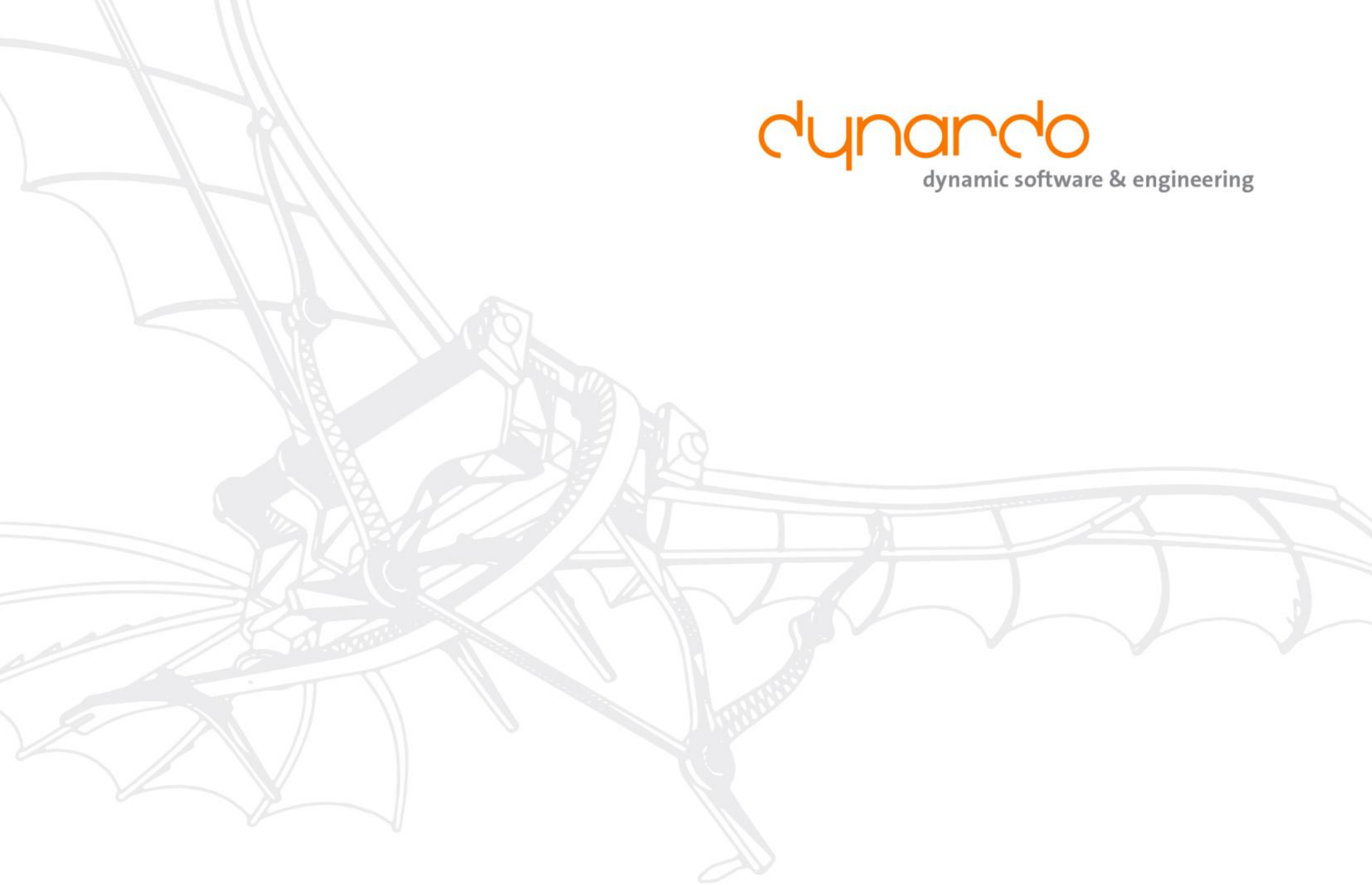

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Variation Analysis as Contribution to the Assurance of Reliable Prognosis in Virtual Product Development

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Variation Analysis as Contribution to the Assurance of Reliable Prognosis in Virtual Product Development

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Abstract:

A fast implementation of product innovations is often the key to success on the market and competitiveness. The resulting innovation speed can just be achieved with the help of virtual product development. The necessary introduction of virtual product development requires the massive use of many numeric simulation methods. Not only the complexity of products, but also the complexity of CAE-based simulation models and simulation methods increases. So the reliability of the simulation results is crucial for the success of virtual product development. To assure a sufficient prognosis ability of the simulation results, variant calculations of single simulation results and validations of single simulation results with measurements are involved. Nevertheless, a high uncertainty remains within complex simulation models, if the model is still secure for prognosis when small changes are done.

A methodology is introduced which can examine the reliability of the prognosis of response parameters via variation analysis and statistic follow-up evaluation as well which can validate the behavior of numeric models on experience values or measurement results.

The example of a robustness evaluation of a passive passenger safety system shows how numeric failures of the models can be identified. As a result, numeric models can be improved and the prognosis quality of the results can be increased. The example of a sensitivity analysis for machine tools displays how variation analysis can be used for the identification of important correlations between optimization parameters and performance parameters. Founded correlations of the numeric models are the basis for the validation of model behavior by using experience values and measurement results.

