Robustness evaluations concerning virtual dimensioning of passive vehicle safety

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Summary

One of the most important tasks of vehicle development is the steady improvement of passive safety systems. Therefore collision scenarios, which are predefined by law and consumer protection, are pre-estimated in virtual product design and verified in various test scenarios. In these crash tests significant scatter of important performance values of the restraint systems can be determined. This is caused by scatter of input variables, parameters of dimensioning of passive safety systems and vehicle structure as well as the test conditions. Considering input scatter in virtual product design as well as economical dimensioning of restrain systems concerning an acceptable probability of transgression of scattering performance variables can only be achieved by integrating stochastic simulation methods into virtual product development. In the first part of this paper necessary constraints for successful integration of stochastic analysis for computational robustness evaluation into the process of virtual development of dimensioning passive vehicle safety as well as the status quo of the implementation at BMW are discussed. In the second part computational robustness evaluations are performed exemplarily.

Keywords: computational robustness evaluations, stochastic analysis

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1 Introduction

One of the most important tasks of vehicle development is the steady improvement of passive safety systems. Therefore collision scenarios, which are predefined by law and consumer protection, are pre-estimated in virtual product design and verified on the vehicle in various test scenarios. In the past deterministic models have been used for the virtual dimensioning of passive safety systems via multi-body or finite element programs. That is deterministic values were used for the input parameters like vehicle geometries, airbag mass-flow or seat position of the dummy.

In reality significant scatter can be detected when performing crash-tests. Cause of scattering of important performance variables is scattering of input variables, as well as scattering of parameters of dimensioning of passive safety systems, parameters of the vehicle structure as well as testing conditions. This leads to the necessity of pre-computation not only of single-values and also to the necessity of extracting preferably exact predictions of scatter of important performance variables concerning expected testing results.

One possible approach, estimating scatter of experimental result via computation of “worst case” cases with inferior or superior boundaries of input parameters, becomes increasingly unfeasible because of the complexity of the restrain systems and their numerical models. In addition the definition of a “worst case” brings up the question, with which probability the “worst case” a possible experimental outcome shall be excluded. If the “worst cases” are chosen very conservatively for want of reliable data on the probabilities, a covering using “worst cases” will lead to uneconomical structures.

Consideration of input scatter in virtual product development, as well as economic dimensioning of restrain systems considering acceptable transgression probabilities of scattering performance variables, can only be achieved by integrating stochastic simulation methods into virtual product design.

At this point it shall be stated that the necessity of stochastic simulation methods furthermore increases through trends in virtual product design.

- Through increasing optimization designs can reach their own limits and become very sensitive concerning scatter.
- Because hardware cycles occur later and more infrequent, the influence of scatter, which was present during hardware tests and its influence that therefore at least was collected in random sample tests, has to be considered in virtual product design.
- If bigger and bigger product revisions (high speed of innovation) take place in shorter periods of time and more and more complex component systems than the a priori knowledge (empirical values) about their reliable

functioning is little. The robustness of the systems has to be evaluated using virtual models.
- Fundamental decisions concerning the vehicle concept have top be made in early stages of development on basis of virtual dimensioning. This requires best possible knowledge of the degree of fulfilment of laws and consumer protection standards (like EURONCAP) and respectively a quantitative estimation of the residual risk.

In order to include the sometimes “chaotically” seeming behaviour of vehicle crash tests and especially its computation in relation to small changes of boundary conditions, at least two essential boundary conditions have to be met.

The present knowledge of input scatter and uncertainties e.g. in boundary conditions, material data or loading characteristic is to be translated into an adequate statistic description, the so called distribution information and integrated into virtual product design as fundamental input information of stochastic analysis. At the same time it is to be made sure that the used numerical models include all physical phenomena that are connected with the significant scatter and that the methods of approximation for computation (explicit FEM, multi-body programs) do not cause to much scatter (numerical noise) of the performance variables.

The resulting prognoses concerning scatter of experimental results are not reliable until all performance variables and significant input scatter are taken into account and the numerical models and CAE-solver allow an appropriate prognosis. It shall be stated that important information about the transmission mechanisms of input scatter can be collected and the quality/ability of prognosis of the computation can be significantly improved en route. It is not to be assumed that all significant input scatter at the begin of stochastic computations can be captured close to reality in practical application, this also applies to the ability of prognosis of the simulation processes. Therefore one realistically will start with relatively rough estimates of the input scatter and improve the knowledge about important input scatter step by step.

