results, correlation matrices can also be defined for the simulation results at parts of the model and for specific time steps. If P is a part of the model and T subset of the time steps, then , can be defined as follows:

$$C_{P,T} := \left[c_{i,j}^{P,T}\right]_{1\le i,j\le n} \text{ and } c_{i,j}^{P,T} := \frac{1}{N_{P,T}} \sum_{p\in P, t\in T} \left(X_i(p,t) - \bar{X}(p,t)\right) * \left(X_j(p,t) - \bar{X}(p,t)\right).$$

($N_{(P,T)}$ denotes the size of P times the size of T.)

The intrinsic dimension of the set of simulation results can be defined as the number of major components in its differences (for more formal definitions see [1], Chapter 3]). Buckling or any other local instability in the model or numerical procedures increase the intrinsic dimension of simulation results at parts which are affected compared to those, which are not affected. Therefore in the context of stability of crash simulation, those parts and time steps for which the intrinsic dimension increases are of particular interest.

Numerically this can be evaluated by determining eigenvectors and eigenvalues of

$$C_{P1,T1} - \tau C_{P2,T2}$$

for the covariance matrices of the simulation results at two different parts P_1 and P_2 and two different sets of time steps T_1 and T_2. If there are positive eigenvalues for a certain choice of τ (which separates noise from real signals), the simulation results at (P_1, T_1) show additional effects compared to those at (P_2, T_2). If v_{P_1,T_1} is the corresponding eigenvector, $\bar{X}\left(v_{P_1,T_1}\right)$ shows the effect on (P_1, T_1) and also the impact on the other parts of the model. Similar methods can be used to remove those effects from this result, which do not affect (P_1, T_1) directly.

A Patent has been granted to Fraunhofer Gesellschaft, Munich (DPMA number 10 2009 057 295.3) for this approach.

Firewall example

As mentioned in the Background chapter a robust model should be able to handle small variations within the model and still produce predictable results. Taking production tolerances into account is a common approach also in other areas of product development and shall be the point to start for us. The variability induced into a vehicle due to the uncertainty/variation during the production phase can have several different origins. Just to mention a few this can be due to material tolerances, uncertainty within production processes like e.g. stamping processes and others. This results in a slight variation of all parts with respect to their specification. While this is inherent in the vehicle production it is not part of the simulation model itself. So introducing the production based variability of parts into the robust analysis is a more detailed representation of the real world and allows us to improve model robustness as well as it helps understanding more about the crash behavior of the model. The risk of running into unforeseen results in the vehicle confirmation test will also be decreased.

Especially for the analysis of front crash results the intrusion of the firewall is an important safety parameter. Thus having a predictable behavior at the firewall is important to fulfill safety requirements so our focus for this analysis lies on the scatter at the firewall. The model investigated here is the Chevrolet Silverado available from the NCAC ("The model has been developed by The National Crash Analysis Center (NCAC) of The George Washington University under a contract with the FHWA and NHTSA of the US DOT").

Following the prescribed approach a set of 30 simulation runs was generated based on a random variation of part thicknesses within the range of ±3%. Within a first statistical analysis the maximal variation among all the simulation runs is computed and visualized on the contour of the geometry in Figure 1.

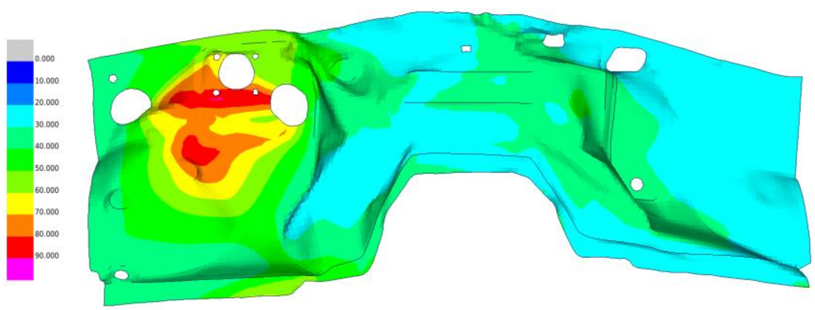

Figure 1: Scatter of 30 simulation runs on the firewall for initial design in mm

As can be seen the 30 simulation runs vary with a maximum of almost 90mm at the firewall although only a small overall variation has been applied. The effect of production tolerances therefore can have a heavy impact on the simulation results. Having the intention to improve robustness of the model the next task is to find out where this result dispersion comes from. What are the key events within the model causing the strong scatter occurrence at the firewall? Using PCA now for the firewall delivers the important scatter modes, rather than having to analyze the complete set of 30 simulation runs. In Figure 2 and Figure 3 the dominating scatter mode of the firewall is seen in his characteristics for other parts of the model. As can be seen, the shape deformation information contained in this mode reveals a different crash behavior for the shock absorber (Figure 2) on the one hand, and for the longitudinal rail on the other (Figure 3) hand.

