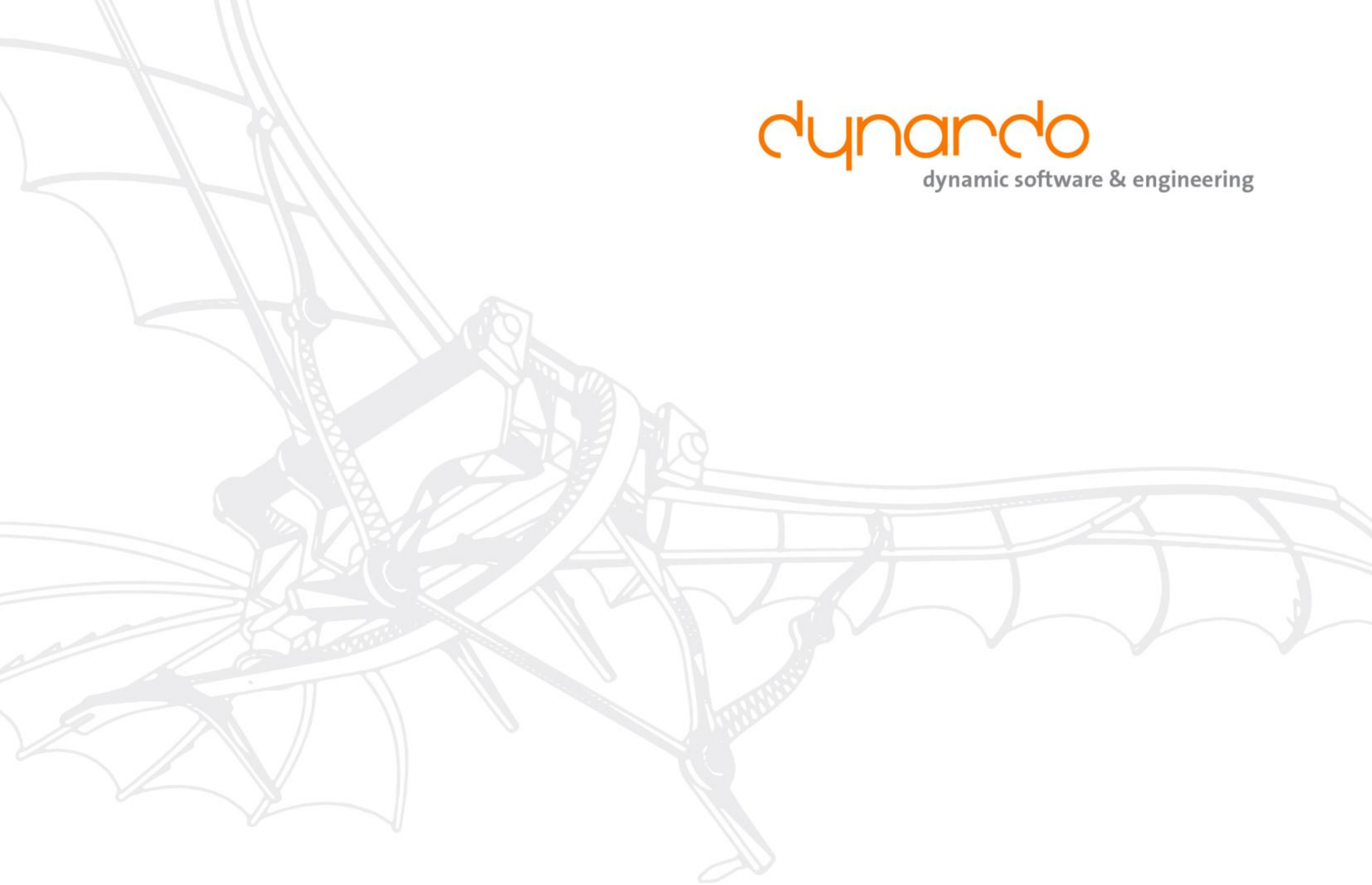

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Introduction of robustness evaluation in CAE-based virtual prototyping processes of automotive applications

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Introduction of robustness evaluation in CAE-based virtual prototyping processes of automotive applications

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1. Introduction

The automotive industry is one of the drivers of CAE-based virtual product development. Due to a highly competitive market, the development cycles of increasingly complex structures have to be constantly reduced while the demand regarding performance, cost and safety is constantly increasing. The development of innovative, high quality products within a short time which are able to succeed in the international car producer competition is only possible by using **virtual prototyping**. One of the greatest challenges is the increase of numerical simulation of large test and analysis programs including CAE-based optimization and CAE-based stochastic analysis while reducing the number of hardware tests. It is important to note that increased application of virtual prototyping itself increases the necessity to perform stochastic analysis. If the number of hardware tests has to be reduced, it is essential to implement the scatter, which is always present in those tests (such as loads, material, geometry), into the computational model. The increasing application of structural optimization also requires the robustness analysis of "optimized" designs. In many cases, the optimization of cost, performance and weight may lead to highly sensitive designs which can lead to substantial robustness defects especially in nonlinear systems. It is no surprise that the increase of virtual prototyping in conjunction with the reduction of hardware tests and development times combined with a very high innovation speed of new materials or electronic components do have some risks. This can be seen in the statistics of product recall which have increased significantly in the last time, particularly for new cars [6]. Therefore, the topic of robustness evaluation assuring serviceability, safety and reliability should be taken into account in virtual prototyping as early as possible. Here, robustness characterizes the sensitivity of the system response in respect of unavoidable scatter in the environmental conditions. Consequently, probabilistic methods using CAE-based stochastic analysis have to be utilized in order to quantify robustness, safety and serviceability.

Dependent on the robustness evaluation criteria, variance-based robustness evaluation (usually called robustness evaluation) or probability based robustness evaluation (usually called reliability analysis) have to be utilized. In variance-based robustness evaluation procedures, usually a sample set of possible realizations of input variables is generated by stochastic methods. The scatter of the input variables is described by probability distribution functions and correlation structures of scattering inputs. The scatter in the system responses and their significance are investigated by statistical methods with respect to their properties regarding correlation and variation. In probability-based robustness evaluations usually small event probabilities are determined using gradient (FORM) [8] or sampling based (ISPUD [3], adaptive sampling [4], and others) stochastic analysis methodology.

The introduction of stochastic analysis into virtual prototyping needs a balance between the knowledge and the definition of input scatter, of reliability, of the stochastic analysis itself and of the reliability of the statistical evaluation procedure. For example, it is not useful to evaluate a rare event probability (6 sigma value) with pure knowledge about possible input scatter using 100 Monte Carlo simulations. That is very much in contrast to the introduction of CAE-based optimization. Here, "black box" algorithms can be used and the designer can limit his design space for optimization almost without the risk of producing useless results. In the optimization task, this would "only" result in pure or missing design improvement. But the absence of important input scatter or the use of non–reliable stochastic methods or non-reliable statistic measurements leads to useless and dangerous assessments of design robustness. That fact is one of the reasons that practical applications of CAE-based robustness evaluation are still rare compared to CAE-bases optimization.