Numerical robustness evaluations are performed in order to evaluate the scatter of performance variables which result from deficiencies of the used models or from errors in the approximation methods. During these evaluations numerical parameters like time step, scaling factors and contact settings are varied and their influence on the result variables is analysed. In order to secure the ability of prognosis the “scatter” of important performance variable as a result of numerical noise of numerical models should be marginal compared to the scattering of performance variables from physical input scatter (which occurs in the real vehicle). At this point it should be stated that separate analysis of numerically caused scatter and physically caused scatter is strongly recommended. When confronted with problems that include bifurcation points the separation of influences caused by numerical noise and those caused by physical phenomena includes identification of physical parameters that operate on bifurcation points. If it is not possible to keep the scatter caused by numerical influences marginal the ability of prognosis of the pre-computation might not be reliable.

2 Computational Robustness Evaluation

2.1 Statistical Description of the Input Variables

Physical input scatter is described using a distribution function. Important distributions are e.g. uniform distribution for friction values, normal distribution for airbag mass flow parameter and log-normal distribution for material yield stress. If correlations between scattering input variables exist they have to be taken into account concerning the input information.

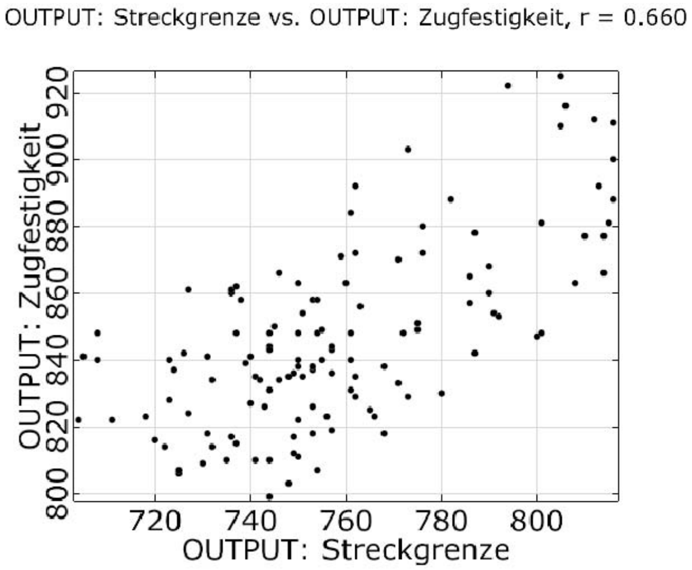

Figure1: Correlation between scatter of tensile strength and yield strength of steel

An example of an important correlation between input scatter is the correlation between tensile strength and yield strength of steel. Here for example one would determine the correlation coefficients between both of the scattering input variables from existing measured data of an intake control (see figure 1) and consider them as input information of stochastic sampling methods.

It shall be pointed out that naturally the significance of stochastic computation depends mainly on the quality of the stochastic input data. Often the distribution functions are estimated in the beginning of processing based on relatively rough assumptions about possible scatter. If the important input variables are identified via robustness evaluation one has to verify the assumptions concerning the scatter and if necessary re-evaluate those assumptions.

2.2 Robustness Evaluations

Robustness evaluation analyse the scatter of the performance values as well as the sensitivity of important performance values concerning scatter of physical input variables. Considering the input information of the scatter some amount of possible realisations are created and computed using stochastic sampling methods. Then correlations (connections between variables) and the variance of the performance variables are analysed and evaluated using statistical measures. In order to keep the amount of necessary computations for reaching an acceptable error of the estimate of the statistical measure small Latin Hypercube Sampling is used. For typical robustness evaluations of restrain systems using Latin Hypercube Sampling and an acceptable error of the estimation of the linear correlation coefficients of 0.5 ±0.1 about 100 supporting points are sufficient.

Important statistical measures for evaluation of robustness are:
- Coefficient of correlation of linear and quadratic correlation hypotheses between input scatter and response variable show pair wise dependencies. The higher the absolute value of the correlation coefficient the higher the linear or respectively the quadratic correlation between the two variables.

- Principal Component Analysis (PCA). The input vectors of the correlation matrix show dependencies from several input variables to several result variables. This way mechanisms of the correlation structure can be identified.

- Coefficients of determination of the correlation hypotheses. Coefficients of determination of response variables determine what percentage of the variation of a response variable can be explained via identified correlation to all input variables. If the coefficient of determination is large (maximally 100%) then the significant correlation can be determined using the underlying correlation hypothesis. The smaller the coefficients of correlation are the larger the ratio of variance in the result variables that can not be explained using the correlation hypotheses (e.g. linear and quadratic). Than typically non-linear correlations, clustering, outlier or a high amount of numerical noise exist. Therefor the coefficients of determination also provide information about the possible ratio of numerical noise and that provides an important quality characteristic for the used numerical modelling.