In comparison to common methodologies of variation analysis, the presented methodology has the advantage of a high independence of the numeric effort regarding the amount of the potential input parameters which need to be examined. In both appliances it is shown that important relations between input and output variations can be identified amongst a variety of possible causes.

Keywords:

Variation analysis, robustness evaluation, sensitivity studies, reliability, model validation, coefficients of determination, optiSLang

1 Introduction

A fast implementation of product innovations is mainly the key to success on the market and competitiveness. The resulting innovation speed can only be reached with the help of virtual product development. The consequent introduction of virtual product development requires the massive use of many numeric simulation methods. Not only the complexity of products, but also the complexity of CAE-based simulation models and simulation methods increases. So the reliability of the simulation results is crucial for the success of virtual product development.

In this context, reliability means that simulation results can be used as a valid basis for the evaluation of the product features to be secured. This sets great demands on the methodology planning and the numeric simulation models. The assurance of reliability more demanding product features within more and more complex numeric models requires a high degree of model validation and therefore numeric effort. At the same time, the pressure of the market calls for shorter development times and cost efficiency in the virtual development. To fulfill these requirements, continuous method planning and optimization in cooperation with CAE-service providers and CAE-software developers are necessary. Only then, primary product demands can be reliably precalculated and the prognosis of the precalculation is suitable for decisions and releases in virtual product development.

To assure a sufficient prognosis ability of the simulation results, variant calculations of single simulation results and validations of single simulation results with measurements are pulled up. Nevertheless, a high uncertainty remains within complex simulation models, if the model is still secure for prognosis when small changes are done. If the precalculation includes the prognosis of the variation of important response parameters as result of scattering input parameters, then computational robustness evaluations [1] will be done and the verification and validation is extended to the scatter of the response parameters. In that case, the adjustment includes the model behavior at variations of the parameters.

The introduction of robustness evaluations into virtual product development processes has pointed out that robustness evaluations offer a valuable contribution to the reliability assessment of simulation models. The identified correlations between input variation and output variation serve as verification basis regarding expectation attitude and experience values. They secure the intellectual control over simulation results in more and more complex numeric models. Beyond that, robustness evaluation can be used for the quantifying of the parameter correlations by analyzing the coefficients of determination. Vice versa, the robustness evaluation yields a quantification of still unknown (by chance) response variations. The validating of correlations and the numeric estimation of the coefficients of determination of response parameters achieves a notable contribution to the quality assurance of numeric models.

At first sight, the including of robustness evaluations into the evaluation of the reliability of prognosis may astonish, because they bring additional certain variations into the calculation model. But when looking more intensively, it really contributes to the quality assurance of numeric models.

The robustness evaluations discussed in that paper use specialized Latin Hypercube Sampling methods. This method is a special form of variation analysis and it helps to create a bridge according to common methods of model validation. The easiest common approach of model validation uses variant calculations; normally one simulation per parameter change is carried out and assessed. However, this approach is already quiet unclear and impracticable with a few variations to be viewed. If the approach is systemized, the so-called Design of Experiments (DOE) is used. Here, the design variants are chosen systematically, so that approximation models (Response Surface Methods - RSM) of correlation can be generated via regression approaches. The effort for DOE and RSM increases highly with the amount of variables to be viewed and with the nonlinearity of correlations. That is why DOE and RSM variation analysis can only be done in relatively small design spaces (10 to 15 variables). Key advantage of specialized Latin Hypercube Methods in combination with statistic correlation analysis is that the amount of necessary calculations does not depend on the amount of the variables. The amount of necessary calculations depends on the actual dimensionality of the correlation between single response parameters and input variations as well as on the nonlinearity of correlation. Normally 100 to 200 calculations are sufficient to indicate the most important relations and to determine the coefficients of determination, because the actual dimensionality of the correlation between single response parameters and input variations is often small.

2 Background on robustness evaluations and sensitivity studies using variation analysis

Causative computational robustness evaluation is used for prognosis of scattering result variables as well as identification of connection between input and output scatter [1]. Thereby when performing robustness analysis stochastic methodology is used for generating a set of possible design realizations within the defined limits of the input scattering (probability space). The generated design realizations are computed and afterwards the variation of the results is evaluated using statistical measures. The correlation analysis which accompanies the robustness evaluation furthermore determines the correlation between the variation of input parameters of the numerical models and the resulting variance of significant result variables.

This approach of robustness evaluations within the space of scattering parameters can be carried forward to general variation spaces. Variation analysis using Latin Hypercube Sampling indeed also is very successful within the variation space of tasks in optimization [2] or in tasks involving the comparison between measurement and computation [3]. If the variation analysis is performed within the space of possible design changes then the identification of correlations between design changes and result variables and therefore the validation of the model behavior is of greatest significance. This is then called sensitivity study.

2.1 Scanning of variation space using Latin Hypercube Sampling methods

The robustness evaluations and sensitivity studies discussed in this paper use a specialized Latin Hypercube Sampling method [4]. The Latin Hypercube Sampling creates design realizations within design space in such manner, that the distribution functions and the variation range of the input variation respectively are represented as good as possible. At the same time it is secured, that the error of the known correlations of input variables is minimized within the chosen number of computations. Thereby the methods scan the design space using the chosen number of design realizations as good as possible and the design set furthermore is optimized for statistical correlation analysis.