Figure 2: Scatter mode deformation shapes for shock absorber – brake unit interaction

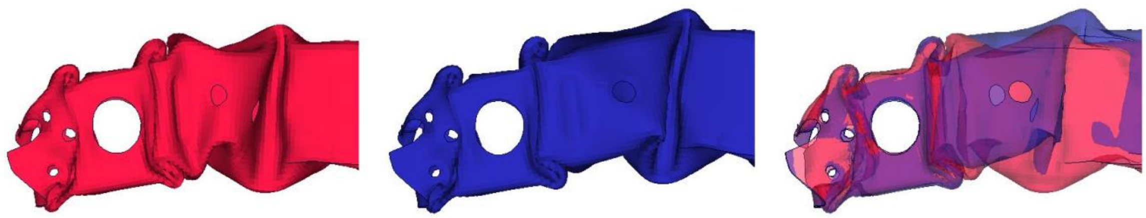

Figure 3: Scatter mode deformation shapes for left longitudinal rail

The shock absorber hooks up to the power brake unit for some runs, while for others they pass each other. The former pushes the power brake unit towards firewall and leads to a higher intrusion of the firewall.

At the longitudinal rail the kink is not triggered as intended for all runs, so that for some runs the area around the kink stays stiff (no kink). As a consequence the longitudinal rail pushes further towards the rear and also works as a lever elevating the wheel case. Further investigations have shown that latter event does not solely trigger the shock absorber hooking up to the power brake unit, even though it supports it. To counteract the bifurcation points a deterministic behavior is intended with two design adaptations. Exemplary the shock absorber was smoothened and cut so that it is way more difficult to have an interaction with the brake unit. On the other hand the notch at the longitudinal rail was slightly moved and adapted to allow a more consistent kinking behavior.

To verify the design adaptations and test whether the adapted model is more robust it is necessary to rerun a set of 30 simulation runs including production tolerances to be able to make a comparison before and after the design changes. The outcome can be seen in Figure 4. The adaptations made lead to a significant reduction of our target part the firewall. While there was scatter occurrence of up to 90mm for the unchanged model the improved design delivers way more robust results with only a variation of around 20mm at the firewall.

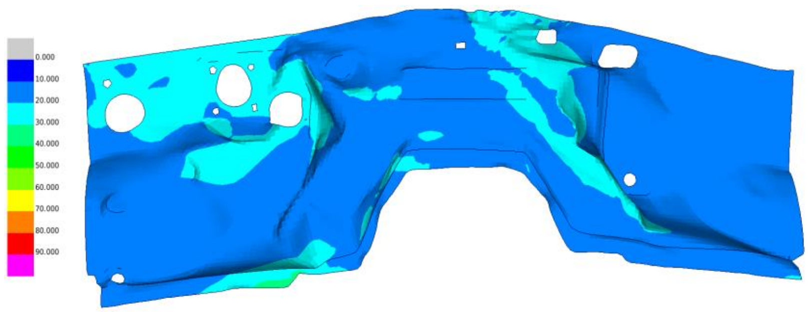

Figure 4: Scatter of 30 simulation runs on the firewall for revised design in mm

Robust Optimization I

In trying to reduce the weight of the car without sacrificing certain limits regarding its crash behavior the common procedure is to generate a meta model e.g. for the fire wall intrusion and optimize the fire wall intrusion and weight by using optimization strategies on this meta model. This strategy is supported by varies tools like LS-OPT®. There are, however, two issues:

1. How to measure the target objective of fire wall intrusion?
2. Which thicknesses should be taken into account?

The measurement of the firewall intrusion in this case is performed based on the contribution of the first deformation mode of the fire wall to each of the simulation results. The robustness analysis described in the previous chapter has shown that there is only one major deformation mode of the fire wall, which describes the difference among the simulation runs. Instead of selecting distances between points, this target has a smoother behavior and takes the whole area of interest into account instead of just a few single points.