Dynardo started in 2002 with the integration of robustness evaluation into (almost linear) NVH applications [10]. Here, the evaluation of linear and quadratic correlation coefficients mainly solved the task of robustness evaluation of driving comfort criteria. The challenge is "only" the number of scattering variables which continuously increases, today up to 600 full car robustness evaluations. In 2004, we started with the integration of robustness evaluation into forming simulations [13] and passive safety applications [12]. In forming simulations, it became necessary to evaluate the robustness of forming limit criteria at the finite element structure. Therefore, projection and visualization of statistical measurements became a key feature for successful robustness evaluation for forming applications [11]. In passive safety applications using hybrid MKS/FE-models, the quantification of numerical robustness became an important part of the design robustness. By developing a quantitative estimation of numerical noise via coefficients of determination [14], robustness evaluation of passive safety applications became accepted for regular procedures in virtual prototyping [15]. In 2005, we started robustness evaluations of FE-based crash analysis for passive safety and crashworthiness applications. Here, the estimation of the amount of possible numerical scatter became a key feature for the evaluation of numerical robustness. Also, the projection and visualization of statistical measurements on FE-meshes became key features for the investigation of scatter sources Because of the complexity of the FE-models, the high amount of non-linearity and the high CPU requirements, we are still optimizing all components of the robustness evaluation procedure. Today, we are in the productive level of FE-based passive safety application (side crash, head impact) and for low speed application (insurance crash). High speed front crash loading still remains a challenge. [16].

2. Variance-based Robustness Evaluation

Based on a reference simulation with a deterministic set of input variables, which for example corresponds to the mean values of the uncertain variables, a robustness evaluation creates a set of possible realizations of the design regarding the naturally given input scatter. To generate the sample set, stochastic analysis methodology is used.

Because in the discussed automotive application it is not necessary to account small event probabilities, robustness evaluations using variation analysis [14] are the methodology of choice. The primary goal of robustness evaluations is the determination of a variation range of significant response variables and their evaluation by using definitions of system robustness. The secondary goal of robustness evaluations is the identification of correlations between input and response scatter as well as a quantification of the thereby explainable components of the variation of result variables.

The definition of the uncertainties forms the base the stochastic generation of the sampling set. The characteristic of input scatter is described by using statistical distribution functions and it defines the probability space of possible realizations. In practical applications, the existing knowledge of scatter is translated into a suitable distribution function. Thereby, the bandwidth reaches from detailed data from receiving control of material properties to raw estimates of scatter and uncertainties. The software used for the robustness evaluation should be able to consider the available knowledge regarding the input information completely. This requires that suitable distribution functions (normal distribution, truncated normal distribution, log normal distribution, Weibull distribution or uniform distribution) can be used and correlations of single scattering input variables or of partially correlated stochastic fields can be considered.

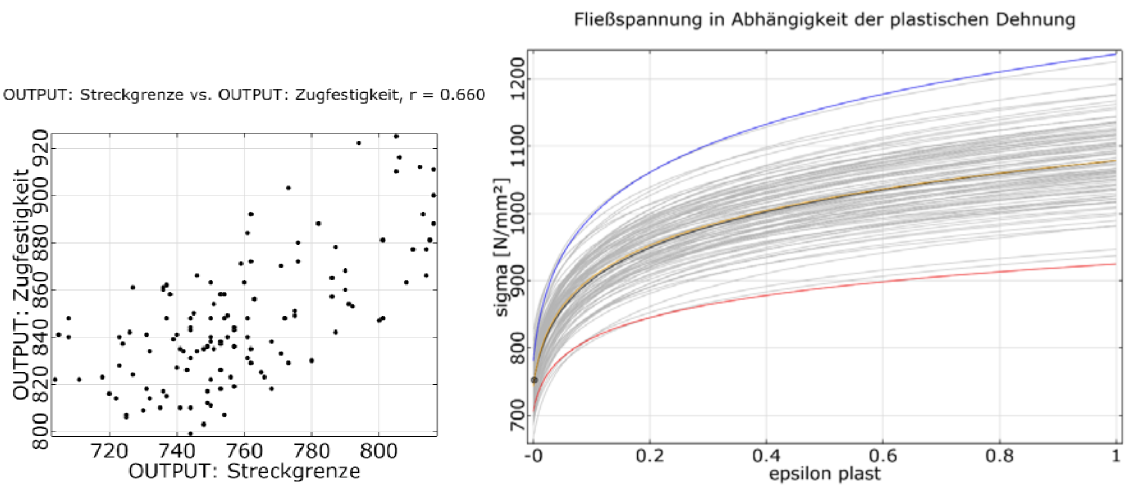

Figure 1: correlation between yield stress and tensile cut of, flow curves generated from input parameter yield stress, tension cut of, limit plastic stain using Ludwick equation

The necessity of this shall be illustrated using the example of material formulation of steel. Commonly, the flow curve for forming simulation is described with a set of scattering parameters with significant correlation for example between yield stress and tensile strength (figure1). Only the consideration of the complete statistical information of the distribution function and variable correlation leads to a realistic flow curve created from a "random" choice of the associated scattering parameters in the sampling process.

At this point, it shall be explicitly stated that the reliability of statistical measures of the result variables depends on the quality of the input information on scattering input variables. Therefore, if only rough assumptions can be made about the input scatter, then the statistical measures should only be evaluated as a trend. The estimation of statistical measures from a sample of possible realizations is naturally afflicted with an error. To keep this error as small as possible, Latin Hypercube Sampling methods are to be preferably used when creating samples. Research, regarding the estimation of linear correlation coefficients [14], shows that for the same expected statistical error Latin Hypercube Samplings are more than ten times more efficient than Monte Carlo samplings. Thereby, the required amount of computations for securing a certain confidence interval on correlation coefficients depends on the total amount of scattering input variables plus the total amount of estimated output variables. In other words, the probability rises that the maximum error of single correlation coefficients increases with an increasing amount of output variables. Typically, in many engineering disciplines only a small amount of important result values is considered when doing robustness evaluations. When doing robustness evaluations of forming or crashworthiness simulations, the necessity may arise to visualize the spatially correlated statistic measures on the FE-structure and therefore a high number of correlation coefficients need to be estimated. Projection methods [11] are used to suppress the "noise" of the statistical errors in the estimations of correlation measurements and to identify important correlations.

Statistical measures from the histogram form the base for the estimation of response variability. Other important measures of variation are coefficient of variation, standard deviation, min/max values. In practical applications, the robustness of result values is often determined by examining if certain boundaries are exceeded. The boundary values thereby are often compared with the min/max values.

If the scatter of output variables is not tolerable, it is searched for apparent correlations between the variation of individual input variables and the variation of individual output variables. Correlation coefficients, determined from linear and quadratic correlation hypothesis, describe a measure of correlation. The correlation coefficients in return form the base of measures of determination. Measures of coefficients of determination (CoD) are percent wise estimates, which ratio of variation of an output variable to the variation of individual input variables can be explained by using the correlation hypothesis.

3. Requirements for the Successful Integration of Robustness Evaluations into the Virtual Product Development Process

From our experience in the implementation of variance based robustness evaluation in automotive applications, following boundary conditions have to be met:

- Numerical model and simulation methods have to posses the ability of prognosis and therefore have to be able to show all significant physical phenomena and compare them to single experimental data.
- Simulation processes often need to be improved regarding parametric, automatic repeatability and automatic result extraction to be ready for process integration in optiSLang.
- The existing knowledge on input scatter and uncertainties for example in boundary conditions, material values or load characteristics are properly to be transferred to an appropriate statistical description and have to be integrated in virtual product design as significant input information for stochastic analysis. The know-how about the uncertainties needs to be continuously collected, updated and validated.
- A stochastic method has to be used for robustness evaluations which make sure that the errors within the estimation of the statistical characteristics are small enough and therefore that the results can be used as reliable foundation of a robustness evaluation. The stochastic methodology needs to be optimized regarding the necessary number of design evaluations resulting in reliable statistic evaluation criteria.
- The statistical post processing needs to be automated.
- Standardization of robustness evaluation needs to be established at a care producer as well as at a component supplier virtual prototyping process.

