Integration of Computational Robustness Evaluations in Virtual Dimensioning of Passive Passenger Safety at the BMW AG

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Summary

One of the most important tasks of vehicle development is the steady improvement of passive safety systems. In the past deterministic models were used for the virtual dimensioning of passive safety systems. In reality, however, significant scatter can be observed when performing crash-tests. Cause of this scatter of important vehicle performance variables is scatter of variables concerning the dimensioning of passive safety systems and vehicle structure, the material, the loads and the testing conditions. This results in the necessity to pre-compute not only single values but also to be able to extract information about the scattering of important evaluation variables from simulation as reliable as possible. Considerations of input scatter, as foundation of an economical dimensioning of restraint systems concerning scattering performance variables, can only be obtained by integrating stochastic observation and simulation methods into virtual product design [1-2]. The BMW AG uses systematic computational robustness evaluations obtained by stochastic analysis for dimensioning of restraint systems since beginning of 2005. After one year of methodical covering of the procedure [3] computational robustness evaluations will become a defined milestone of their virtual development process of passive safety systems in 2006. Primary result of the robustness evaluations is the calculation of the scatter-band of performance variables and of the connected probability of achieving safety goals. Secondary result is the investigation of the numerical stability of the models and identification of the input scatter, which is responsible for the output scatter. The robustness evaluations thereby give important information about necessary improvements of the numerical models as well as information about the necessity to reduce input scatter or information about necessary modifications of the restraint systems.

1. Introduction

In the past deterministic models were used by multi-body or finite element programs for dimensioning of passive safety systems. In reality, however, significant scatter can be observed when performing crash-tests. Cause of this scatter of important vehicle performance variables is scatter of variables concerning the dimensioning of passive safety systems, vehicle structure, the material, the crash-test dummies, the loads and the testing conditions. This results in the necessity to pre-compute not only single values but also to be able to extract information about the scattering of important evaluation variables concerning the expected test results as reliable as possible. The BMW AG uses systematic computational robustness evaluations obtained by stochastic analysis for dimensioning of restraint systems since beginning of the year 2005.

The necessity of integration of stochastic simulation methods is determined by further trends in virtual product design.

- By increasing optimisation, designs can reach their limits and become very sensitive towards scattering
- Because hardware cycles occur later and less often, the influence of scatter, which was still prominent in hardware tests and its influence thereby was at least detected by sampling, has to be taken into account in virtual product design.
- If larger changes in construction are made within very short time (high innovation speed) and more and more complex component systems concur the a priori knowledge (experience) about reliable functionality possibly is very small. Therefor the robustness of the systems has to be determined using virtual models.
- Substantial vehicle concept decisions have to be made in an early stage of development basing on virtual dimensioning. This requires best possible knowledge about the degree of fulfilling the goals (laws, consumer protection) and respectively a quantitative estimation of the remaining risk.

2. Computational Robustness Evaluation using Variation Analysis

Computational robustness evaluations examine the sensitivity of important evaluation parameters concerning the scatter of physical input parameters [4]. Primary goal of computational robustness evaluations is the calculation of the range of variation of important response variables and the evaluation by standards of “robust” restraint systems. In passive safety the legislator sets limit values and the vehicle developers set their own target values with a security distance to the limit values. Furthermore the vehicles should get an as good as possible evaluation in tests by consumer protection (e.g. EURONCAP). These requirements should be met by the majority of the vehicles. However verifying rare transgression probabilities (one in one million) is not the main goal. Therefore variance analysis is suitable for robustness evaluation of passive safety systems. Hereby all of the potential input scatter or uncertainties in the modelling are introduced in virtual product design by using scattering input variables in the numerical models. Using appropriate sampling methods a sample set of n-possible vehicles and n-possible constraints for the crash test are generated and then computed n-times. After the computation the sample set is then evaluated using statistical methods for estimation of variance and correlation analysis. In order to estimate the scatter of the result variables from the sample usually mean value, standard deviation, coefficient of variation and the range of variation (min/max value) are determined for every response variable. If the detected ranges of variation lie to close to the limit values or even exceed these, one has to ask for the frequency (probability) of exceeding the limits. If overstepping occurs in the calculated support point set, the frequency can be counted. In statistics one would talk about determining the empirical probabilities directly from the histogram. Alternatively distribution functions of the result variables can be assumed and the probabilities can then be computed from the characteristic values of the distribution function. It shall be noted at this point that it has to be verified if the chosen distribution (for example the normal distribution) is a sufficient approximation of the actual distribution. Since usually only the histogram of the 100-200 computations is available, determining the transmission probabilities directly from the available raw data (the histogram) is recommended for probabilities in the percent range. Usually the base of verification is missing for reliable estimations of significantly smaller transmission probabilities from distribution hypotheses. If small probabilities (for example smaller than 1 in 1000) shall be ensured, methods of reliability analysis should be applied [5-8]. Since they are only affordable in relatively small parameter dimensions, robustness evaluations using variance analysis normally are a necessary preliminary stage for reduction of the parameter space.

For significantly scattered result variables or transgression of limits the responsible input scatter is identified using correlation analysis. For this purpose pairwise linear and quadratic correlation coefficients of result and input scatter are computed. The correlation coefficients can obtain values between 0 and 1 (-1) and show the pairwise interrelation between a single input scatter and a single output scatter. For identification of mechanisms in which multiple input scattering affects on output scatter the principal components (the eigenvectors of the correlation-matrices) can be evaluated.

In the following it is estimated how much of the result variation can be explained using the calculated (linear and quadratic) correlations. This is done by using measures of determination [9]. The determinedness of a result variable regarding the variation of all input scatter describes which percentage of the result variation can be explained by the found correlations to the input variables. If the coefficient of determination of a result variable is high (at most 100%) the fundamental interrelations can be described using the underlying correlation hypothesis. The smaller the coefficients of determination are the larger the part of the variation of result variables becomes which can not yet be explained by the correlation hypothesis (e.g. linear and quadratic). Typically then non-linear correlations, clustering, “outlier” or a high amount of “numerical noise” exist. This way the measure of determination also provides information on the possible ratio of numerical noise and should be used as an important quality measure for the used modelling. In the robustness evaluations performed so far it could be detected that for coefficients of determination larger than 80% the influence of numerical noise on the performance variables was acceptable.

Choice and complexity of the sampling methods have to be adjusted according to the important statistical measures which are to be estimated. Normally the complexity of the sampling method is adjusted according to a reliable identification of linear coefficients of correlation. Thereby the number of computations for robustness evaluations of restraint systems results in about 100 to 200 per load case that is to evaluate [9]. The type of sampling method also is optimised for as reliable as possible estimations of correlations. Suitable method for this is a Latin-Hypercube-method which fulfils an input distribution function as well as it minimises the deviation between defined input correlations and input scatter.