2.2 Statistical correlation analysis

Using correlation analysis it is determined if correlations between input and output variation can be identified from the design set. Therefore coefficients of correlation between input and output variation are determined pair wise. How much every identified correlation between single input variation and single output variation contributes to the total variation of the result variable is evaluated using coefficients of determination. The coefficients of determination thereby show a significant correlation and the coefficients of determination quantify the correlation. Usually linear and quadratic correlation hypothesis are used.

For a more detailed description of the method see further readings [5] and the optiSLang manuals [4].

Of special importance for determining the reliability of the simulation results are the measures of determination of the result variables compared to all input variables. If these are small the result variation can not be explained via the tested correlations. Practical experience shows that measures of determination of linear and quadratic correlations below 80% point out that the reliability and plausibility of the result variables should be checked. Theoretically non-linear correlations between input variation and output variation can of course exist, they however should be validated. In practical tasks even when confronted with highly nonlinear tasks [6] one could observe, that small measures of determination where often correlated with numerical problems of the simulation models.

3 Example of use for robustness evaluation of passenger passive safety systems [7]

The contribution of robustness evaluations for securing the reliability of the simulation in virtual product design is presented and discussed using the example of dimensioning of passenger passive safety systems.

3.1 On numerical robustness of crash test computations

The analysis of numerical robustness of models of crash test computations results from the experience that small variations of numerical parameters of the approximation methods or the variation of numerical parameters can already lead to large scattering of the result variables or lead to obviously unfeasible results respectively. Scatter resulting from the approximation results of numerical computation are called numerical noise. If in robustness evaluations (including naturally occurring scatter of input variables) n-Design are to be computed and their variation is to be evaluated statistically the question occur which proportion of the result variation can be attributed to problems within the approximation methods and the numerical modeling respectively.

The quantitative influence of numerical noise on the result variables can be estimated by the coefficients of determination of the robustness evaluation. If the coefficient of determination of the robustness evaluation is large only a small proportion of not yet explainable variation remains of which could be caused by numerical noise. In order to use the determination as a quantitative measure for the numerical model robustness the determination ratios of the found correlations of course have to be estimated with sufficient statistical security. This formulates standards for the sampling method, the number of computations and the statistical algorithms for the evaluation of coefficients of determination [5]. After very positive experience of evaluating the influence of numerical noise via measures of determination from robustness evaluation the method is used for serial production at BMW since 2006. Thereby generally measures of determination in consideration of linear and quadratic correlations and after elimination of clustering of over 80% could be determined for “numerically” robust models. If the measures of determination were significantly below 80% it was seen as an indicator that this result variable may have a high amount of numerical noise. This was mainly caused by deficiencies of the numerical models in interaction with the numerical approximation methods. After repairing the numerical models the measures of determination usually rose to over 80% again.

It shall be stated that it theoretically is not possible to determine the proportion of numerical noise without doubt. The detour using a process of elimination of linear and quadratic correlations as well as the influence of outliers and clusters on the coefficients of determination however identify a remainder of “unexplained” scattering of the result variable which potentially is caused by potentially higher dimensional (cubic, sinusoidal, etc.) correlations, further non-linearities (bifurcation points) or from numerical noise. From this diagnosis excluded are of course systematic errors or the inability to map important physical effects from input variation on output variation. The fundamental ability for prognosis of numerical models has to be evaluated by verification using experimental data.

3.2 Robustness evaluation load case USNCAP

Since beginning of 2006 computational robustness evaluations using optiSLang at three milestone of serial production executed for all relevant load cases for dimensioning of passenger passive safety systems [6]. The procedure is exemplarily introduced for one load case. For the load case USNACP (front crash 56 km/h against steep wall) the robustness concerning significant evaluation parameters of the driver was tested. The model was constructed and computed using the multi-body program MADYMO. The robustness evaluation was performed using optiSLang. Important parts of the restraint system and the dummy were used as multi-body formulation for the airbag a finite element formulation was used. The simulation model of the airbag was validated by the supplier using component experiments and integrated into the BMW passenger car model.