Furthermore, one can assume that a consequence introduction of stochastic computation methods can be divided into 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
- Inspection of model robustness/stability using coefficients of determination
- Robustness evaluation of most important load cases, estimation of the variance of important performance variables, inspection if limit values are exceeded by the variation of the performance variables
- Extraction of most significant correlations between scattering input variables and 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 questions have to be discussed and arranged:

- At which point in time in the virtual development process, the robustness evaluations of components, modules or whole vehicles are performed?
- For which input scatter the assumptions about the scatter have to be verified?
- How can the scatter of critical performance variables 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 the virtual product process.
- Assuming that all important input scatter was 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.

4. Crashworthiness and Passive Safety Applications

4.1 Numerical Robustness of Crashworthiness and Passive Safety Applications

The inspection of numerical robustness of numerical models of finite–element-based crash analysis results from the experience that the variation of numerical parameters of the approximation method or the variation of demonstrable insignificant physical parameters can lead to large scattering of the result variables or lead to obviously unfeasible results. If stochastic analysis computes multiple designs and evaluates their variation statistically, the question arises which proportion of the resulting variation can be attributed to problems of the approximation method and the numerical modeling respectively.
In the beginning of robustness evaluations, we performed in parallel “physical” robustness evaluations of physically scattering parameters (scattering in reality) and “numerical” robustness evaluations regarding variation of numerical parameters. We stated a model as numerically robust, if the variation caused by the numerical robustness evaluation was small compared to the scatter caused by physical robustness evaluation. But of course, that statement was very much depended on the variation interval of numerical parameters and we could not repeat numerical robustness evaluations at every point in the physical robustness space. Therefore, a process was needed to estimate the quantity of the numerical noised within a physical robustness evaluation. At the end, we quantified the influence of numerical noise on the result variable by using the coefficients of determination [14]. If the measure of determination of the robustness evaluation is high, only a small proportion of unexplained variation, which could be caused by numerical noise, is left. In order to use the measure of determination of result variables as a quantitative measure for the numerical model robustness, the proportion of determination of the found correlations has to be estimated with sufficient statistical security. This formulates the standards for the sampling method, the number of computations and the statistical algorithms for the evaluation of measures of determination. After a positive experience of evaluating the influence of numerical noise via measures of determination from robustness evaluation, this method is used for the serial production of BMW since

2006 [15]). From our experience, we selected the role of thumb that for “numerically” robust models, measures of determination, considering linear and quadratic correlations and after elimination of outliers and clustering of over 80%, should be determined. If the measures of determination in practical applications decreased significantly below 80%, it was usually indicated that the corresponding result variable possesses a significant amount of numerical noise. A reason therefore may be insufficiencies in the result extraction or insufficiencies of the numerical models interacting with the approximation methods. After repairing the numerical modeling, the measure of determination usually increased up to over 80%.

It shall be stated that in theory it is impossible to determine without a doubt the proportion of numerical noise. This diagnosis of course excludes systematical errors or the inability to actually map significant physical effects in the numerical models. The fundamental prognosis ability of the numerical models has to be verified by using experimental data. On motivation of aiming at high coefficients of determination for robust designs, the correlations between input variation and output variation should be identifiable. These correlations also show the possibilities of influencing the result scatter. In order to reduce transgression probabilities, it is possible for example to move the mean value of important scattering input variables in the linear correlation case or for quadratic correlations to reduce input scatter or alternatively to change the transmission behavior between input and output scatter.

4.2 Passive Safety Applications

Since the beginning of 2006, computational robustness evaluations using optiSLang [7] are a defined milestone of the serial production at the BMW AG, executed for all relevant load cases for dimensioning of passive safety systems [15]. The procedure is exemplarily introduced for the load case FMVSS 208 (figure 2: front-crash 40 km/h, unbelted, against steep wall). The robustness concerning significant evaluation parameters of driver and passenger was tested. The model was created and computed in MADYMO. A multi-body-formulation was used for most parts of the restraint system, tthe dummy and a finite-element-formulation was used for the airbag. For the robustness evaluation, 200 variants were created in optiSLang by using Latin Hypercube Sampling and then they were computed. Overall, 27 physical parameters of the multi-body/finite-element-modeling were varied and 18 dummy result variables were analyzed in the robustness evaluation. For the definition of the scatter, uniform distributions and truncated normal distributions with cut offs at 2 or 3 Sigma Level were used.

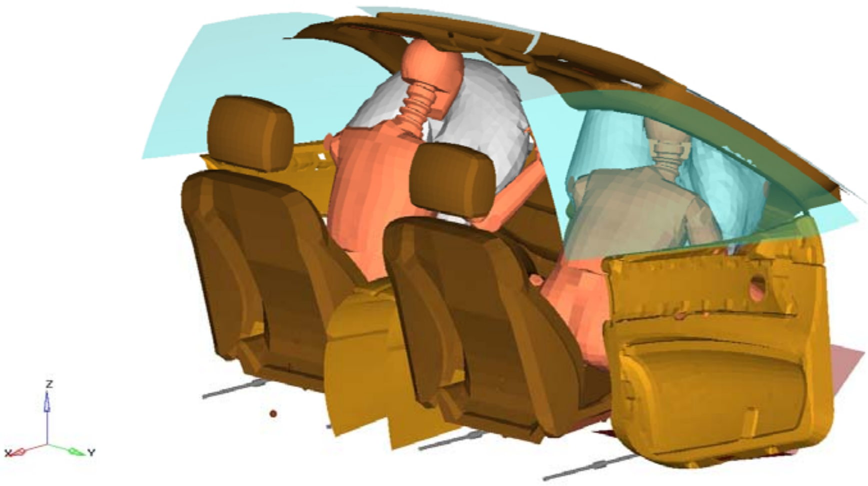

Figure 2: Simulation Passenger Safety Load Case FMVSS 208

The following scattering input parameters were considered in robustness evaluation:

- Scattering of the time to fire the 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 the impact pulse
- Scattering of feet space, foot rest, pedal

The robustness of all important dummy injury criteria, like head, chest and pelvis accelerations and displacements, HIC-values or neck forces were investigated. Most important statistical result of the robustness evaluation were the predicted intervals of variation for the scatter of the evaluation parameters (figure 3). Even though no limits were exceeded, the scatter of single evaluation parameters is high. Out of the 29 sources of input scatter, only 9 input variables show noteworthy correlations to the output variables. As it can be seen in the matrix of the linear correlations (figure 4), not for all output parameters significant linear correlations (with coefficient of correlation > 0.50) to input scatter could be found. This can be an indicator for a high proportion of numerical noise. Therefore, it was investigated, if higher measures of determination could be achieved by using quadratic correlations and by eliminating non-linearities (outliers or clustering). However, no correlations which significantly contribute to the measure of determination, besides linear correlations, could be identified. Typically, the determination of the individual result variables strongly varies. For example, the maximum force in the femur (figure 5) can be explained with a high determination (90% figure 5), while the variation of the HIC-value can only be explained with less than 50% (figure 6).