3. Requirements for Systematic Integration of Computational Robustness Evaluations

For the systematic introduction of stochastic computation methods at least two essential boundary conditions have to be fulfilled.

- The available knowledge about input scatter and uncertainties e.g. in boundary conditions, material values or load characteristics is to be transferred to an adequate statistic description and is to be integrated into stochastic analyses in virtual product design as fundamental input information.
- At the same time it has to be ensured that the used numerical models include all physical phenomena which are connected to fundamental scatter and that the approximation methods (explicit FEM, multi-body dynamics) do not create too much scatter (numerical noise) of the performance variables.

The quality of the prognosis of the output scatter does explicitly depend on the close to reality definition of the input scatter. Only if it is ensured that the entire input scatter, which is fundamental for the evaluated performance variables, is captured and that the numerical models and the CAE-process allow an adequate prognosis, the resulting scatter of the result variables is reliable. It should be stated that on the way to that point already valuable insights on the transmission mechanisms of single input scatter could be gathered and the quality of numerical simulation can be improved significantly. In practical applications one often can not assume that all fundamental input scatter can be captured close to reality at the beginning of stochastic computations and that all simulation models have a sufficient numerical quality. Therefore one will realistically start with relatively rough assumptions about the input scatter and the input uncertainties respectively and then improve as well the knowledge about important input scatter and the numerical models quality step by step. Significant scattering input variables in virtual dimensioning of restraint systems are e.g. scattering of the airbag variables, scattering in the belt-system and the seat position of the crash-test-dummy. Numerical dummy models are available as validated FE- or multi-body-formulation. Besides dummy models also so called “stochastic” dummies are available. Here the input scatter of dummy variables is identified from an amount of validation experiments. Considering this input scatter the “stochastic dummy” shall generate a similar scatter of important dummy variables, as they were observed in the validation experiments. It shall be pointed out that all stochastic dummies known to us are “only” tuned to a corridor of the experimental results. Information about the distribution within this corridor was not taken into account during validation. These stochastic dummies are therefor only suited for calculation of a variation range and not for the calculation of overstepping probabilities concerning legal limits and consumer protection criteria, wherefore they were not used so far at BMW. For the validation of new “stochastic” dummies histograms of the input scatter from the identification of the n-validation experiments shall be identified and used as foundation for the statistic input information. Then also the distribution information is included and transgression probabilities resulting from dummy scatter can be determined.

3.1 Statistic Description of Input Variables

Physical input scatter is described using distribution functions. Important distribution function types are e.g. uniform distribution for friction values, normal distribution for mass flow values or log-normal distribution for material strength. If correlations between single scattering input variables exist, they have to be taken into account for the input information using adequate correlation models.

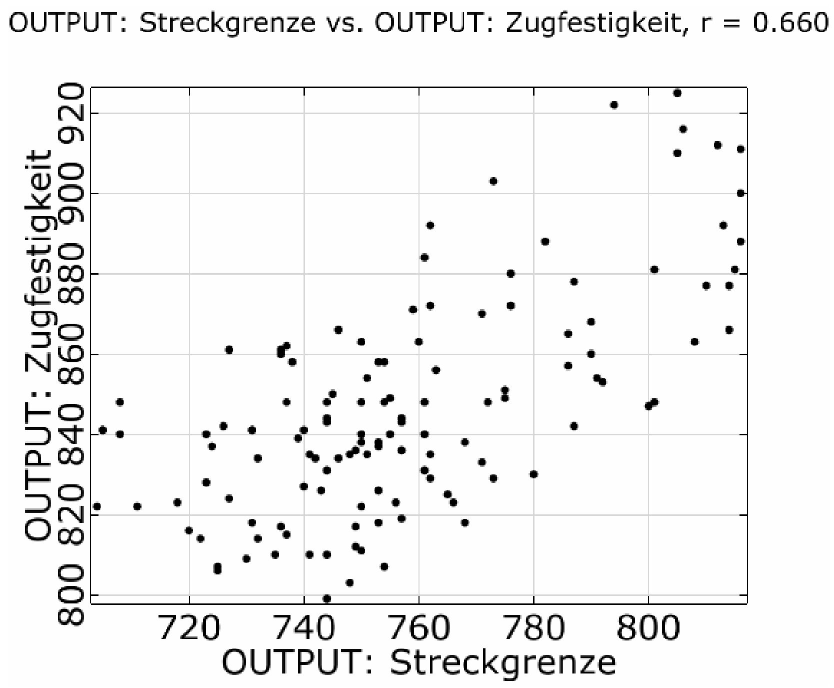

Figure 1: Correlation between the scattering tensile strength and the yield strength of steel

As an example for important interrelations between input scatter the correlation between tensile strength and the yield strength of steel shall be mentioned. In this case one would determine the linear correlation coefficient between both of the scattering input variables for example from available experimental data (shown in figure 1 with a correlation coefficient of 0.66) and consider it as important input information in sampling methods.

3.2 Requirements for the Automation of CAE Processes

Besides the fundamental standards of an automated succession of the realisation and computation of a varied design as well as the extraction of performance variables even more standards for the automation of the CAE-process can result from robustness evaluations.

The scattering in the positioning of the dummy often significantly influenced the scatter of important response variables of passive safety load cases. So far one abandoned the readjustment of the positioning of feet and arms when automatically varying the x- and z-position of the dummy. Therefor the feet did not stand exactly in the feet room. However, since the stochastic variation of the dummy position was a decisive factor in many robustness evaluations the need for automation in positioning arose. In 2006 an update of the dummy position after variation of the H-point was introduced for some MADYMO dummies and included into the automated workflow of robustness evaluations.

3.3 Numerical Robustness of CAE Process

For all load cases parallel robustness evaluations concerning input parameters scattering in nature and "numerical" robustness evaluations concerning the variation of numerical parameters were performed in the beginning of the systematic introduction of computational robustness evaluations. The evaluation of numerical robustness of the model results from the experience that already the variation of numerical parameters of the approximation method leads to large scatter of result variables and respectively sometimes leads to obviously unusable results. If n-designs are computed and their variation is analysed statistically one has to ask how much of the result variation derives from problems within the approximation method. Evaluation criteria to tell if a model is numerical robust was the proportion of the resulting output scatter. If the scatter came from the influence of variation of numerical parameters, like time step increment, hourglass mechanisms or contact settings were for example a power of ten smaller than the scatter resulting from physical input scatter, one assumed that the models delivered prognoses which were numerically stable compared to the expected real scatter. However, the question by what degree a numerical parameter should be varied arose quickly. Respectively it was asked how reasonable a variation of numerical parameters which often had been "adjusted" by component verification is overall. In summary it had to be concluded that numerical problems of the models can be discovered (amount of resulting scatter clearly is to high or occurring of obviously wrong results) using numerical robustness evaluations but it was not possible to quantitatively evaluate if the numerical models were "robust" enough. It should also be stated that numerical robustness evaluations can differ for every point in the "physical" space of the robustness evaluation. Contact algorithms shall be pointed out as an example which flawlessly execute in the reference design as long as the numerical parameters are varied but when considering the scatter of geometric parameters fail.