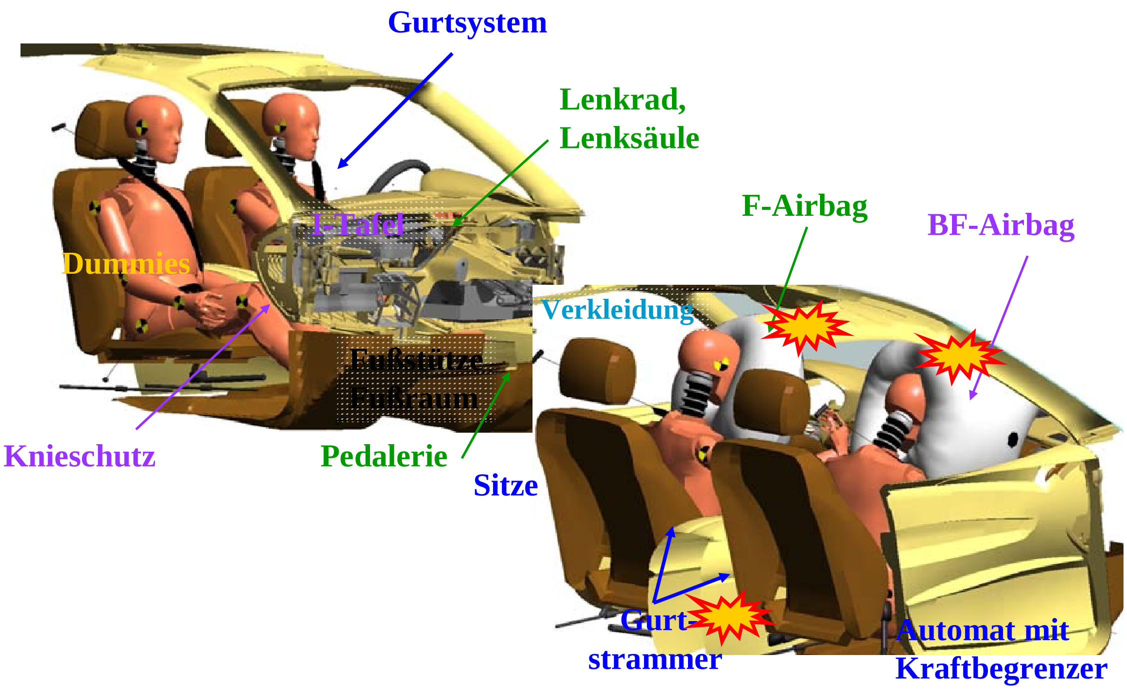

Figure 1: Simulation frontal crash load case USNCAP

For the robustness evaluation over 200 variants were created using the Latin Hypercube Sampling and computed. Overall 9 physical parameters of the multi-body/FE-model were varied and 12 dummy result variables were examined in robustness evaluation. For the definition of the scatter a normal distribution and cut off normal distribution were used. The following heavily scattering input parameters were considered in robustness evaluation:

- Scattering of the time to fire of airbag and load-limiter
- Scattering of the dummy seat position
- Scattering of mass flow, permeability of the airbag
- Scattering by the load limiter
- Scattering of friction between dummy and airbag as well as between dummy and belt

The following result variables were examined in the robustness evaluation:
- Head resultant acceleration 3 ms
- Chest resultant acceleration 3 ms
- Pelvis resultant acceleration 3 ms
- HIC15 head injury criterion 15 ms
- HIC36 head injury criterion 36 ms
- Viscous criterion
- Shoulder belt force
- Chest deflection maximum
- Head x- / z-displacement
- Femur compression left / right

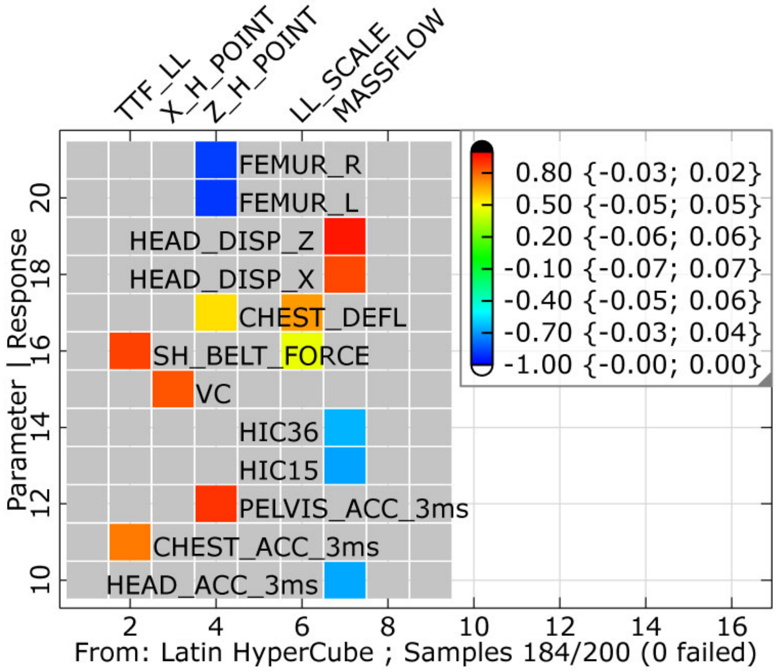

Figure 2: Linear correlation structure

Of the 9 scattering input variables only 5 input variables exhibit a significant correlation to the result variables. In the matrix of linear correlation (figure 2) for all important performance variables significant linear correlations to the input scatter could be determined (correlation coefficient > 0.50). For most of the result variables a high coefficient of determination (>80%) of linear and respectively quadratic correlation (shown in figure 3 with 97 % determination for the maximum of the femur forces) could be determined. The significant output variable HIC36, however, only showed a coefficient of determination of 66 % (figure 4).