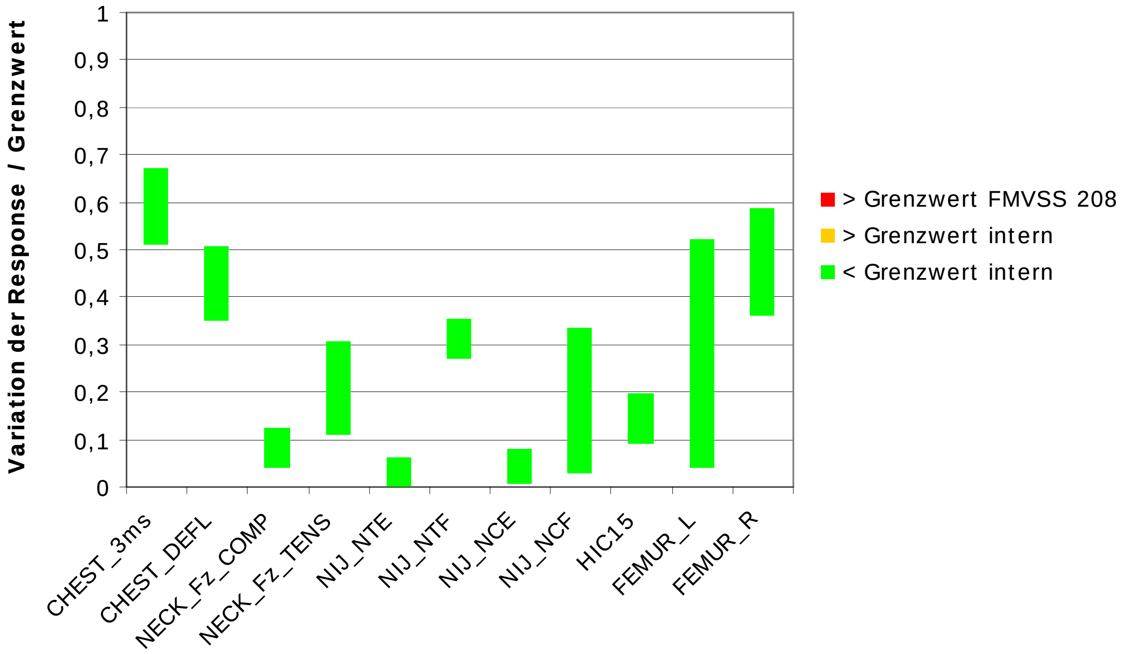

Figure 3: Visualization of the Variation Ranges

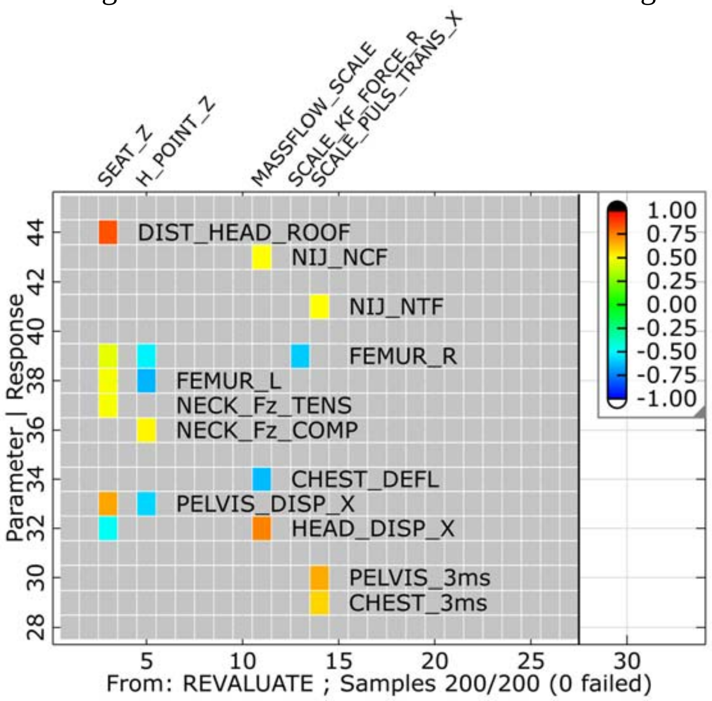

Figure 4: Matrix of Linear Correlations

Therefore, a numerical robustness evaluation was performed by using the reference model and 5 to 10% of variation of some numerical parameters. Overall 8 numerical parameters, e.g. scaling-factors of the time-steps, the contacts or the “numerical” damping-factors of the multi-body/finite-element-modeling, were varied. The scattering of 18 result variables was evaluated.

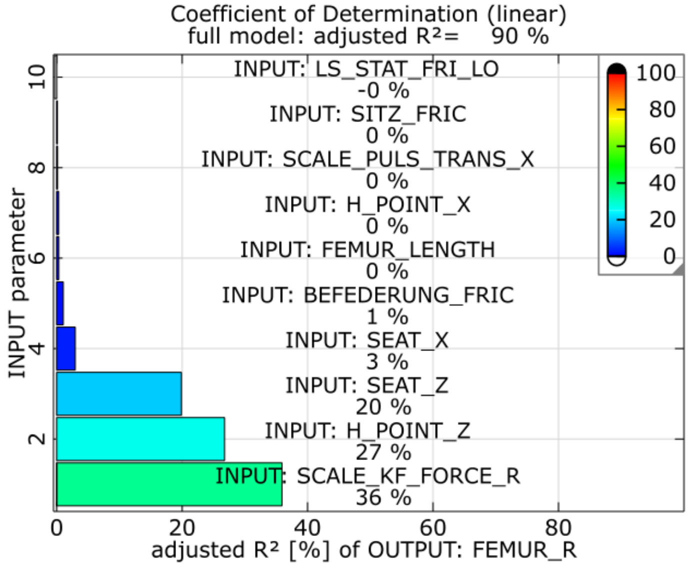

Figure 5: Measure of Determination Femur Force Right

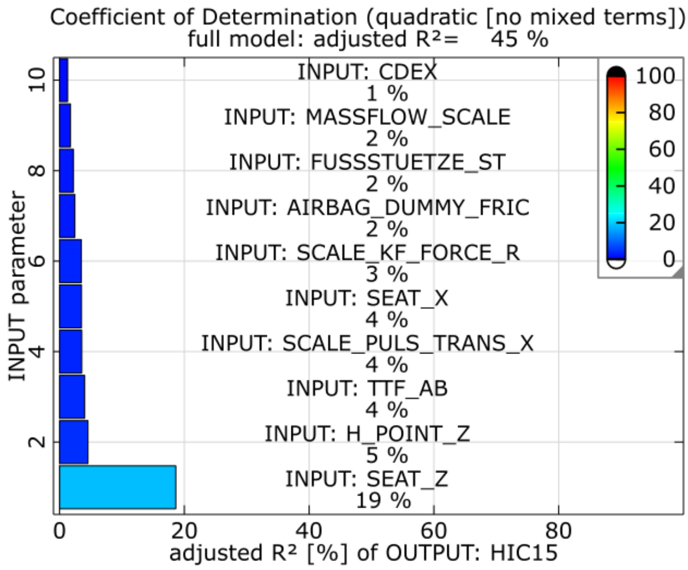

Figure 6: Measure of Determination HIC15

The resulting scatter of the evaluation parameters was compared to the scatter of the physical robustness evaluation (figure 7). As expected, the numerical noise of variables

with high coefficients of determination of the physical robustness evaluation, like the femur forces, was of negligible proportion. For the evaluation of parameter HIC15 a significant scatter occurred as expected, caused by the variation of numerical parameters. The large scattering of the chest-values in comparison to the physical robustness evaluation are also critical in this model. Although, these evaluation parameters show measures of determination of about 80%, in the physical robustness evaluation their scatter caused by the variation of numerical parameters is very high. As can be seen in this example, one can not assume that the measure of numerical noise related to the variation interval can be obtained linearly from the measures of determination.
If noteworthy variations occur within the numerical robustness evaluations, one can assume that the prognosis of scatter of the physical robustness evaluation tends to be too high. By checking designs with minimal and maximal performance values, often sources of numerical problems can be identified and hints can be given to improve the numerical models.

