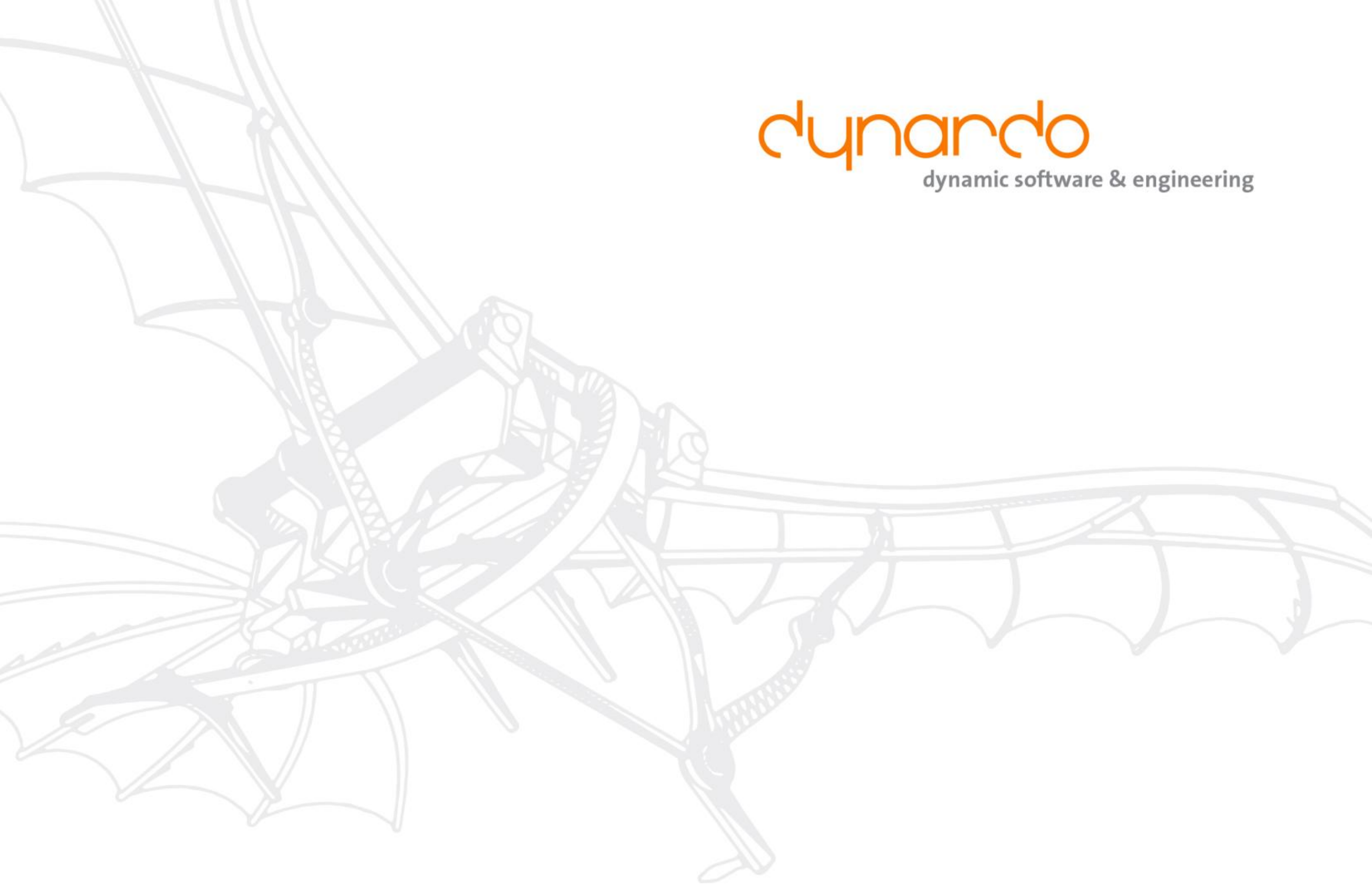

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Robustness Evaluations for CAE-based Virtual Prototyping of Automotive Applications

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Robustness Evaluations for CAE-based Virtual Prototyping of Automotive Applications

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Keywords: Robustness Evaluation, stochastic analysis, Coefficient of Determination (CoD), Coefficient of Prognosis (CoP), meta-model of optimal Prognosis (MoP)

Abstract. *Due to a highly competitive market, the development cycles in the automotive industry have to be constantly reduced while the demand regarding performance, cost and safety is rising. 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* ***CAE-based virtual prototyping****. One of the greatest challenges is the replacement and reduction of hardware tests by* ***CAE-based robustness evaluations****. Here, robustness evaluation characterizes the sensitivity of the important system response in respect of given scatter in the environmental conditions. Consequently, probabilistic methods using* ***stochastic analysis*** *have to be utilized in order to quantify robustness, safety and serviceability.*
At the same time, 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 contain some risks. This can be seen in the increasing number of product recalls. Therefore, the topic of robustness evaluation assuring serviceability, safety and reliability should be taken into account in virtual prototyping as early as possible.