3.4 Using Measures of Determination to Secure Model Robustness

The influence of numerical noise on the results should better be estimated using the measure of determination of robustness evaluations concerning scatter as it occurs in nature. If the coefficient of determination of the robustness evaluation is large only a small of proportion variation remains unidentified. This proportion may include numerical noise. In order to use the coefficient of determination of result variables as quantitative measure for numerical model robustness the determination proportions of the found correlations have to be estimated with sufficient statistic certainty. This formulates also requirements of the sampling method, the amount of computations and the statistic algorithms for estimating the coefficient of determination [9]. This resulted in important specifications for further development of the stochastic methods, which were included in optiSLang [19] step by step within the first stage of the project. After having made very positive experience with the estimation of the influence of numerical noise using coefficients of determination of robustness evaluations, the workflow was reconverted for virtual product development process. Now robustness evaluations regarding real-world scatter are performed for all important load cases and only in the case of low coefficients of determination the numerical robustness evaluation is used for diagnosing numerical problems. Thereby as a general rule coefficients of determination of over 80% could be determined for "numerically" robust models after incorporating linear and quadratic correlations and after eliminating outliers and clustering. So far it was a certain sign that the result variable contained an unacceptable coefficient of numerical noise if the coefficient of determination fell below 60%. This was caused by insufficiency of the result extraction and especially by insufficiency of the numerical models interacting with the numerical approximation methods. After repairing the numerical model the coefficient of determination normally rose to over 80%.

It shall be stated that it is theoretically not possible to identify the proportion of numerical noise doubtless. The detour eliminating linear and quadratic correlations as well as the influence of outliers and clustering on coefficients of determination identifies a remainder of "unexplained" scatter of the result variables, which potentially derives from higher dimensional (cubic, sine-shaped) correlations, further nonlinearities (bifurcation points) or from numerical noise. This diagnosis excludes systematic errors or the inability to map significant physical effects of input variables to the output variation. The fundamental ability of prognosis of the numerical models has to take place by verifying experimental data. The topic of bifurcation points has to be taken into account separately. Systems with bifurcation points, which can be traversed within the scatter range of input variables and lead to fundamentally different system responses, would be something that should be prevented in terms of robust design. Basically one, however, also has to be able to find correlations associated with that type of incident, otherwise it would be implied that these bifurcations happen randomly and we are dealing with very sensitive dynamic systems. In general the correlation between input variables and output variables should be identifiable for robust design. These correlations then show the possibilities to influence the result scatter. They can be used for reduction of the probability of overstepping e.g. for linear correlations by moving mean values or for quadratic correlations by reducing input scatter or changing the transmission behaviour of input scatter and output scatter by constructive changes.

4. Integration of Robustness Evaluations in the Virtual Development Process of Restraint Systems

One should assume that a consequent introduction of stochastic computation methods can be divided in at least two phases.

Phase 1: Scatter and uncertainties of input variables are estimated from a few measurements and empirical values:

- Transfer of existing knowledge on input scatter and uncertainties of testing conditions in distribution functions as suitable input for stochastic methods.
- Robustness evaluation of important crash-test load cases, estimation of the variance of important vehicle performance variables, inspection if limit values are exceeded by the variation of the performance variables.
- Inspection of model robustness/stability using coefficients of determination.
- Extraction of significant scattering input variables and coefficients of determination of transmission behaviour of the input scatter on important performance variables as well as the matching of these mechanisms with expectations and knowledge based on the experiments.

Within and respectively as result of phase 1 the following has to be discussed and arranged:

- At which point in time robustness evaluations of components, modules or whole vehicles are performed
- For which input scatter the assumptions about the scatter have to be re-evaluated and as the case may be verified
- How scatter of critical performance variables can be reduced or relocated
- Which exceeding probabilities are tolerable for the performance variables

Phase 2: sensitive scattering input variables are known and the assumptions about their scatter are verified:

- With secured knowledge about the input scatter robustness evaluations are performed at predefined milestones of virtual product process
- Assuming that all important input scatter were considered close to reality and that the numerical models show negligible numerical noise then the estimate of the scatter of important input variables is trustworthy.

In the second year of the serial use of stochastic analysis in passenger simulation at BMW we currently are in phase 2. The following surplus value could be obtained concerning dimensioning and increase of the robustness of the restraint systems:

- Development of a better understanding of the transmission mechanisms of input scatter on significant performance variables
- Identification of the significant scattering input parameters and securing of knowledge about their scattering
- Identification of model weaknesses and reduction of numerical noise of significant vehicle performance variables. Thereby increasing the model robustness/stability and of the quality of prognosis of crash-test computations

- Recognising of robustness problems of the restraint systems and in cases of high exceeding of aimed at limits with the consequence of redesign of components
- Further development of the numerical method of robustness evaluation (quadratic correlations, coefficients of determination, trustworthy estimation of probabilities to exceed limits from the histograms)
- Further development of the degree of automation in robustness evaluation by automatic readjusting of the dummy positioning for MADYMO models

5. Practical Application

5.1 Robustness Evaluation USNCAP

For the load case USNCAP (front crash 56 km/h into rigid wall) the robustness concerning important performance variables of the driver was evaluated. The model was constructed using MADYMO. The robustness evaluation was performed using optiSLang [10]. Important parts of the restraint systems and the Dummy were used in multi-body-formulation. The FE-model of the airbag was validated by the supplier with component experiments and integrated into the BMW passenger model.