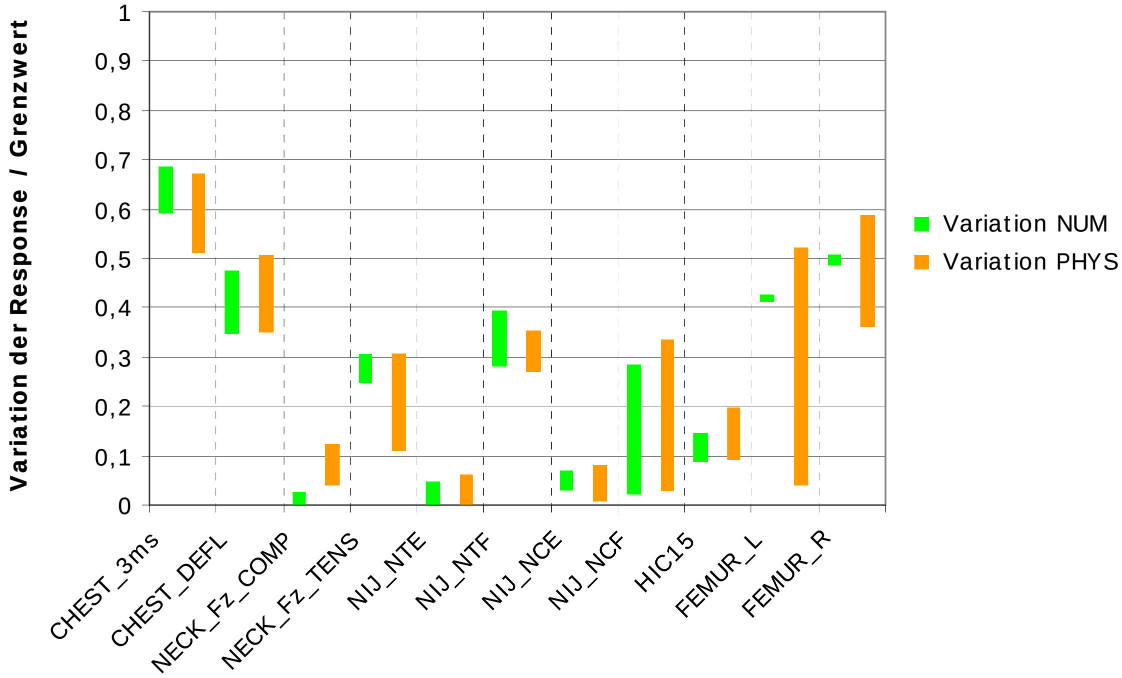

Figure 7: Comparison of the Variation Intervals of physical and numerical robustness evaluation

The robustness evaluation in the early stage of vehicle development showed that the evaluation parameters, including the consideration of input scatterings, lie below target limit values. At the same time, it was shown that the hybrid multi-body/finite-element model shows a high amount of numerical noise for this load case, which leads to a high amount of uncertainty within the prognosis of deterministic results (single values) or of stochastic values (variation ranges). Therefore, until the next milestone, the models are reworked with the goal of reducing the numerical noise.

Until 2007, more than 100 robustness evaluations were performed at the BMW virtual prototyping for passive safety systems. In the third year of the serial use of stochastic analysis, the following added value could be obtained concerning the dimensioning and increase of the robustness of 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
- Recognizing robustness problems of the restraint systems and in cases of high exceeding, of limits with the consequence of re-design of components.

4.3 Crashworthiness Applications

The robustness of a crash simulation in deterministic analysis is already a task which has to be investigated while evaluating the crash test results. To limit problems with scatter of performance values resulting from numerical approximations of the crash FE-solvers, often quality regulations of modelling, software versions and hardware platforms exist. From the viewpoint of stochastic analysis, this evaluation of “numerical noise” needs additional quantification in relation to the physical scatter which occurs in reality to the performance values. To illustrate that, an injury criteria is scattering in physical test about 50%, then 5% scatter coming from numerical approximation solution are usually tolerable. Because we assume that the numerical scatter overlays the physical scatter and results in a larger variation between min and max, the 5% can be handled with a larger safety distance from critical performance values. But of course, if physical scatter and numerical noise have the same quantity, the reliability of deterministic or stochastic simulation results are questionable.

On request of the FAT working group 27 of the German automobile industry, a front-crash load case of the ULSAB car body with a velocity of 14 m/s against a rigid wall (figure 1) was evaluated concerning robustness. The goal of the study was to show the possibilities of computational robustness evaluations in crashworthiness. LSDYNA was used for FEM computing. optiSLang (oS) was used for the robustness evaluation. Evaluation parameters of the robustness study were energy, forces and deformation of the main crash boxes as well as the relative displacement of the front wall. The input scatters were sheet thickness and yield stress of 36 car body parts in the front end, the coefficient of friction as well as the test boundary conditions barrier impact speed and barrier impact angle. Normal distribution was assumed for the scattering value sheet metal thickness and a lognormal distribution for the scattering value tensile strength and yield strength. For the scattering of the test boundary conditions, normal distribution and for the coefficient of friction, a uniform distribution was used. For the robustness evaluation, 169 variants of the 84 overall input scatters were created by using Latin Hypercube Sampling. During the evaluation of the variation intervals, significantly too large scatters could be detected concerning nodal intrusion values of the front wall (figure 9, left).

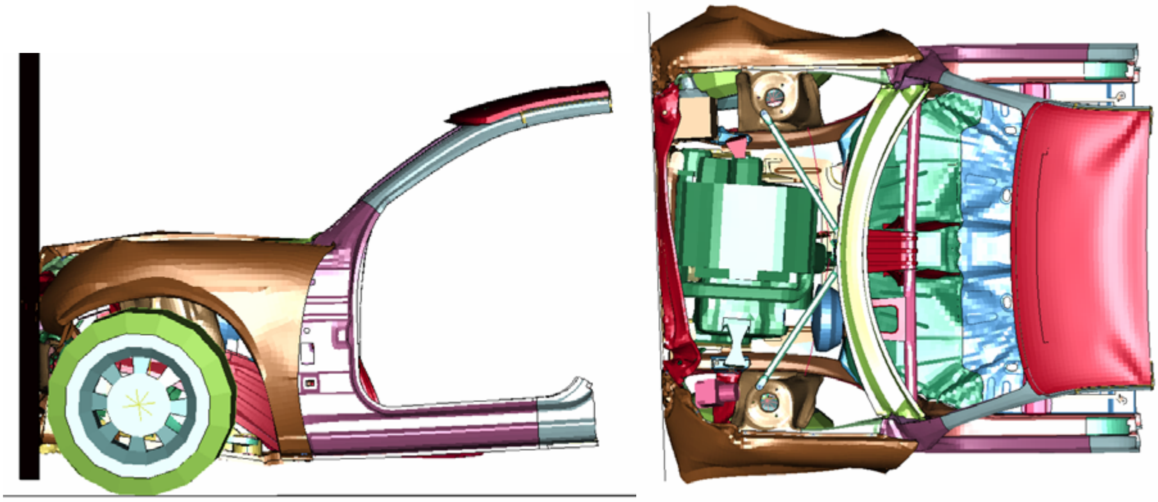

Figure8: Front-Crash ULSAB Car Body, Side View and Top View

By using correlation analysis and evaluation of the coefficients of determination, the reasons for the scatter of the result variables were investigated. While high measures of determination larger than 90% were calculated for some evaluation parameters, like for the maximum force in the crash box, the measures of determination of the front wall intrusion considering linear and quadratic correlations were small, lying in the range of 50% (figure 10, left). This leads to the question, whether the high proportion of inexplicable intrusion is caused by nonlinearity or if it is caused by numerical noise.