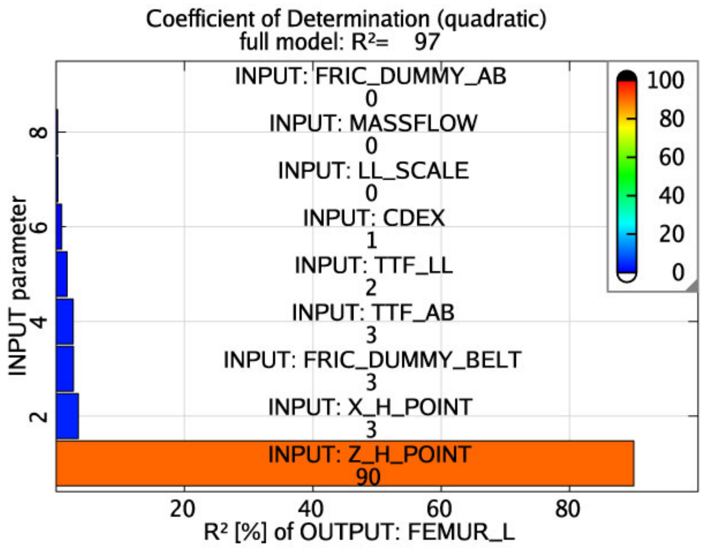

Figure 3: Coefficients of determination femur force left

Also test for quadratic correlations, outliers and clustering could not show any more correlations. Since concerning the scatter of the HIC36-value a large amount of the scatter could not be explained using the found correlations a significant amount of numerical noise is expected. Therefore the reference design for the driver was evaluated concerning numerical stability. Overall 17 numerical parameters, like for example scaling factors of the time steps, the contacts or “numerical” damping factors of the multi-body and finite element models were varied and 22 dummy result variables were examined in the robustness evaluation.

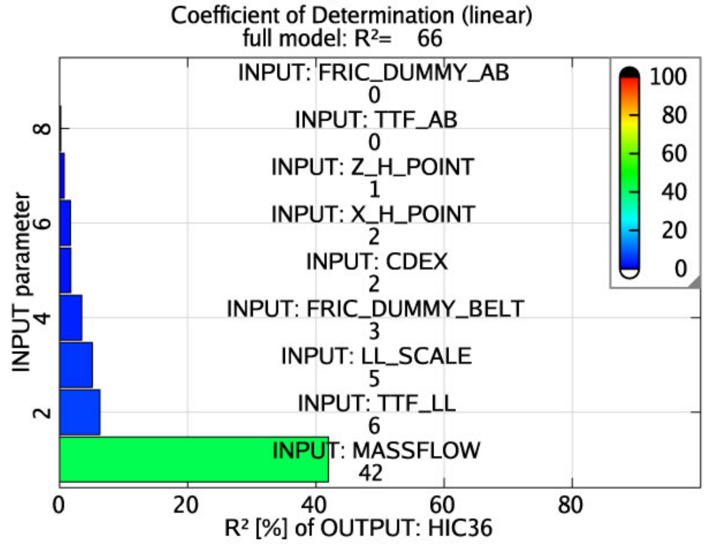

Figure 4: Coefficient of determination HIC36

For the USNCAP evaluation two response variables (thorax acceleration 3ms, HIC36) from the set of the observed response variables were evaluated. Deciding criteria of the numerical robustness is the measure of variation of important input variables concerning the expected scatter of a physical robustness evaluation. As a plot in the star range shows (figure 5) very large variation could be observed which were about the size of the scatter which is caused by physical input scatter for this load case. Since this magnitude of numerical noise is unacceptable the responsible input variables were identified.

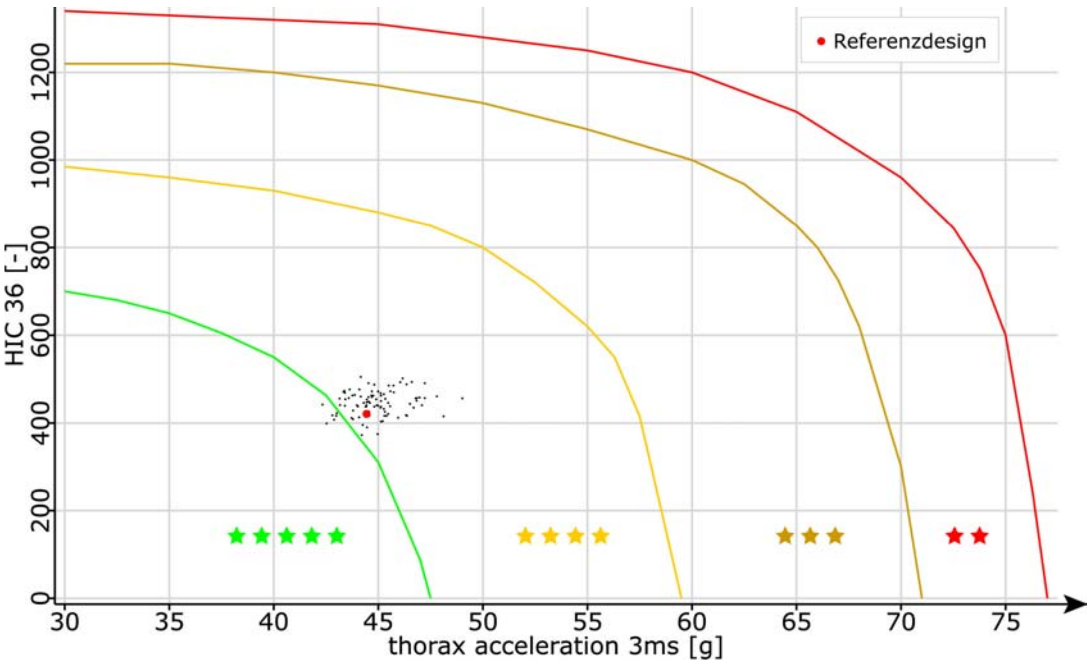

Figure 5: Visualization of the numerical scatter in the star diagram, USNCAP Rating

In the matrix of the linear correlations (figure 6) it can be easily seen that significant correlation to the variation of a multi-body time step exist, which obtain a correlation coefficient of 0.7. Furthermore clustering could be identified in the anthill plots (figure 7). By analyzing “suspicious” result sets some incapacities of modeling the contact between airbag and dummy could be identified and eliminated. A final numerical robustness evaluation proved a significantly smaller scatter caused by the variation of numerical parameters (figure 8), which could be ignored considering the scatter from physical input variables. Thereby the numerical robustness of the improved modeling could be proven and the foundation for evaluation and optimization of the restraint system was laid. (Notice: At this point in time the performance value of the reference design had been relocated in the 5-star area by constructive measures). Recapitulating for this load case modeling errors could be identified and eliminated and the final robustness evaluations showed an acceptable measure of scattering of important input variables.