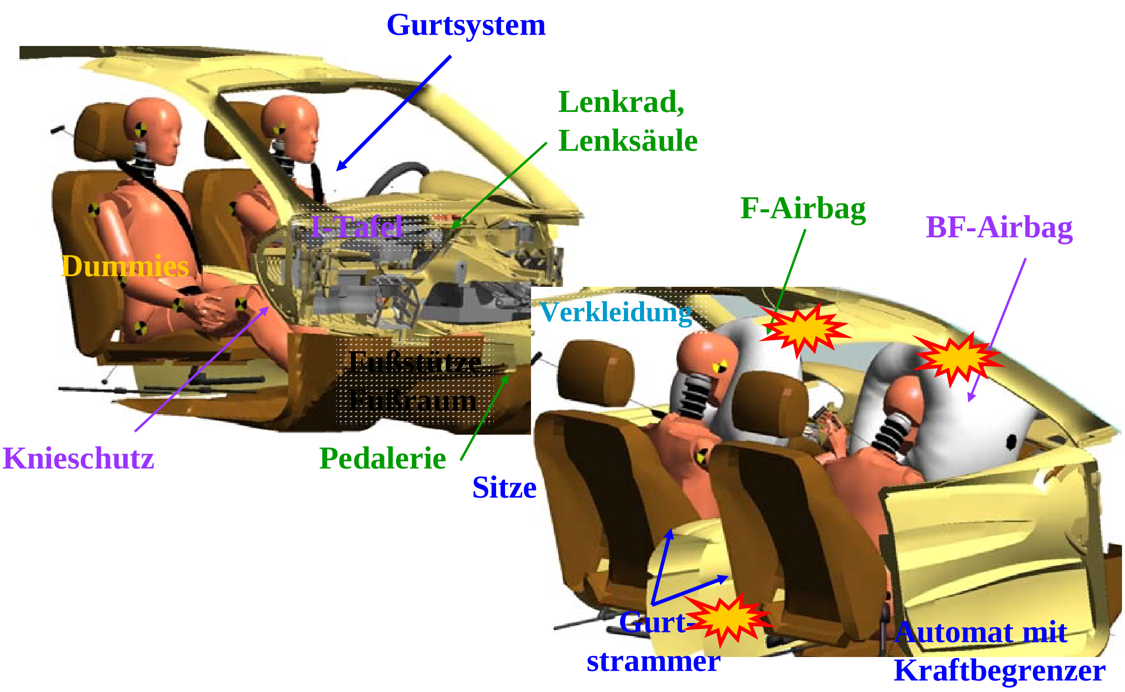

Figure 2: Simulation frontal crash load case USNCAP

For the robustness evaluation 200 variants were generated using Latin Hypercube Sampling and then computed. Overall 9 physical parameters of the multi-body/FE-modelling were varied and 12 dummy result variables were evaluated in robustness evaluation. For the definition of scatter the normal distribution and respectively cut-off normal distribution were used. The following scattering input variables were taken into account during 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

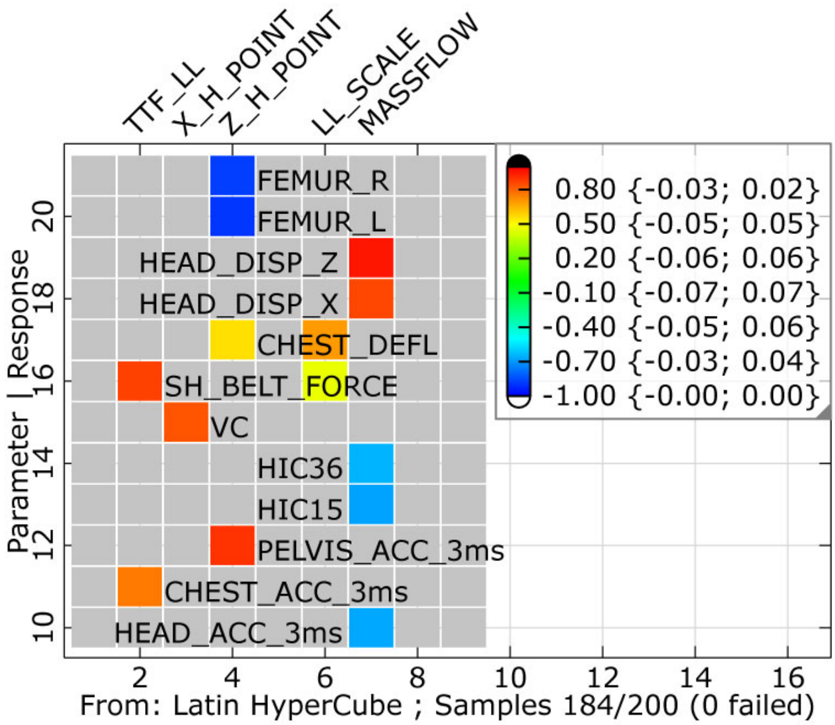

Figure 3: Linear correlation structure

Of the 9 input scatters only 5 input variables feature notable correlations to the result variables. In the matrix of linear correlation (figure 3) 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 4 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 5).