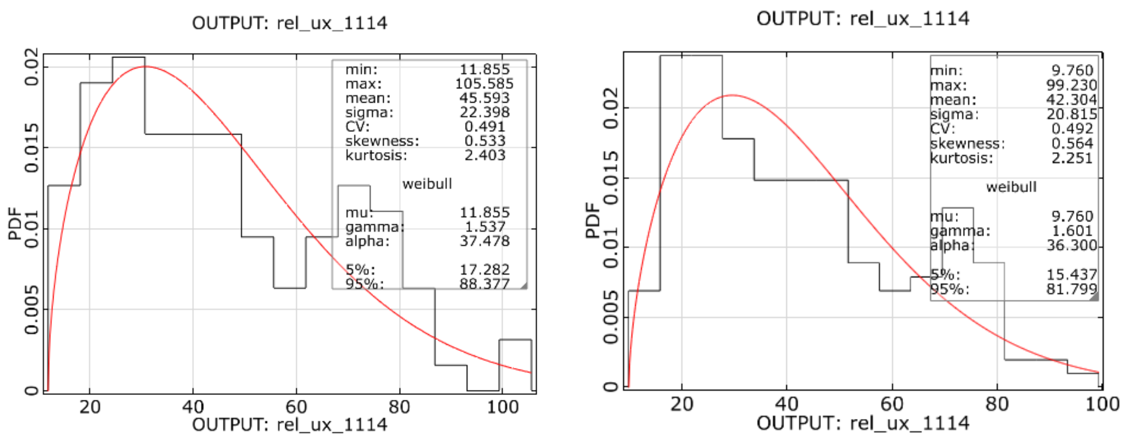

Figure 9: Histogram of the Intrusion at Node 1114, left: 84 Scattering Inputs, right: 15 Scattering Inputs

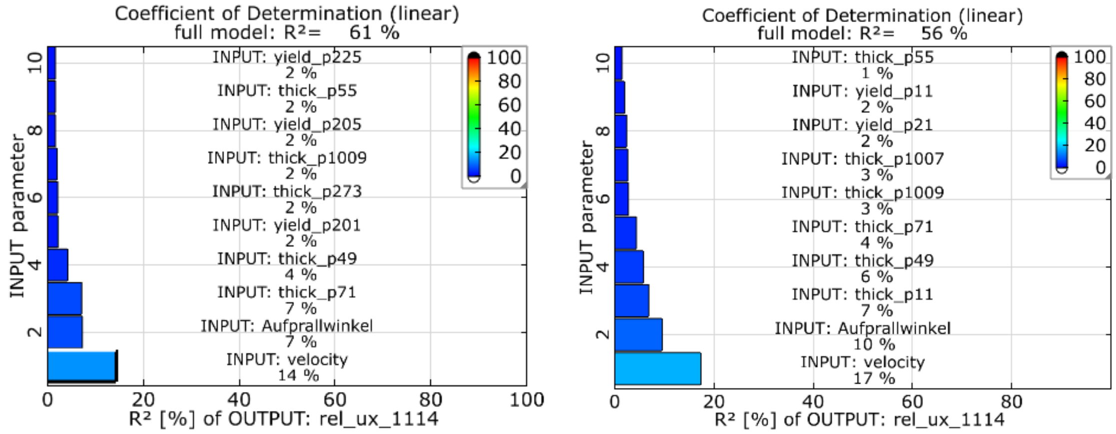

Figure 10: COD of Intrusion at Node 1114, left: 84 Scattering Inputs, right: 15 Scattering Inputs

In order to determine the significance of the statistical measures, the parameter space was reduced to those 15 variables which had shown significant linear or quadratic correlations in the 84-dimensional response space and a second robustness evaluation was performed. Essentially, those scattering parameters were the sheet thickness and yield strength of crash box, further sheet metal component in the load transfer path as well as scattering of the test boundary conditions. In the 15-dimensional space, 100 variants were generated and evaluated by using Latin Hypercube Sampling. Fortunately, the variation prognosis (figure 9, right) as well as the measure of determination (figure 10 right) turned out to be very stable. Thereby, it could be shown that the variables which were preliminary selected as of no importance indeed had no significant influence on the result scattering and that the determined statistical measures are trustworthy. However, still only about 50% of the result variation could be described by linear and quadratic correlation.

In order to further investigate the cause of the unexplained variation components of the front wall intrusion, the statistic measures of the 100 computations on the FE-structure were investigated by using the post-processor Statistics_on_Structure [9]. The evaluation of the measures of determination (figure 11, left), standard deviation (figure 11, right) and correlations at the finite element structure show the largest differences in the interconnection between the crash box in the front wall. The comparison of load cases with minimal and maximal (figure 12) relative displacement at this point showed that the crash box sometimes fails during the crash loading and one could have reasoned that the low determination of the relative displacement could have been associated to this bifurcation problem of the buckling crash box.

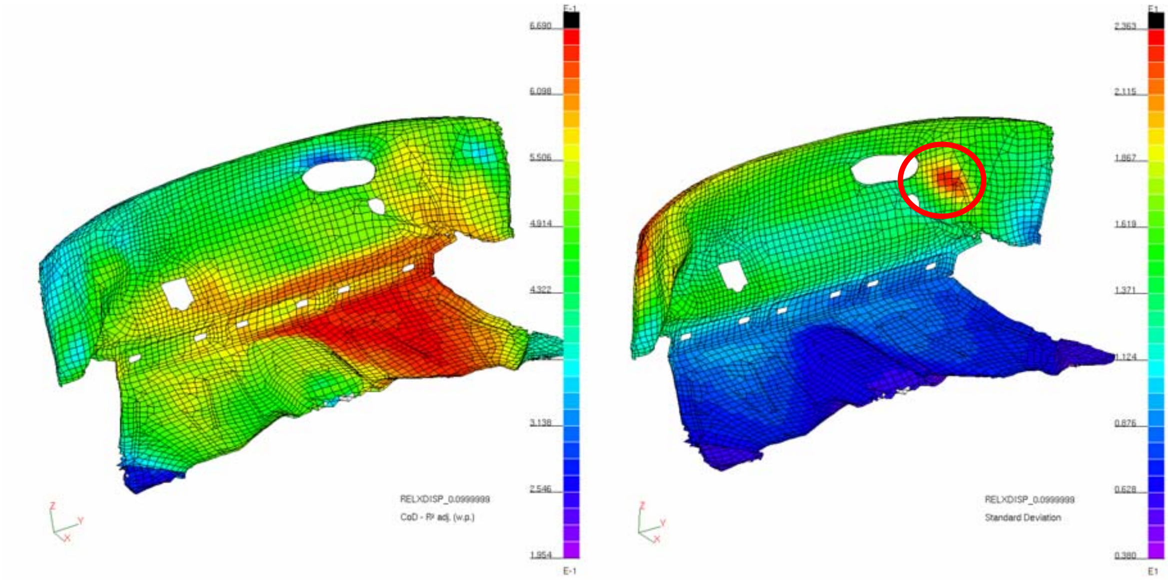

Figure 11: left: Measure of Determination of the Relative Displacement, right: Standard Deviation of the Relative Displacement