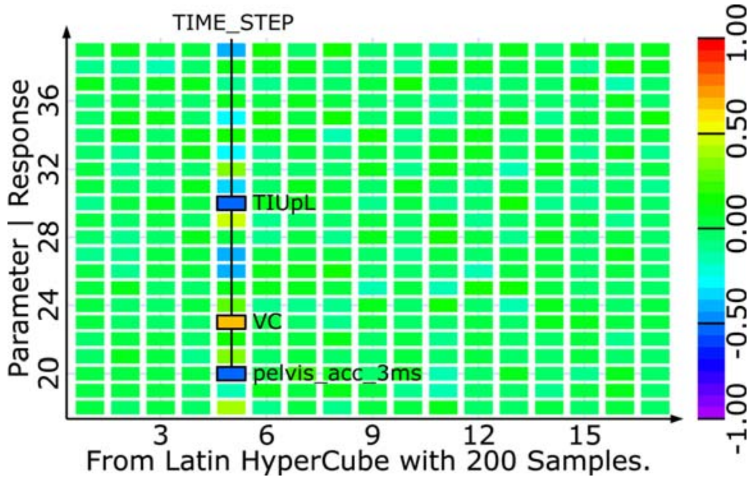

Figure 6: Linear correlation matrix

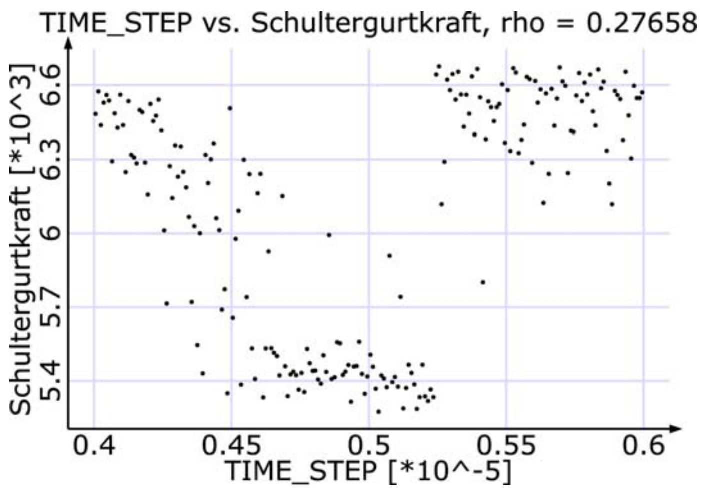

Figure 7: Visualization of correlations between the variation of multi-body time step and the shoulder belt force in the anthill-plot

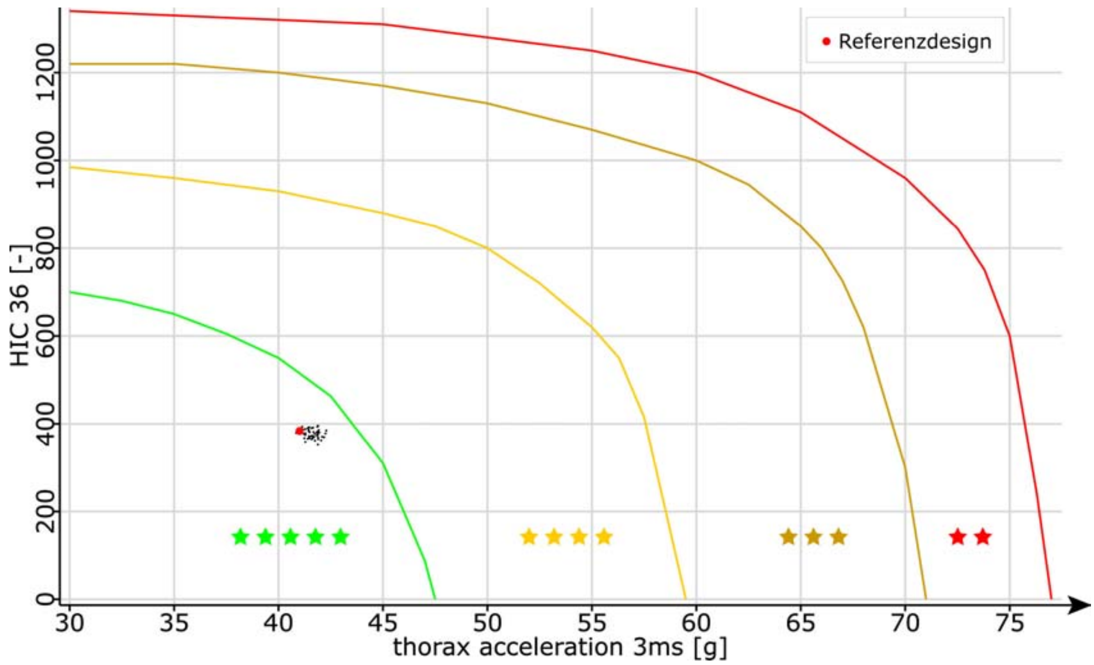

Figure 8: Visualization of numerical noise in the star diagram, USNCAP Rating

4 Application Example Sensitivity Study at Virtual Tool Interpretation

The contribution of sensitivity analysis on the validation of numeric models and with that to the assurance of the reliability of the prognosis of numeric models in virtual product development is displayed at the example of the virtual development of a machine tool. The examinations are carried out within the scope of one of the BMBF supported research project (SimCAT [8]). The sensitivity analysis uses optiSLang and the CAE calculations use the finite element program PERMAS.