- Histograms including mean value, coefficient of variation, standard deviation, minimum and maximum values of the evaluation variables. Usually scattering around mean values is evaluated when performing robustness evaluations. When evaluating minimum and maximum value it shall be pointed out that these are estimates from a “random” sample. Furthermore it shall be pointed out that in order to secure very unlikely events it is necessary to compute the corresponding appearance probabilities. Because often only a small amount of samples (100-

200) are computed, only probabilities in the percent range can be estimated reliable.

2.3 Integration of Robustness Evaluations in Virtual development and dimensioning of Restraint Systems

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

Phase 1: Scattering and uncertainties of the input variables are estimated from a few measurements and experience values.

- Transferring of the existing knowledge about input scatter and uncertainties of the test conditions into distribution functions as adequate input of stochastic methods.
- Review of model robustness/model stability concerning the variation of “numerical” parameters.
- Robustness evaluation of the test loading cases concerning “physical” input scatter.
- Extraction of important scattering input variables and determination of the response characteristics of the input scatter onto important performance variables as well as the alignment of these mechanisms with the expectations and experiences from the experiments.
- Review if as result of the variation the performance variables limits are exceeded.

Within and respectively as result of this phase 1 the following is discussed and constituted

- At which point in time of virtual development robustness evaluations of components or complete vehicles are performed.
- For which important input scatter the assumptions concerning the scatter are to be reviewed and possibly verified.
- Which significant input scatter can be decreased.
- How critical scatter of performance variables can be decreased or relocated.
- Which probabilities of exceeding are tolerable for the response variables.

Phase 2: sensitive scattering input variables are known, the assumptions concerning this scatter are verified

- With secured knowledge about the input scatter robustness evaluations are performed at defined milestones of the virtual product design process.
- If it can be assumed that all important input scatter are considered close to reality and the numerical models are sufficiently reliable then the estimates of scatter of important result variables are trustworthy.
- In order to secure small exceeding probabilities one can perform reliability analysis after the significantly scattering parameters are known.

Since beginning of 2005 the BMW AG uses systematic robustness evaluation for the dimensioning of restraint systems. After a year of serial use of stochastic analysis we are at the end of Phase 1. The following surplus values could be achieved within the robustness evaluations of the restraint systems:

- Formulation of a better understanding of the transmission behaviour of input scatter on important performance variables.
- Identification of significant scattering input parameters
- Identification of model weaknesses and thereby increase of the model robustness/model stability concerning the variation of numerical parameters and thereby an improvement of the prognosis quality of the crash test computations.
- Identification of robustness problems of the restraint systems in cases with common exceeding of aimed at limits with the consequence of redesign of components.

3 Practical Applications

3.1 Example concerning numerical Robustness

In order to optimally construct the loading case USNCAP (frontal crash 56 km/h against a rigid wall) the simulation model for the driver initially was examined concerning numerical robustness. The model was generated and computed in MADYMO. The robustness evaluations were performed using optiSLang. Important parts of the restraint system and the dummy are used as multi body-formulation and a FE-formulation for the airbag.