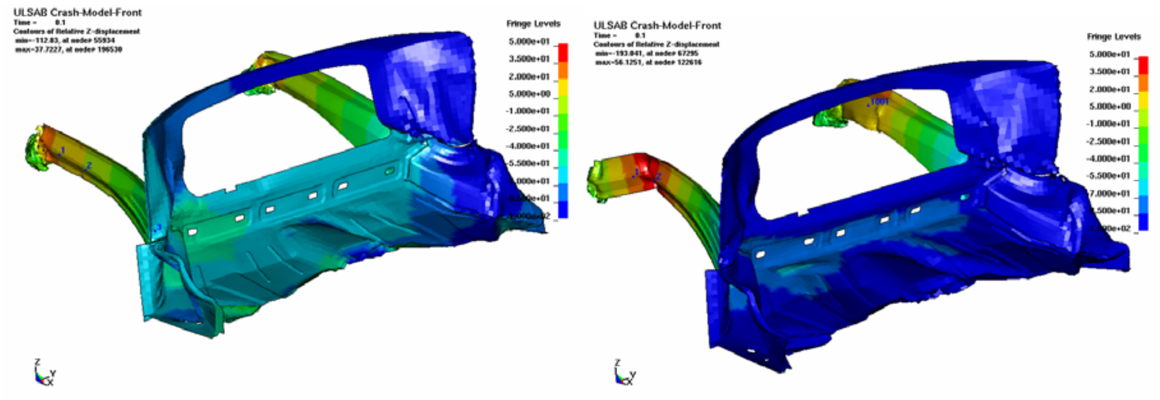

Figure 12: left: Design with Minimal Front Wall Intrusion, right: Design with Maximal Front Wall Intrusion

In order to verify, if the robustness of the structure is depending on the amount of scattering, the input scatter was decreased. A third robustness evaluation, only concerning the input scatter of the test boundary conditions velocity and impact angle, was performed. Furthermore, the input scatter of impact velocity and impact angel was reduced by 90% in the fourth robustness evaluation. By using the Latin Hypercube Sampling, 36 variants were created and computed. As can be seen in table 1, the variation interval of the relative displacement is only reduced by 30%, even if the input of the two variables is reduced to 10% of the original values. This leads to the conclusion that either the connected “physical” correlation is relatively independent of the input scatter (and therefore the structural response is very instable) or that numerical perturbation causes a significant amount of scatter in the response behavior.

Intrusion = relative X-Displacement Node 1114 [mm]	Robustness 1 84 scattering parameters	Robustness 2 15 scattering parameters	Robustness 3 2 scattering parameters	Robustness 4 2 scattering parameters 10% scatter
Mean Value	42.5	44.5	52	53
Variation Interval Max-Min	89.5	93.7	63	68
Coefficient of Determination R^2/adjustedR^2	61/23	56/47	43/35	

Table 1: Comparison of Statistical Measures

Therefore, a "numerical" robustness evaluation, only concerning the time step of the explicit time step integration, was performed. The 10 computations showed a significant amount of numerical noise varying from 20 to 60 mm (figure 13), nearly the same variation like robustness evaluations 3 and 4.

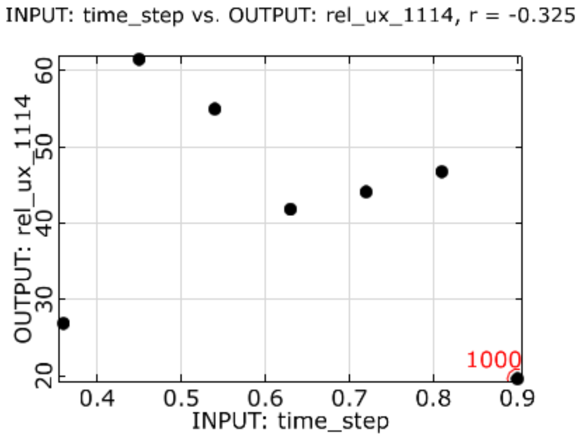

Figure 13: Anthill Plot of the Variation of Critical Time Step Scaling concerning the Displacement of the Node 1114

Following, further analysis for identifying the problem was performed and an insufficient meshing of some parts of the crash box and their supporting structure was assumed to be a reason for numerical problems. Therefore, the crash box and the supporting structure were meshed with a finer mesh size. The robustness analysis was repeated in the 15 dimensional subspace of important scattering input variables using 100 Latin Hypercube samples (Robustness 5). Because of the finer mesh, the crash mechanism of the crash box (figure 15/16), the crash box cross section force history (figure 14) and the statistical values (table 2) of the front wall intrusion (a little bit unexpectedly) changed dramatically. The evaluation of the crash box deformation showed much more and frequently failure scenarios using the fine mesh (figure 15).

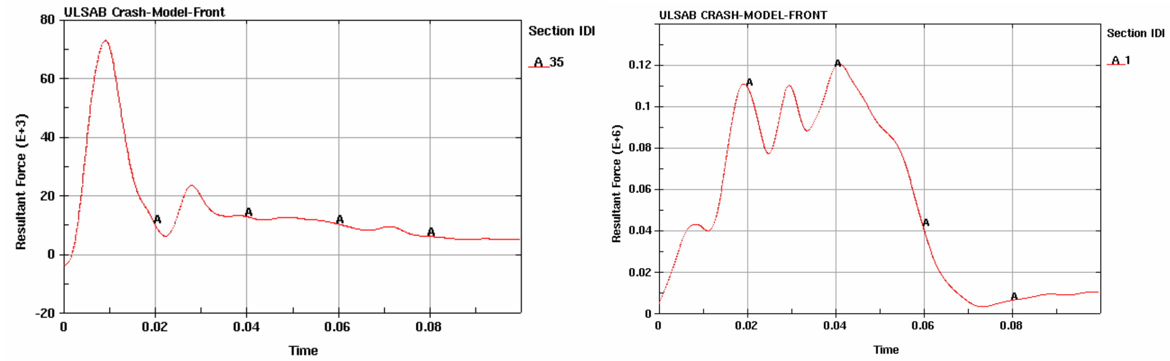

Figure 14: History of resultant crash box cross section forces (left-original mesh, right-fine mesh)

Intrusion = relative X-Displacement Node 1114 [mm]	Robustness 2 15 scattering parameters vel.=14 m/s	Robustness 5 15 scattering parameters finer mesh vel.=14 m/s	Robustness 6 15 scattering parameters finer mesh vel.=10 m/s
Mean Value	44.5	22.5	11.6
Variation Interval Max-Min	93.7	38.1	16.0
Coefficient of Determination R^2/adjustedR^2	56/47	31/19	43/34

Table 2: Comparison of Statistical Measures

Because of the multiple failure mechanism, the coefficient of determination of linear and quadratic correlation of front wall intrusion drops down to 30% (figure 17 left). To investigate the robustness evolution reducing crash box failure, we reduced the crash velocity to 10 m/s in the robustness evaluation six. Now, failure occurs only for two runs (figure 16), the mean and variation interval decrease (table 2) and the COD increases (figure 10 right) as expected. But with a COD of approximately 50% and a failure of the crash box, occurring only at 2 runs, the result value is still very noisy.

Thereby, this benchmark example could demonstrate within different sub spaces of the robustness problem in exemplary manner that robustness evaluations can provide reliable statistical measures for the quantitative estimation of the influence of “numerical noise” on result variables. In practical applications, it would be advisable after the first robustness evaluation with small measures of determination to search for the cause of numerical problems by comparing single computation runs and using the projection of statistical measures on the FE-structure. The final statement about the ULSAB model in the load case front crash is that only about 50% of the scatter in the front wall intrusion can be explained with identified correlations to input scatter and a significant amount of output scatter is supposed to result from numerical noise.