4.1 Sensitivity Analysis for the Effect of Material and Component Damping on the Dynamic Behavior of a machine tool [2]

An important aspect of the project SimCAT was the task of the transfer of the current modal damping existing in tools calculations on local dampers to improve the display of specific behavior of connection elements in the calculation model. To verify the machine understanding and the expectation attitude on the numeric model, a sensitivity analysis was done for the evaluation of the effects of material and component damping on the dynamic behavior of a lathe.

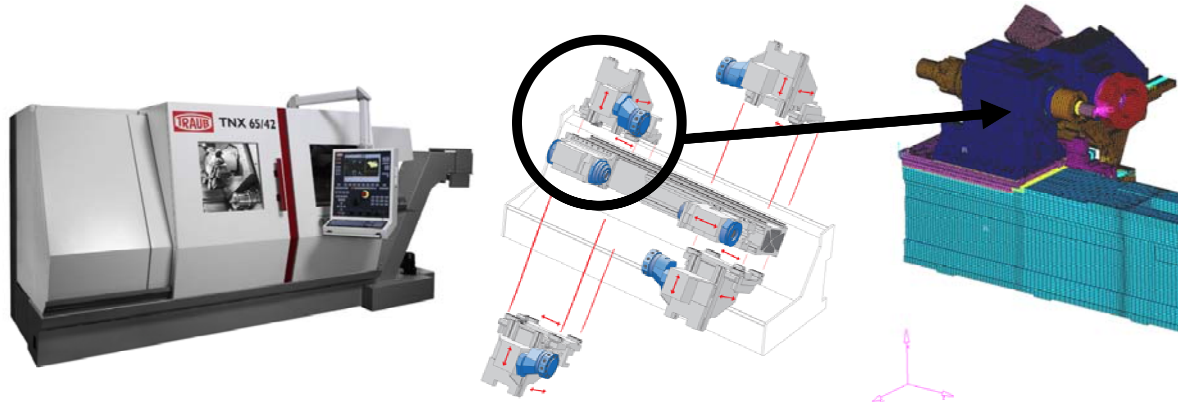

Figure 9: machine tool Traub TNX65

The model consisting of machine bed, main spindle unit and XYZ tool carrier is parameterized in a way that the damping is only explained by local dampers. Not only viscose damper elements of all supports and guides, but also the structure damping for different massive components of the model were included which led to 104 parameters describing the damping. A sensitivity analysis was carried out with these parameters. The allowed variation areas of the parameters were determined on 10% - 1000% of the start value. The different harmonic response functions in all room directions serve as quality function and they were adjusted with the result of a reference run with modal damping (which was validated by measurements).

The result of the study shows that only 9 of the 104 parameters have a significant impact on dynamic flexibilities. Among them, there is the structure damping of several assemblies in the main spindle and local damping values of single linear bearing of the tool girder unit (Figure 10).

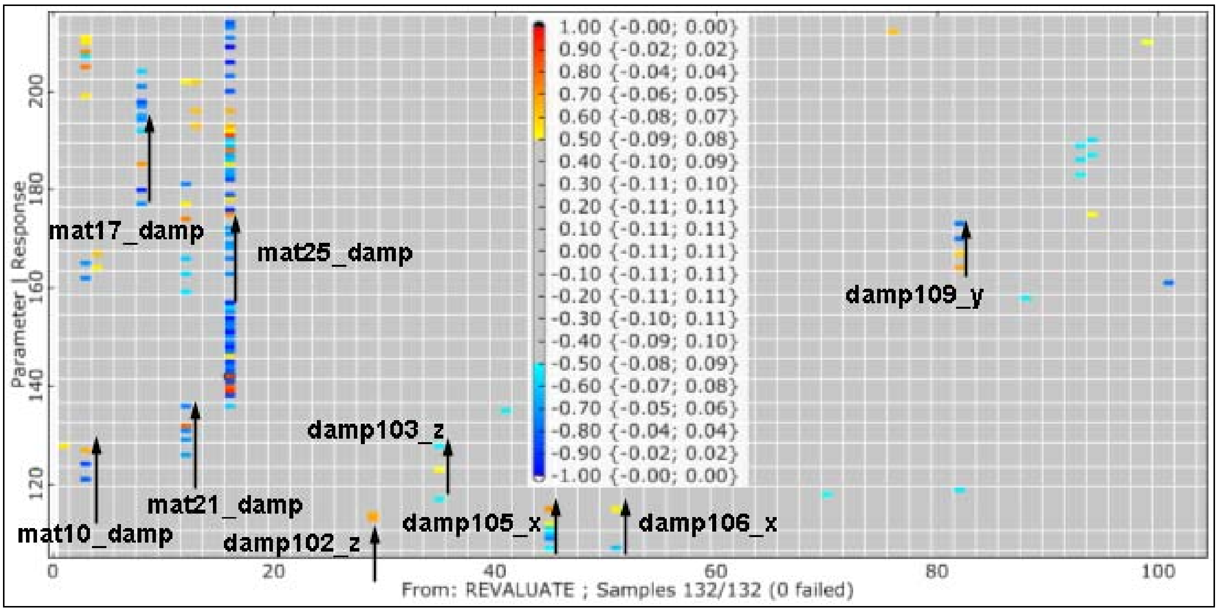

Figure 10: correlation matrix of the sensitivity study of component and material damping (correlations < ±0.5 faded out)

An encouraging result of the sensitivity analysis was that a direct allocation of the main responsible parameter could be done for single vibration amplitudes (Figure 11).