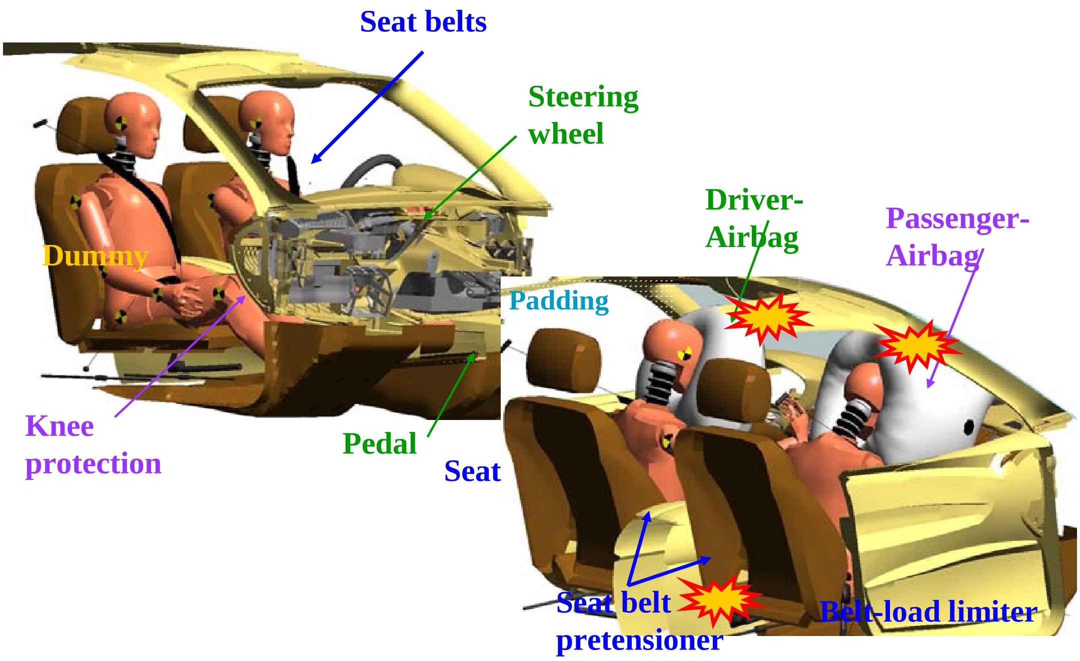

Figure 2: Simulation frontal crash using MADYMO

The simulation model of the airbag was validated by the supplier in component tests and integrated into the vehicle by BMW. Overall 17 numerical parameters of the MBD/FE-model were varied and 22 dummy result variables were examined in the robustness evaluation. Even though only two response variables (thorax acceleration 3ms, HIC36) were evaluated for the loading case USNCAP the following responses were examined:

- Head resultant acceleration 3 ms
- Thorax 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
- Tibia index (4 responses)
- Neck injury (4 responses)
- Neck compression / tension
- Neck tension

Deciding criteria for the numerical robustness is the degree of scatter of significant result variables. As a plot in the star diagram (fig. 3) shows very large variations could be observed, which lie in the order of magnitude of the variation caused by physical input scatter for this loading case. Because this dimension of numerical noise is unacceptable the responsible input variables were identified.

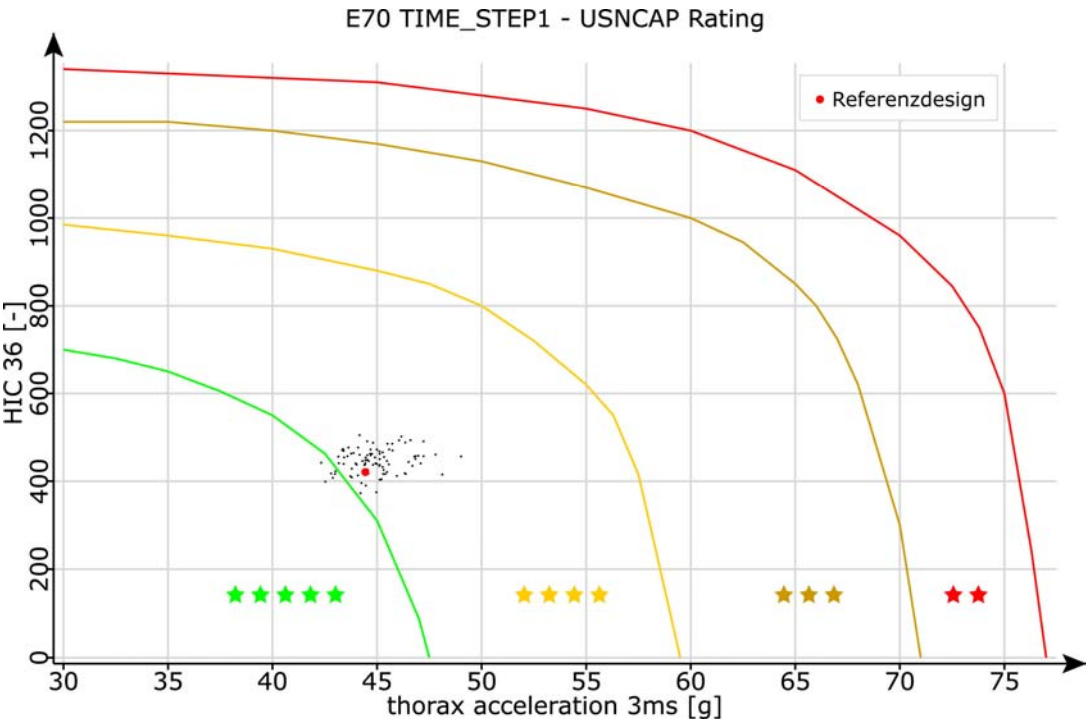

Figure 3: Visualisation of numerical noise in the star diagram

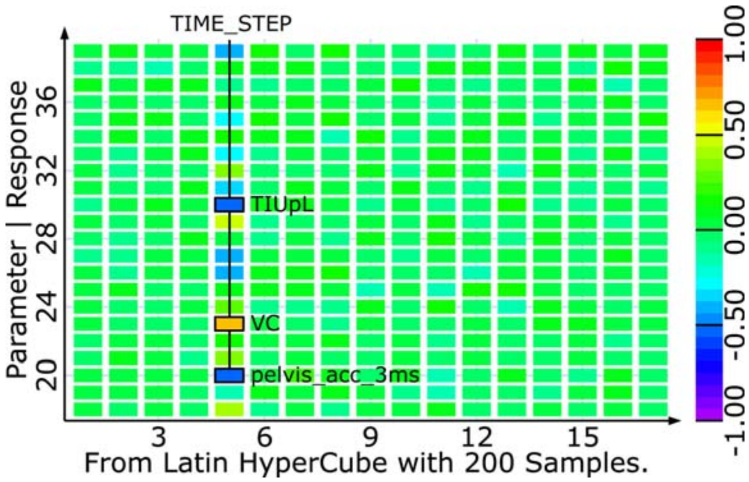

Figure 4: Linear correlation matrix

In the matrix of linear correlation (fig. 4) one can clearly seen, that noteworthy correlations only exist at multi-body time steps, which reach a coefficient of correlation of 0.7 for some of the result variables (fig. 5).