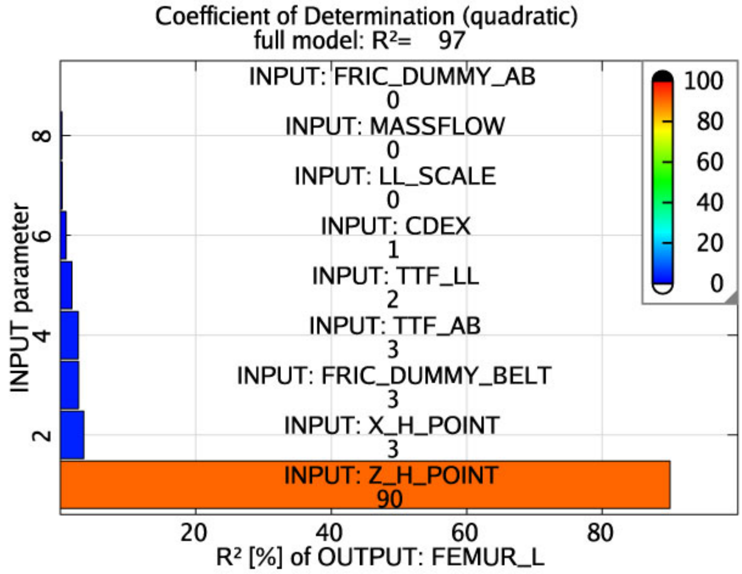

Figure 4: Coefficients of determination femur force left

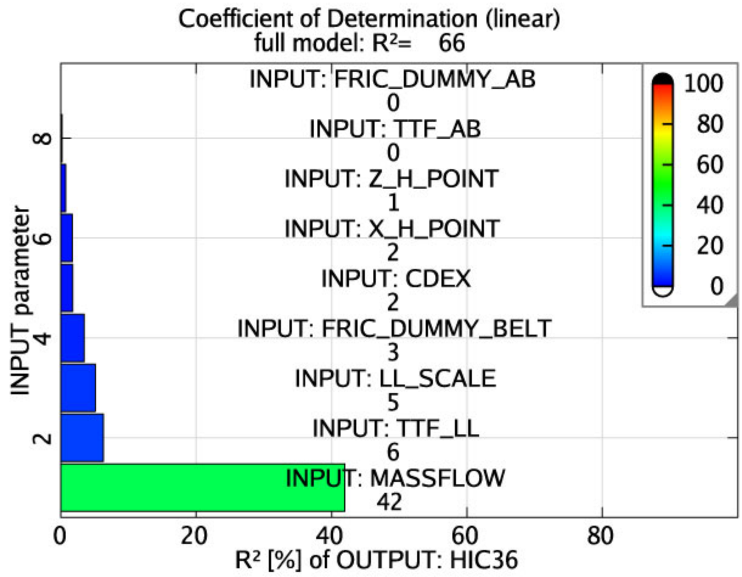

Figure 5: Coefficient of determination HIC36

Also in tests for quadratic correlation, outliers or clustering no further correlation could be shown. Since a large proportion of the scatter concerning the HIC36-Wertes can not be explained using the identified correlations to scattering input variables, a significant amount of numerical noise is suspected here. Therefor the reference design of the driver was examined concerning numerical robustness. Overall 17 numerical parameters, like for example scaling factors of the time-steps, the contacts or the „numerical“ damping factors of the multi-body/FE-modelling were varied and 22 dummy result variables were examined in the robustness evaluation. For the USNCAP evaluation 2 response variables (thorax acceleration 3ms, HIC36) from the set of examined 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 6), very large variation could be observed, which lie about in the range of the scatter caused by the physical input scatter of this load case. Since this dimension of numerical noise is not acceptable, the responsible input variables were identified.

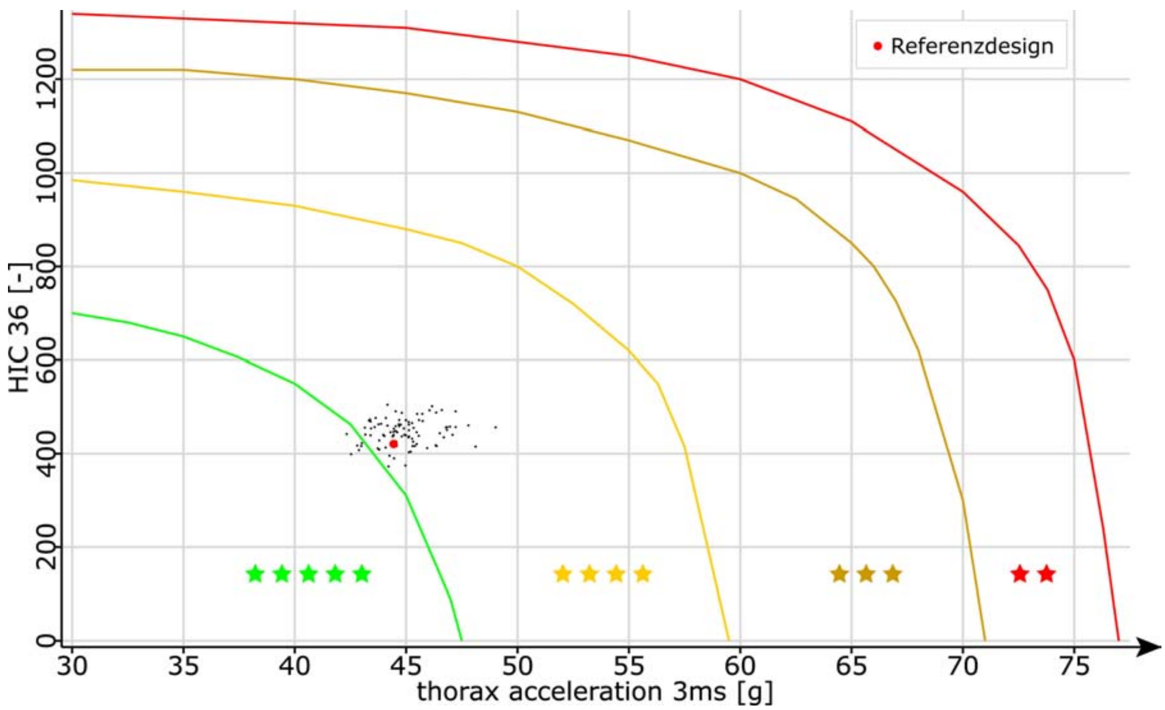

Figure 6: Visualisation of the numerical scatter in the star diagram, USNCAP Rating

In the matrix of the linear correlations (figure 7) 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 8). By analysing “suspicious” result sets some incapacities of modelling 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

9), which could be ignored considering the scatter from physical input variables. Thereby the numerical robustness of the improved modelling could be proven and the foundation for evaluation and optimisation 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 modelling errors could be identified and eliminated and the final robustness evaluations showed an acceptable measure of scattering of important input variables.

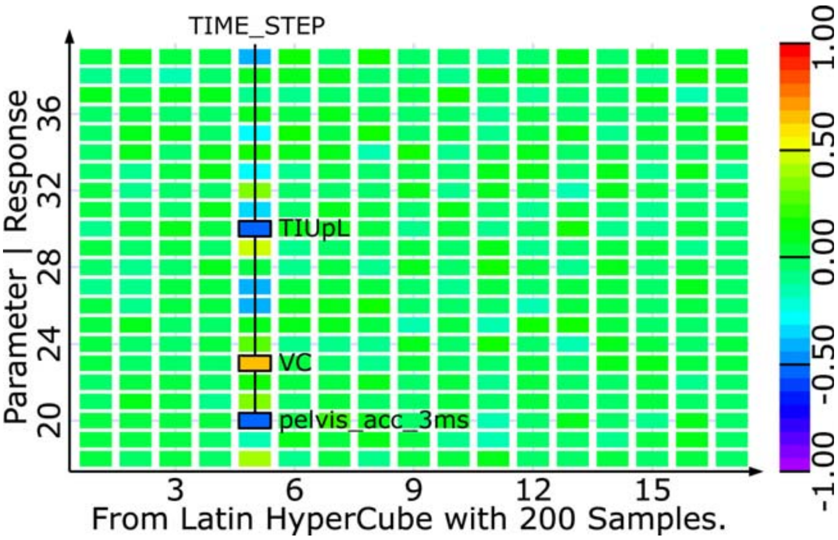

Figure 7: Linear correlation matrix

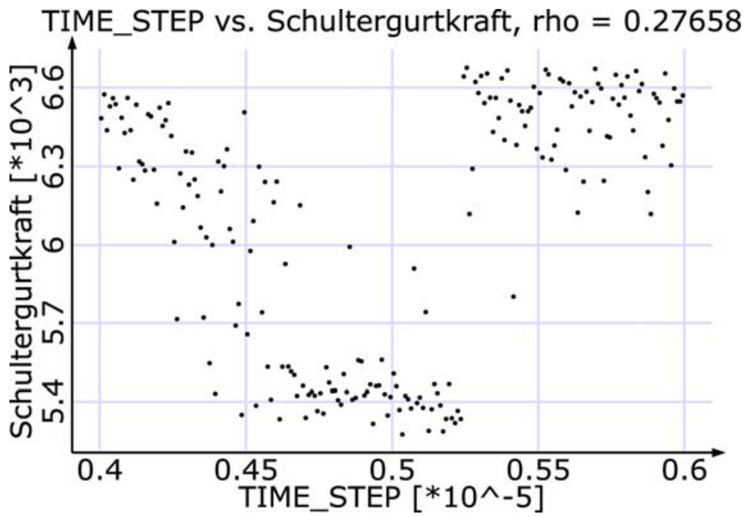

Figure 8: Visualisation of correlations between the variation of multi-body time step and the shoulder belt force in the anthill-plot