All thicknesses of the car model, resulting from the robustness modification, are now varied by +/- 20% in order to determine the dependency of the firewall intrusion mode from the thick variation. For the initial setup of the metamodel the analysis software DESPARO was used [6]. Due to the fact, that there are 682 different parts, the number of simulation runs required for a rigorous analysis is about 500.000 runs. For an engineering process, however, it is important to avoid the special selection of parts, which might be interesting. Therefore we applied a hierarchical approach, which was validated on an artificial test function in [7]. For the initial step we randomly varied all thicknesses for 30 simulation runs and calculated the correlation to the target. Those parts, for which the material variation has real strong correlation with the target, are also identified as parts with strong correlation based on these 30 experiments. However, there are a huge number of parts with a false-true evaluation, because the variation of the thicknesses correlates to the variation of the thickness of a part with real strong correlation. For the second step, the thicknesses are fixed for all those parts, which have a correlation factor below 0.19. Figure 5 shows the correlation factors of all parts after the first and fifth step. In the fifth step the thickness of only 12 parts was varied. Here clearly 2 parts are identified, the thickness variation of which shows a strong impact on the firewall intrusion mode. These parts are the thickness of the right and left longitudinal. Although this result is not surprising, it’s a result of an automatic reasonable expensive procedure.

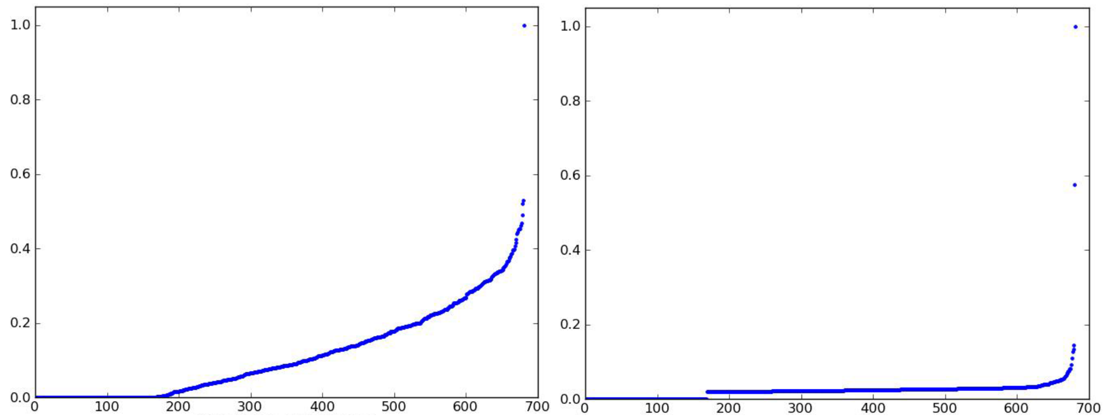

Figure 5: Correlation factor of thickness variation to objective for each part sorted by importance after the first and the fifths iteration.

Therefore now it is possible to build a meta model for thickness optimization based on the thickness of the 2 most important parts.

Robust Optimisation II

In the previous chapter the approach for a model was shown, for which already a robustness analysis was performed and the model itself was stabilized. A second approach allows deriving a stable meta model even starting from the original car model without the modification for robustness.

For this again the thickness of the 12 remaining parts were varied by +/- 20%. 77 simulations out of 100 terminated successfully.

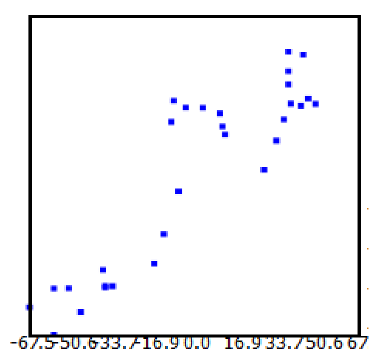

Figure 6: Scatter plot with 1 dot per simulation. X-axis: Thickness of left longitudinal rail, Y-axis: fire wall deformation mode contribution to the simulation result.