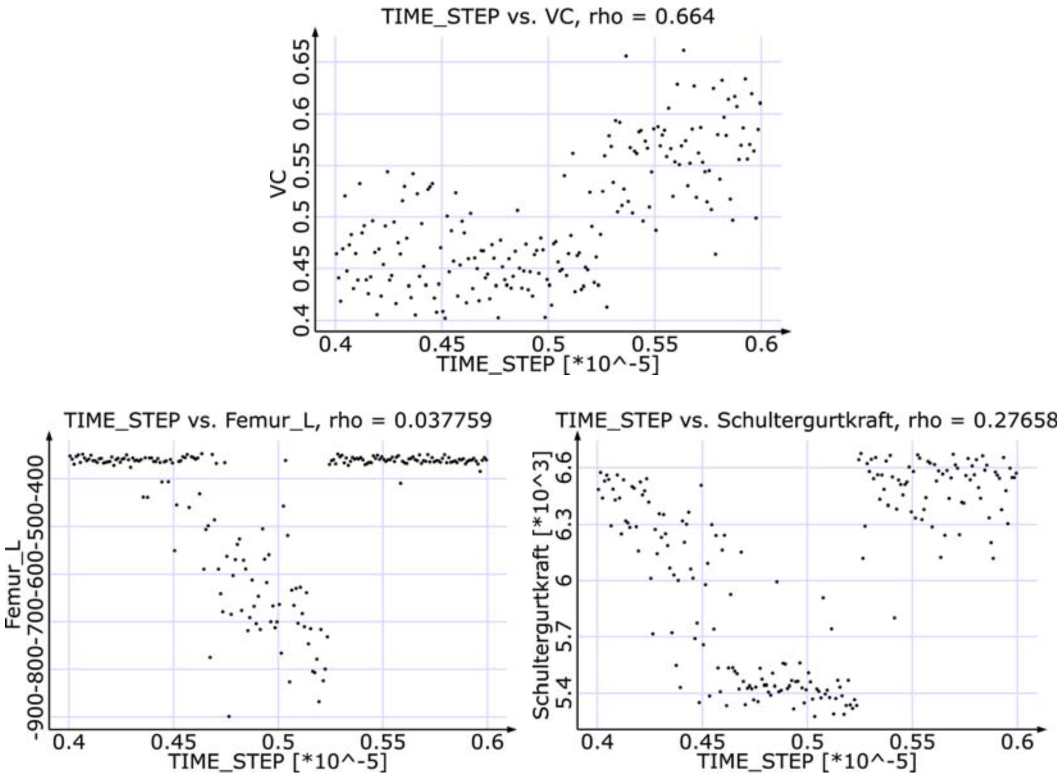

Figure 5: Visualisation of correlations between the variation of the multi-body time step and the dummy result variables in the anthill-plot.

Furthermore only noticeable non-linear correlations and clustering which significantly correlated to the choice of the multi-body time-step could be identified concerning response variables with small measures of determination (smaller than

50%). By analysing suspicious sets of results insufficiencies of the model in correlation with airbag and dummy could be recognised and eliminated. A final numerical robustness evaluation resulted in significantly lower scatter caused by variation of numerical parameters (fig. 6). This scatter was now negligible compared to physical scattering of the input variables. This way the numerical robustness of the improved modelling could be proven and the foundation for a optimisation of the restraint systems could be made.