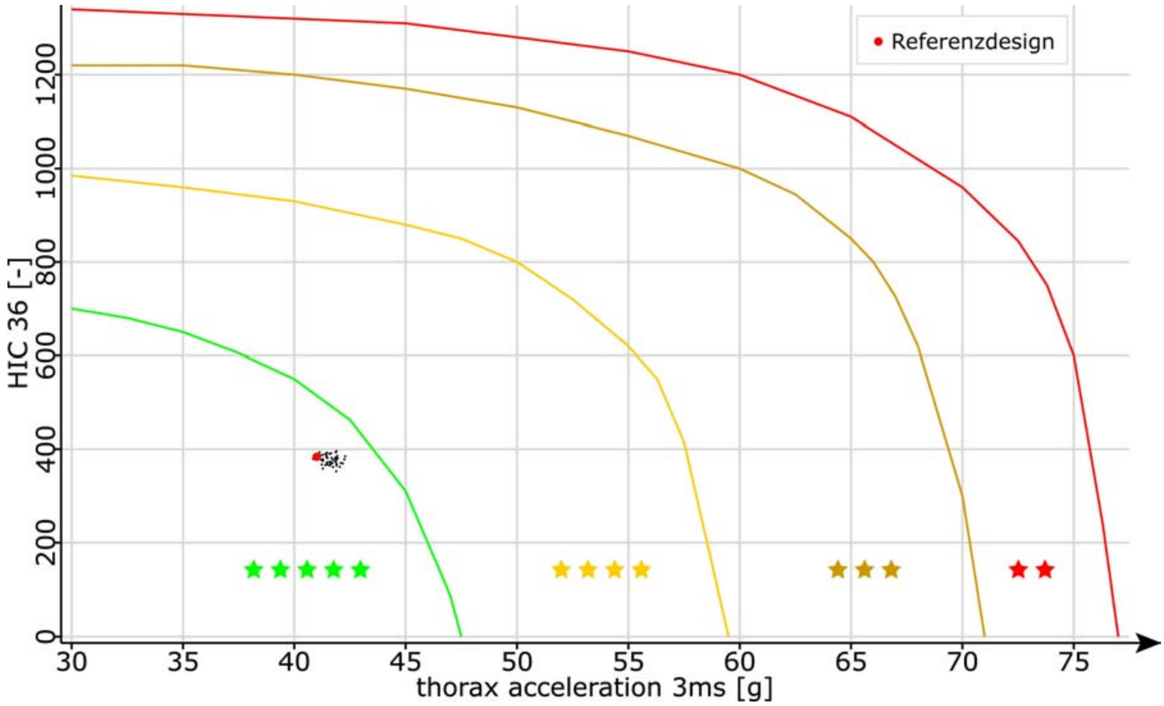

Figure 9: Visualisation of numerical noise in the star diagram, USNCAP Rating

5.2 Robustness Evaluation FMVSS 208

In an early stage of vehicle design the robustness of the load case FMVSS 208 (Frontcrash 40 km/h unbelted into rigid wall) was evaluated concerning important performance variables of the driver and front-seat passenger.

Figure 10: Simulation passenger safety load case FMVSS 208

The model was constructed in MADYMO and computed. Important parts of the Dummy were used in multi-body-formulation whilst the airbag was modelled using an FE-formulation. For the robustness evaluation 200 variants were generated using optiSLang Latin Hypercube Sampling and then computed. Overall 27 physical parameters of the multi-body/FE-modelling were varied and 18 dummy result variables were evaluated in robustness evaluation. For the definition of scatter the normal distribution and respectively cut-off normal distribution were used. The following scattering input variables were taken into account of during 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, airbag and steering wheel as well as between dummy and seat
- Scattering of impact puls
- Scattering of feet space, foot rest, pedal

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
- Head displacement x
- Pelvis displacement x
- Chest deflection
- Steering column displacement
- Neck compression
- Neck tension
- Neck injury: tension-extension
- Neck injury: tension-flexion
- Neck injury: compression-extension
- Neck injury: compression-flexion
- Distance head – roof (virtual penetration)

Most important result of the robustness evaluation was the calculation of variation intervals of the performance variables (figure 11). Even though no limits were exceeded the scatter of single performance variables was high.