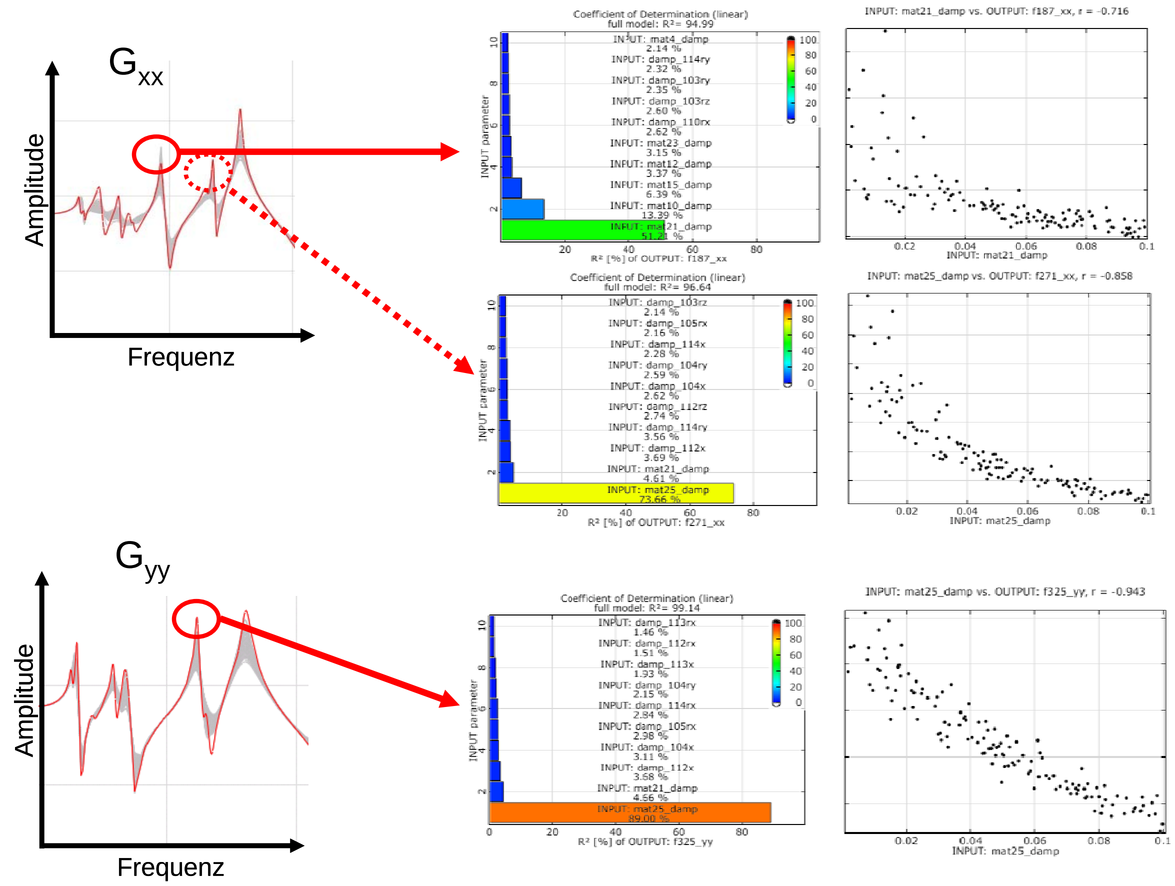

Figure 11: correlations between single amplitudes in NFG and parameters, displayed at coefficients of determination

It could be indicated that sensitivity studies help to identify the most important input variables and their relation with the most important response parameters. At the same time, the behavior of the numeric model was adjusted with experience values and measurement results. Because of the small amount of finally sensitive parameters, the sensitivity study clearly points out that it is principally possible to construct machines according to optimal dynamic flexibility and it shows which positions need intervention.

5 Conclusion

A methodology is presented which can examine the reliability of the prognosis of response parameters via variation analysis and statistic follow-up evaluation or which can validate the behavior of numeric models on experience values or measurement results.

The example of a robustness analysis of a passive passenger safety system is displayed to indicate how numerical problems of the models can be identified. Thus, numeric models can be improved and the prognosis quality of the results can be increased.

The example of a sensitivity analysis of a tool is used to show how variation analysis can be used for the identification of important correlations between optimization parameters and performance parameters. The found correlations of numeric models are the basis for the validation experience values and measurement results.

In comparison to common methodologies of variation analysis, the presented methodology has the advantage of a high independence of the numeric effort on the amount of the potential input parameters which need to be examined. Both appliances display that important relations between input and output variations can be identified amongst a variety of possible causes.

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