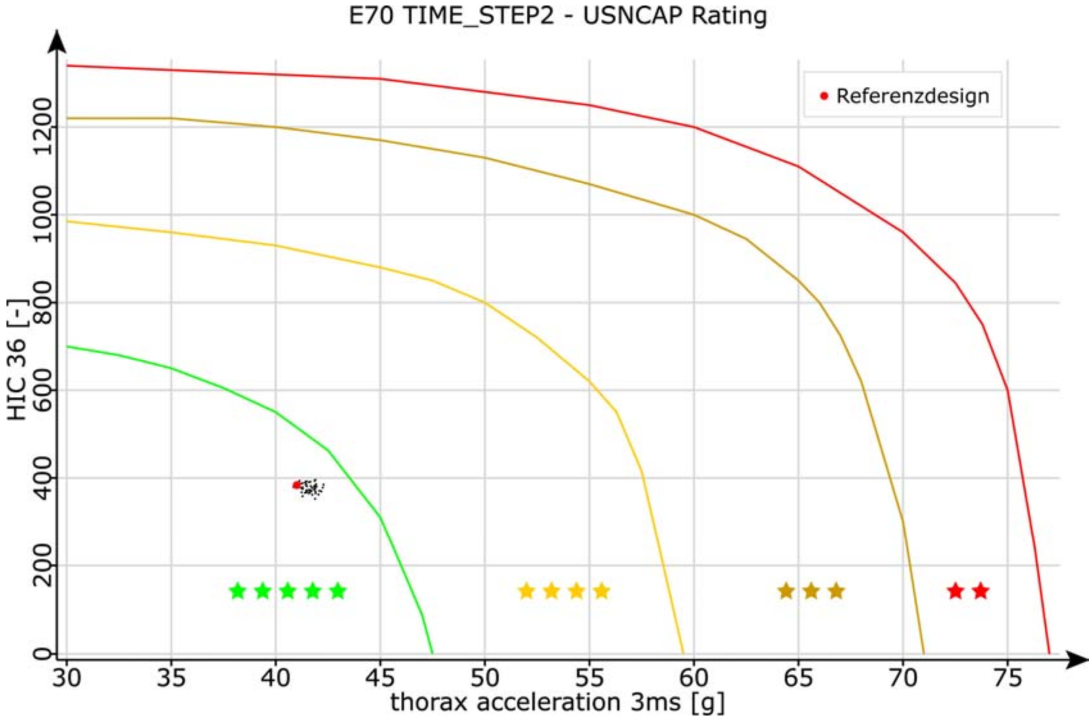

Figure 6: Visualisation of the numerical noise in the star diagram

A characteristic of robust numerical models besides small scatter no noticeable correlations can be observed. Thereby it is of great importance that the sensitive physical input parameters can be identified parallel using physical robustness evaluations and that by optimising these parameters a significant adjustment of the mean value of important result variables can be achieved. The mean value of the evaluation can thereby be moved out of the 4 star into the 5 star region and an achievement of objectives can be largely be secured. Practically this type of optimisation leads to the integration of complex, load case recognising, adaptive restraint systems which are connected with higher costs.

3.2 Example concerning Physical Robustness Evaluation

For the load case side crash according to IIHS the robustness of the restraint system concerning expected scatter of significant input variables was examined in the design stage. The load case was modelled and computed as FE-model using PAMCRASH. The robustness evaluations were performed using optiSLang.

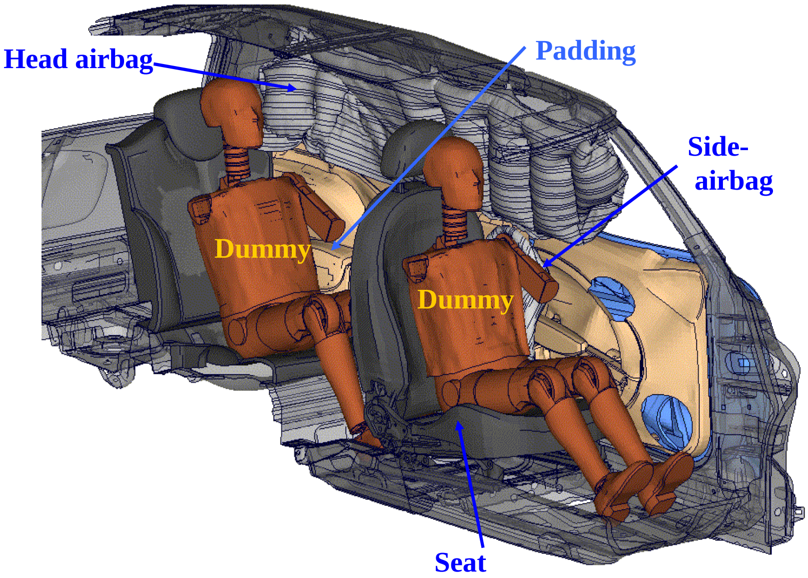

Figure 7: Simulation side impact with PAMCRASH

Overall 13 physical input scatter, mainly scattering input variables of the airbag system, the friction values and the seat position of the dummy were taken into account (table 1) and 20 dummy result variables were examined via robustness evaluation:

- Rib deflection thorax/abdomen (5 responses)
- Deflection rate thorax/abdomen (5 responses)
- Acetabulum force
- Femur force/moment
- Head acceleration
- Iliac force
- Neck compression/tension/moment
- Shoulder deflection
- HIC (head injury criterion)