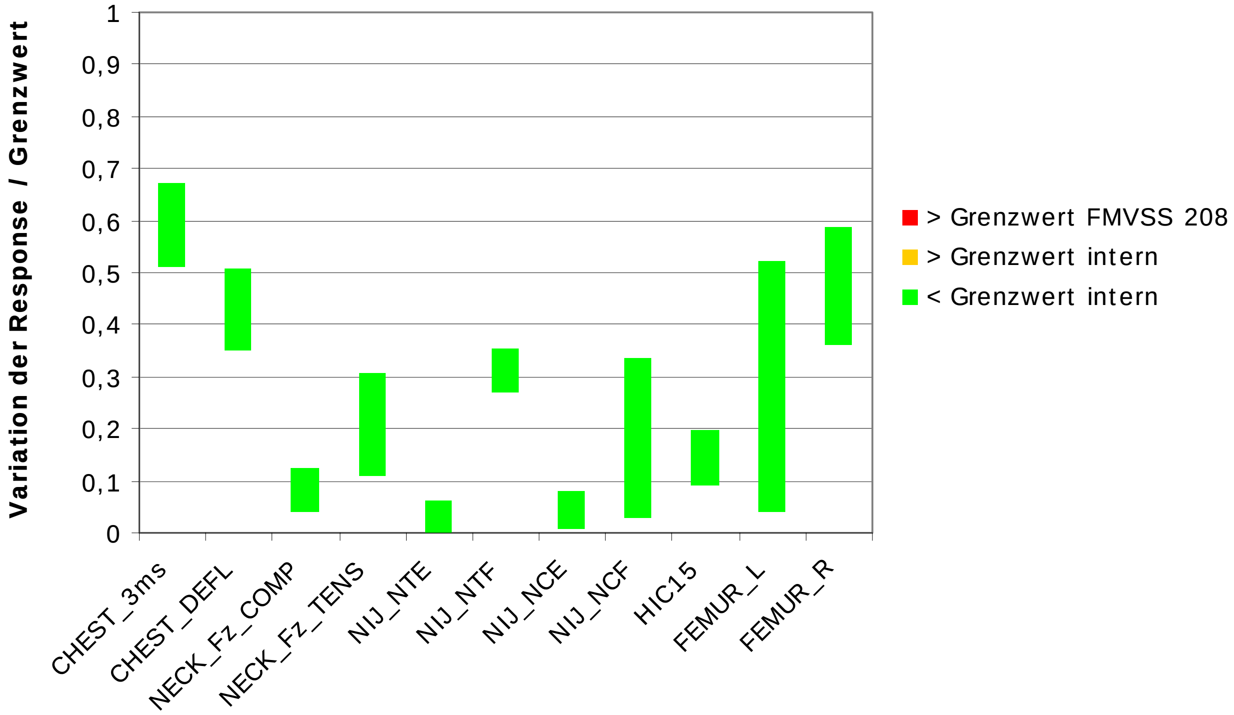

Figure 11: Visualisation of the normalised variation ranges

Of the 29 input scatters only 9 input variables show significant correlation to the result variables. Within the matrix of the linear correlations (figure 12) not for all important performance variables significant linear dependencies (correlation coefficient >0.50) on the input scatter could be determined. This can hint a high amount of numerical noise. Therefore it was examined for the result variables if higher coefficients of determination could be found using quadratic correlations and respectively eliminating non-linearities (outliers, clusters). However, no correlations which significantly affect the coefficients of determination except linear correlations between input and output scatter could be identified. The determination for single output variables thereby heavily varies. Thereby a high maximum femur force (figure 13) can be explained with very high determination, the variation of the HIC-value, however, only to less than 50% (figure 14).