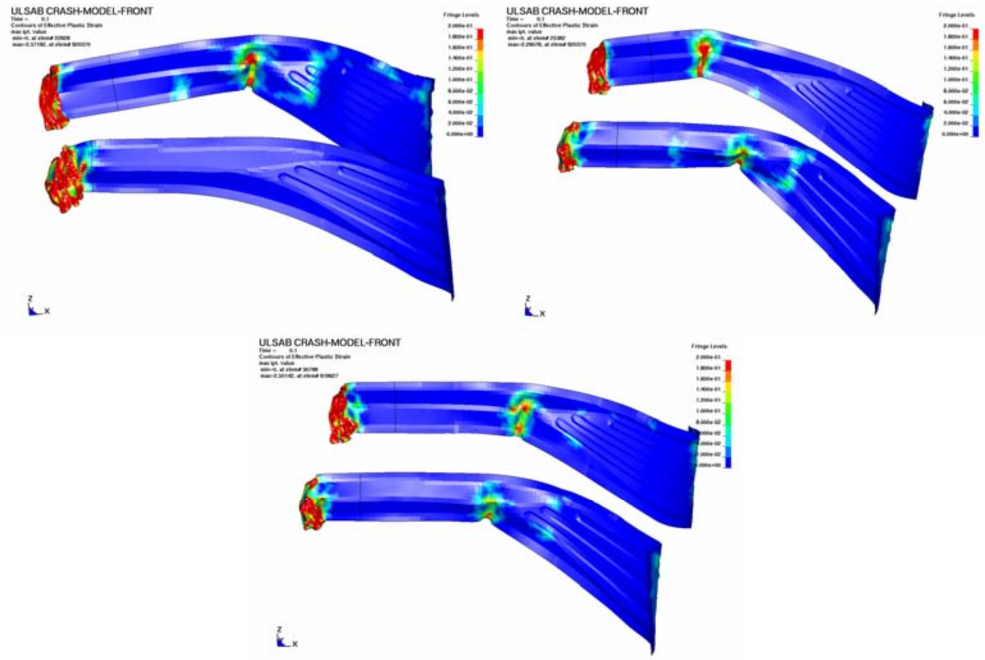

Figure 15: different failure mechanisms, fine mesh, velocity 14 m/s

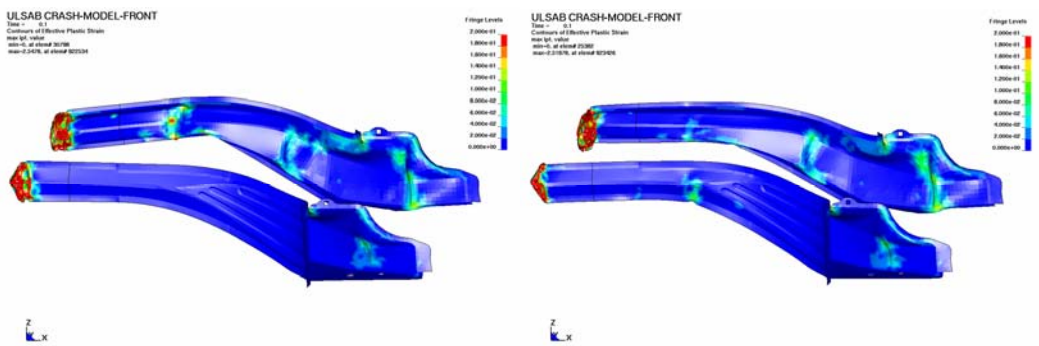

Figure 16: designs with the highest front wall intrusions, fine mesh, velocity 10 m/s

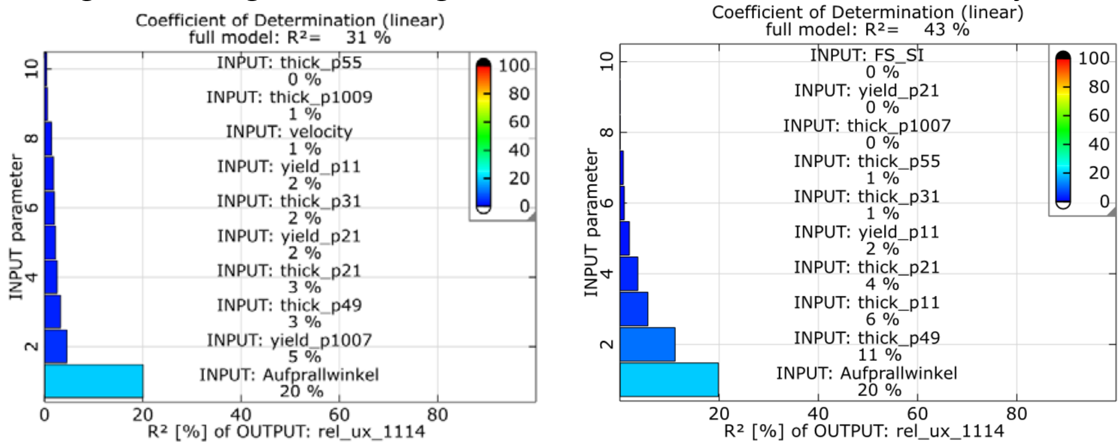

Figure 17: COD of Intrusion at Node 1114, fine mesh, left: 14 m/s, right: 10 m/s

5. Summary and Outlook

A systematic approach was developed for determining the robustness of important performance criteria of automotive applications qualitatively and quantitatively. Primary result of the robustness evaluation is the estimation of the scatter of important result variables. Furthermore, sensitive scattering input variables can be identified and the determination of result variables can be examined. Assumptions concerning activated nonlinear correlations (clustering/outliers/bifurcation) caused by input scatter can be verified.

By using measures of determination, the quantitative influence of numerical noise on the variation of result variables can be estimated and thereby, an important contribution to the reliability of prognosis and quality of the crash test computations can be given.

The breakthrough in practical application and the acceptance of stochastic analysis for robustness evaluations was achieved by using linear/quadratic correlations and the corresponding measures of determination, by using projection of statistical measures on the finite element structure as well as by standardization of robustness evaluation procedure.

The quantitative estimation of the measures of determination and the securing of large measures of determination are not only meaningful in robustness evaluations of final designs. If crash tests are an integral part of multi-disciplinary optimization tasks [5], the measures of determination should also be secured for the result values. Here, the measures of determination in the design space of optimization can be used as quality criteria for the applicability of the results in constraints or objective functions [2].

The productive use of stochastic analysis in virtual prototyping is associated with high requirements on CPU, on the parametric of the models and on the automation of CAE-process as well as evaluation processes. From those requirements, an allocation of CPU-power is often the smallest problem. Also the automation of the CAE process is normally not a real problem. The definition and the automatic extraction of appropriate response values for robustness evaluation are usually one of the main work packages of the engineer who is performing the robustness simulation. The automation of post processing of robustness evaluation including the offer of a filter of variable importance is one of the main topics of the current optiSLang software development and will be available to the public soon. Sometimes costly problems occur, if the parametric of the models needs to be improved for stochastic simulation. For example for passive safety applications, it became very important to reposition automatically the dummy after the perturbation of the design and dummy parameters are introduced. Therefore, we developed a multi body dummy positioner [7] and are facing the problem of automatic reposition of FE-dummies.

Further research and code development is needed, if spatial correlated phenomena have to be taken into account. For example, geometric scatter or the consideration of scatter from forming parts in crashworthiness applications will need to extend the stochastic model of scatter definition to stochastic fields [1].

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