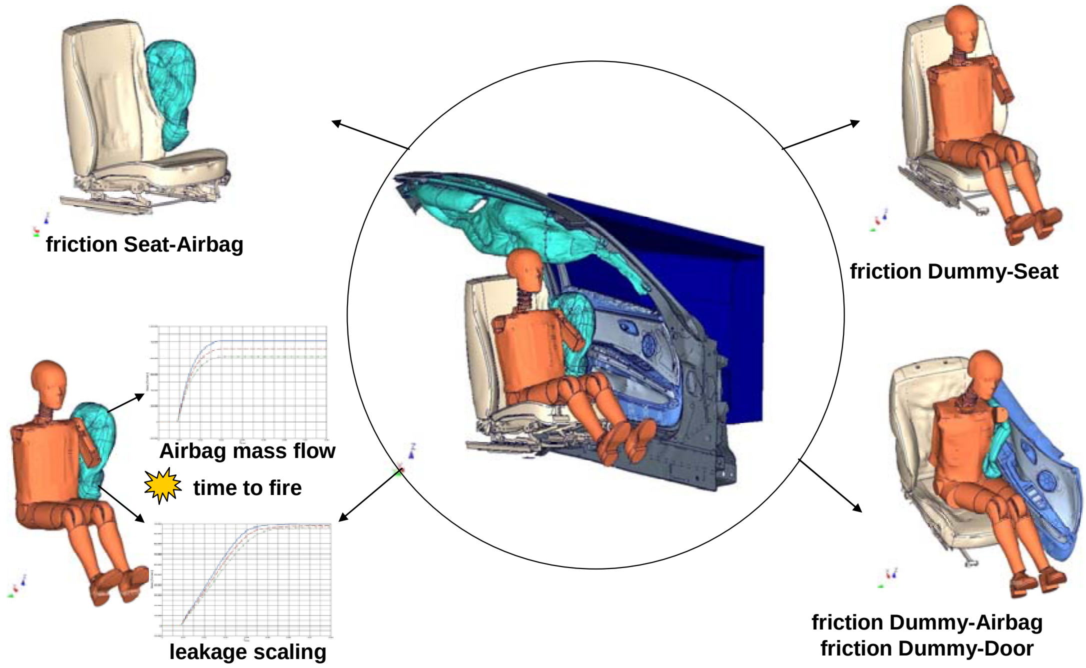

Figure 8: important input scatter of the robustness evaluation side impact

In this case the secure reaching of a BMW defined "good" evaluation of these result variables is an important criterion of the robustness evaluation. For the robustness evaluation no exceeding could be noted within the 94 support points.

	Input parameter	**Type of distribution**
Friction values	Dummy-back	Uniform
	Dummy- door covering	Uniform
	Dummy-airbag	uniform
	Airbag-seat	uniform
	Dummy-airbag	uniform
	Door covering-airbag	uniform
Side-airbag	Leakage	truncated normal
	Airbag mass flow	truncated normal
	Time to fire	truncated normal
	Fabric failure force	uniform
Door covering	Material thickness	truncated normal
	Material curve	truncated normal
Seat position	horizontal/vertical	uniform

Table 1: Scattering input variables as well as associated distribution types at the examination of a side crash model.

In the linear correlation matrix (fig. 9) one can observe that a noteworthy correlation only exists between three of the input scatter (friction value airbag/dummy, airbag time to fire and seat position) and some response values.