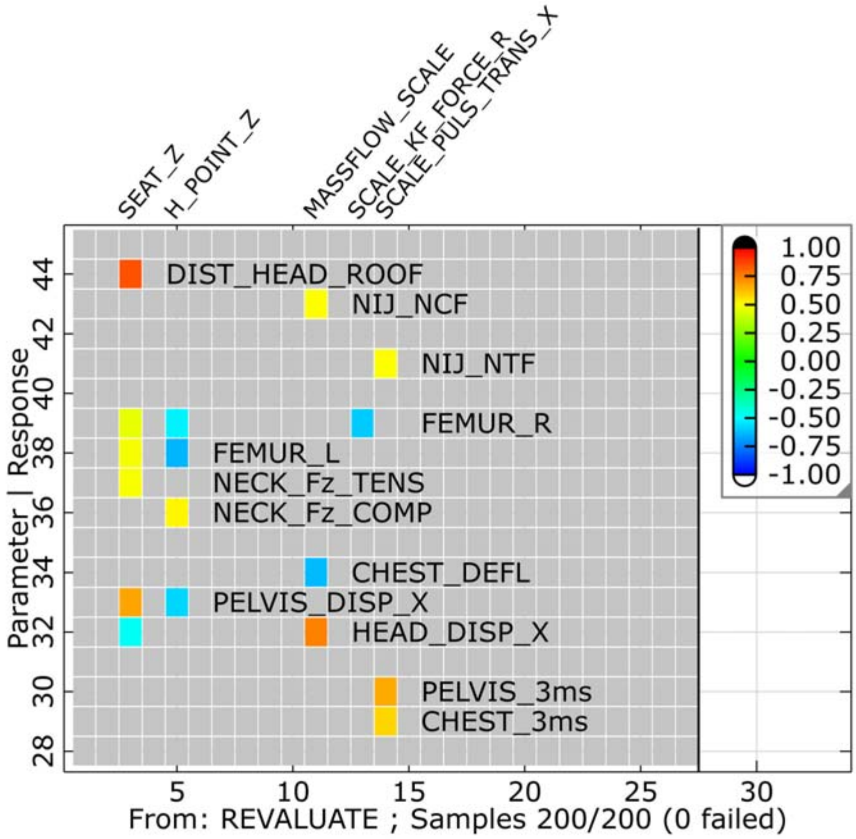

Figure 12: matrix of linear correlations

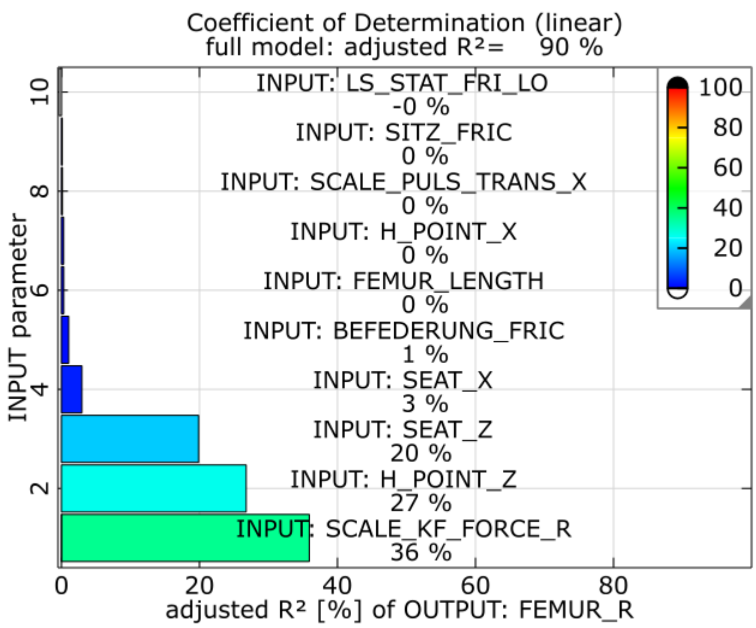

Figure 13: Coefficient of determination femur force right

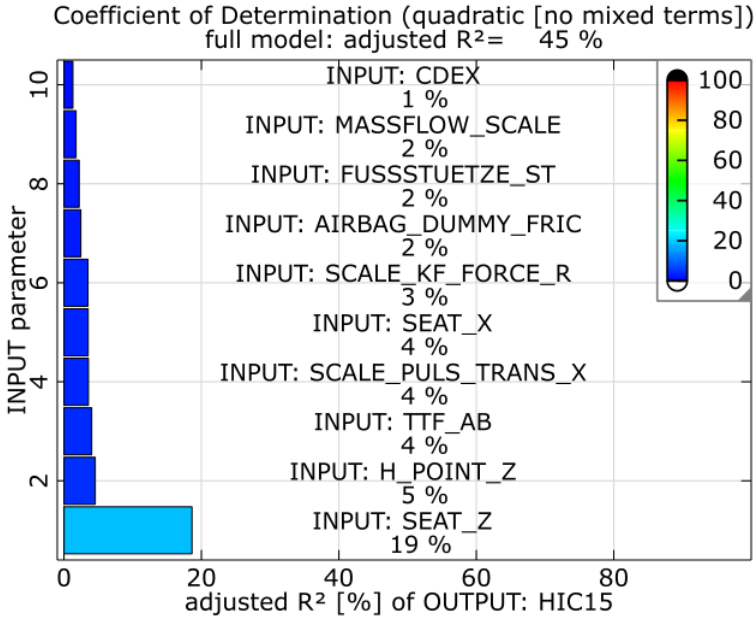

Figure 14: Coefficient of determination HIC15

Therefor a numerical robustness evaluation on the reference model was performed in order to verify the model robustness. Eight numerical parameters, like for example scaling factors of the time steps, contact scaling factors or the „numerical“ damping of the multi-body/FE-modelling were varied and evaluated together with 18 result variables. The resulting scatter of the performance variables were compared to the scatter from the physical robustness evaluation (figure 15). As expected the numerical noise in variables with high coefficient of determination from the physical robustness evaluation, like the femur forces is of negligible dimension. As expected, significant scatter occurs for the performance variable HIC15, caused by the variation of the numerical parameters. In this model the large scattering of the thorax values are also critical compared to the physical robustness evaluation. Even though these performance variables showed coefficients of determination close to 80% in the physical robustness evaluation, their scattering caused by variation of numerical parameters exceed even those of the HIC15-values. This example shows it can not be assumed that the measure of numerical noise concerning the trust-range can be linearly be derived from the coefficients of determination. If significant variation occur in the numerical robustness evaluation one can only assume that the calculation of scatter of the physical robustness evaluation is too large. However, no significant correlation (linear or quadratic) of single input variables of numerical characteristics concerning the observed scatter of performance variables could be seen. Therefor the cause of the numerical noise could not be directly identified from the numerical robustness evaluation.

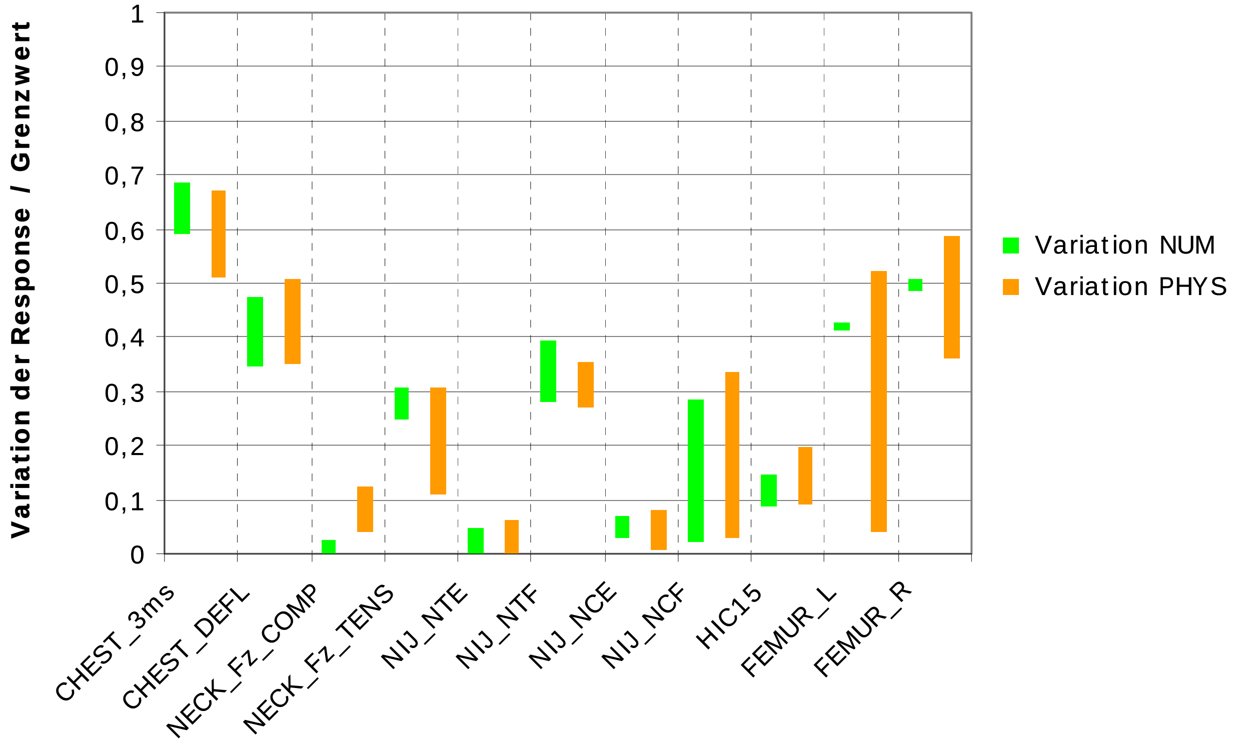

Figure 15: Comparison of the variation intervals of physical and numerical robustness evaluation

The robustness evaluations in the early stage of vehicle design showed that the performance variables including the consideration of input scatter lie beneath the aimed at limit values. At the same time it was shown that the current model stage of the multi-body/FE-modelling includes a large amount of numerical noise which leads to large uncertainties when calculating deterministic results (single values) or stochastic results (variation-ranges). Therefor until the next milestones the models will be reworked with the goal to reduce the numerical noise.

6. Summary

A method was developed and integrated into the virtual development process of restraint system which allows the inspection of the influence of scattering input parameters on significant performance variables. Primary result of the robustness evaluation is the calculation on the scatter range of performance variables and the connected probability of keeping to consumer protection criteria. Secondary result is the securing of numerical stability of the models and the identification of input scatter which is responsible decisively for the output scatter. Thereby the robustness evaluations give important hints for necessary modifications of the multi-body/FE models as well as the necessity of reducing input scatter or hints on necessary modifications of the restraint systems. The assumptions of scattering input variables, which are significantly responsible for the scattering of important result variables, are validated systematically and where possible, backed by experimental data. Central performance measure for the numerical stability of the models is the coefficient of determination. If low measures of determination can be determined for significant result variables, numerical robustness evaluations are performed in order to evaluate the quantity of the numerical noise. At the same time correlations between the variation of numerical parameters and important result variables and comparisons between strongly varying result sets are consulted for identification of numerical problems.

Thereby it is secured that all input scatter that is significant for the performance variables to estimate is captured close to reality and that the numerical models cause little numerical noise as well as that the prognoses about the scatter of result variables is trustworthy.

7. Literaturangaben

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