Figure 6 shows, that the deformation variation mode at the fire wall depends almost linearly on the thickness variation for small values of the thickness. For larger values, there is a substantial scatter. This observation is true, when building a meta model (linear interpolation between neighbors) on a subset of 35 simulation results using 42 results for cross validation. The thicknesses of the two longitudinals are used as design parameters and the contribution of the fire wall variation mode is the target. Figure 7 shows, that if the sum of the thicknesses of the two longitudinals is above a certain threshold, the failure of the meta model becomes larger.

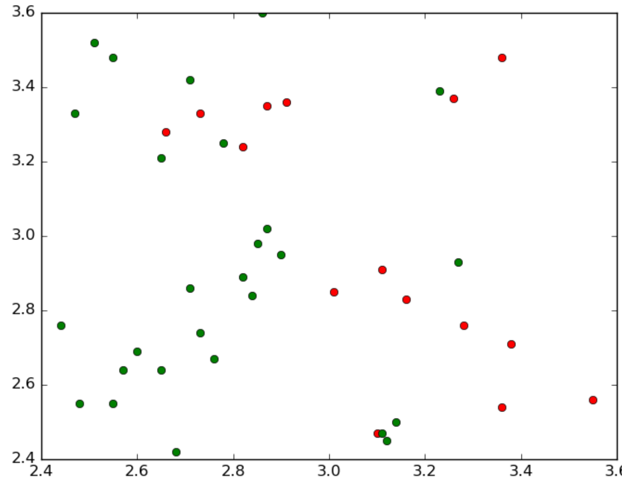

Figure 6: Validation of the meta model: Scatter plot with 1 dot per simulation. X-axis: Thickness of left longitudinal rail, Y-axis: Thickness of right longitudinal rail, colour: red: difference of prediction and simulation of the objective is above 10%: contribution of the fire wall intrusion variation mode to the simulation result

From the robust analysis it is known, that the initial movement of the break unit has a significant influence on the result. If the contribution of the variation mode of the initial movement of the break unit to each simulation result is taken as additional design parameter, the meta model for the fire wall behavior is substantially improved.

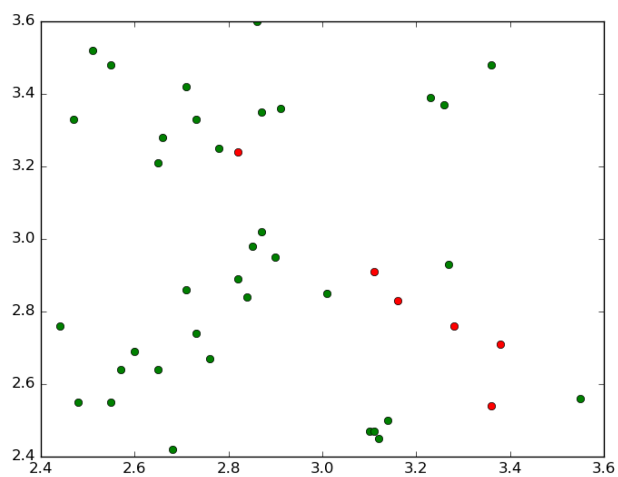

Figure 7: Validation of the extended meta model: Scatter plot with 1 dot per simulation. X-axis: Thickness of left longitudinal rail, Y-axis: Thickness of right longitudinal rail, colour: red: difference of prediction and simulation of the objective is above 10%: contribution of the fire wall intrusion variation mode to the simulation result

Figure 7 shows the result of the enhanced meta model. Only a small corridor shows inaccurate results of the meta model. The corridor, in which both thicknesses are almost the same, shows a good prediction performance of the meta model. This implies, that by an engineering change of the car model itself, which guaranties a certain initial movement of the break unit, it is possible to derive a stable meta model.

By evaluation of this meta model the desired behavior of the break unit can be determined. Fixing the design parameter such that the desired behavior is guaranteed should then still allow using this meta model for optimization purposes.

Conclusion

Thickness optimization using car models, which are robust, allows building accurate meta models and therefore substantially improve the quality of the optimization results. This was shown in a process, which also identifies the most important parts for thickness optimization in a hierarchical process.

This paper also shows, that robustness evaluation can be part of the optimization process itself, and by including the internal parameters describing the uncertainty as design parameters into the meta model. This allows during the optimization process to either select a parameter combination, which works independent of the uncertainty or to assume that the issue causing the uncertainty gets fixed.

DIFFCRASH allows to extract the relevant information from the set of simulations results and provide this information for processing in optimization tools like LS-OPT or DESPARO.

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