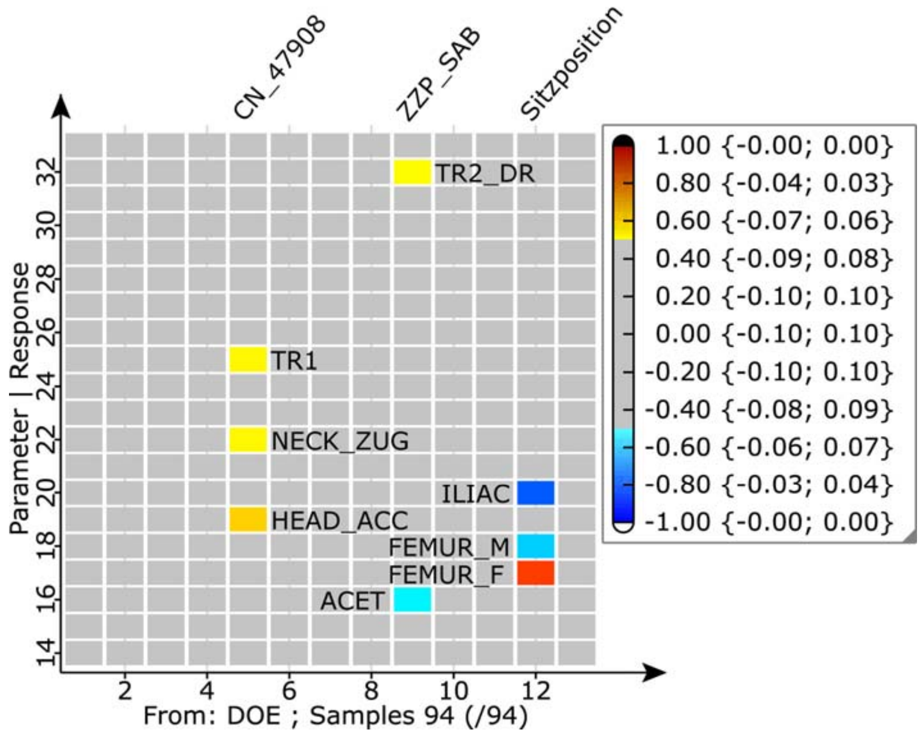

Figure 9: Linear correlation matrix with filter for the correlation coefficients t

The result variable ILIAC-force almost reached the boundary limit of 4400 N (fig. 10), that means it can not be ruled out that this dummy value will be exceeded in testing with a small probability. As clearly can be observed from the coefficient of determination (fig. 11) the scatter of the seat position dominates this event and other scatter does not have a significant influence.

The scatter of the seat position is given as tolerance field by the experimental set-up and therefore can not be reduced. Additionally the seat position itself is for the largest part given by ergonomic demands. Therefore the transmission behaviour between the scatter of the seat position and the scatter of important dummy result variables need to be changed or respectively reduction of the scatter of the dummy variables can only be applied to the interior or the restraint system.

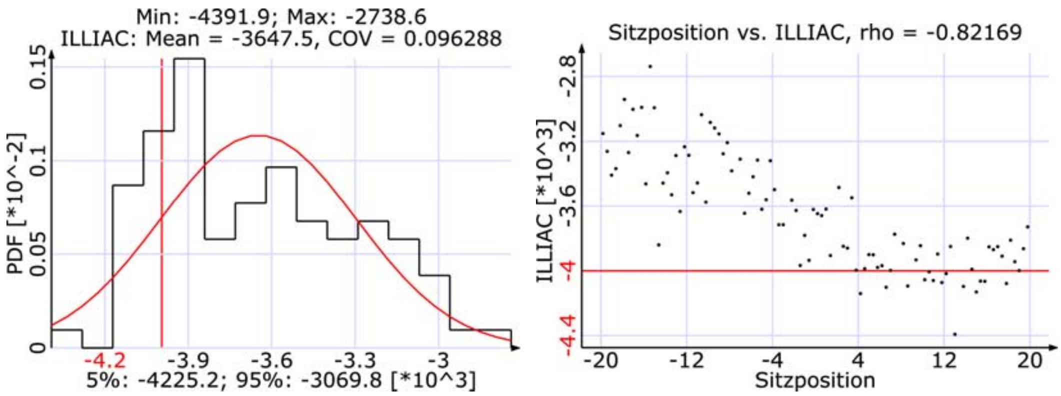

Figure 10: Histogram of the result variable ILLIAC and anthill plot of the dominating input scatter

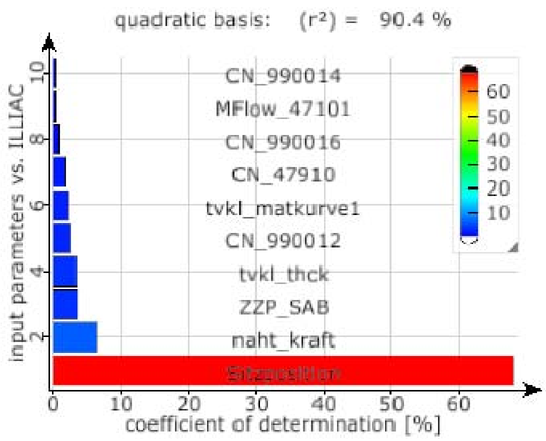

Figure 11: Measure of determination (linear and quadratic correlations) of the result variable ILIAC

4 Conclusion

Computational robustness evaluations for considering scatter of important input variables of restraint systems and test conditions were successfully integrated into the serial product design process of passive safety systems. Besides identification of the significant scattering input variables and the estimation of the variation of important performance variables the understanding of the transmission behaviour of scatter as well as the prognosis quality of numerical models could be increased. Therefore computational robustness evaluations shall already be performed in as early as possible stages of vehicle development and then at defined milestones. In order to secure the quality of prognosis of the stochastic computation the estimations about the scatter of important input variables of the components from suppliers or respectively from the complete vehicle as well as the testing conditions have to be verified.

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