This paper introduces and discusses the state-of-the-art method in applying CAE-based robustness evaluations to automotive applications, NVH application of passenger comfort, forming simulation, passive safety and crashworthiness. A systematic approach to determine the robustness of important performance criteria of automotive applications with a minimum amount of design evaluations will be introduced. This paper also discusses aspects of definition and introduction of scatter using single scattering variables or random field. Special focus will be given on the evaluation of response scatter variation as well as quantification of the contribution of scattering inputs to the response scatter using highly dimensional nonlinear correlation analysis.

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 rising. The development of innovative, high quality products within a short time frame which are able to succeed in the international car producer competition is only possible by using CAE-based virtual prototyping. One of the greatest challenges is increasing the numerical simulation of large test and analysis programs including CAE-based optimization and CAE-based stochastic analysis while reducing the number of hardware tests. The increasing usage of structural optimization may also require 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 few years. 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 given 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 (robustness evaluation) or probability based robustness evaluation (usually called reliability analysis) have to be utilized [1]. In variance-based robustness evaluation procedures, a medium sized number (100 to 150) of samples of possible realizations of input variables are generated by Latin Hypercube Sampling (LHS). After calculating the sample set, the variation of important system responses and their correlation to input scatter is investigated. By running a sample set of around 100 Latin Hypercube samples, reliable estimation of event probabilities up to 1 out of 1000 (2 to 3 Sigma range) is possible. For rare event probability estimations like 1 out of 1000000 (4 to 6 Sigma range), probability-based robustness evaluations using gradient (FORM) or sampling based (ISPUD, adaptive sampling, asymptotic sampling) stochastic analysis methodology [2] becomes necessary.

From our experience, the key for a successful integration of robustness evaluation in the virtual product development cycles is the balance between the proper introduction of input uncertainties, reliability of stochastic analysis methodology and the reliability of the statistical post processing. If we miss the balance of one of the three, the main results of the stochastic analysis, the variation or correlation estimation very often is wrong and useless. For example, if we miss the most important input scatter, the variation prognosis is useless. If we use the wrong sampling (like 100 Monte Carlo Sample), the reliability of correlation measurements is very low or if we test linear correlation only, we may miss the most important correlation between input and output scatter.

Consequently, the best possible translation of all knowledge about input uncertainties and the contribution of all potentially influencing uncertainties are very important. Therefore, in real world applications we need to contribute large numbers of uncertain variables. A result of a robustness evaluation of full car applications in NVH contains several hundred scattering inputs. The Reduction to smaller sets of variables, which is necessary for Robust Design Optimization (RDO) procedures, is only possible by knowledge of the variable unimportance determined by the robustness evaluations. That is very much in contrast to the introduction of CAE-based optimization. Here, the analyst can limit the design space for optimization almost without the risk of producing useless results. In the optimization task, any variable reduction would “only” result in pure or missing design improvement.

Within Robust Design Optimization strategies, the robustness evaluation is a necessary part to evaluate and quantify robustness and can be integrated in iterative or automatic RDO procedures [2] [9].

2 VARIANCE-BASED ROBUSTNESS EVALUATION

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

Considering that in the discussed automotive application it is not necessary to consider small event probabilities, robustness evaluations using Latin Hypercube sampling [3] 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 in the two to three Sigma probability range. The secondary goal is the identification of correlations between input and response scatter as well as a quantification of ”physical” and “numerical” scatter of result variables.

The definition of the uncertainties forms the base of the stochastic generation of the sampling set. Because robustness evaluation asks for the influence of input scatter, the best possible definition of them is essential. Furthermore, the closer we look to response variation and correlation, the more detailed knowledge we need in terms of input distribution information and correlation between scattering input variables. This simple principle may be obvious, but we are often times forced to start with rough assumptions about input scatter violating that principle. Therefore, we frequently have to recommend strongly the validation of results from such robustness evaluations.

In practical applications, it is very important to carefully translate all existing knowledge of scatter into a suitable definition of uncertainty. Thereby, the bandwidth reaches from detailed data coming from quality control of material properties to estimations of scatter and uncertainties out of purchase terms and conditions of materials and parts. The software used for the robustness evaluation should be able to comprehensively consider all available knowledge regarding the input information. This requires the use of suitable distribution functions (like normal distribution, truncated normal distribution, log normal distribution, uniform distribution). Besides the distribution of information of single stochastic variables, significant correlation between variables or significant spatial correlated stochastic behavior called stochastic fields has to be taken into account. Furthermore, to ensure conservative estimations of variation and taking into account if the knowledge base of variation is low, we recommend a moderate increase of observed input scatter.

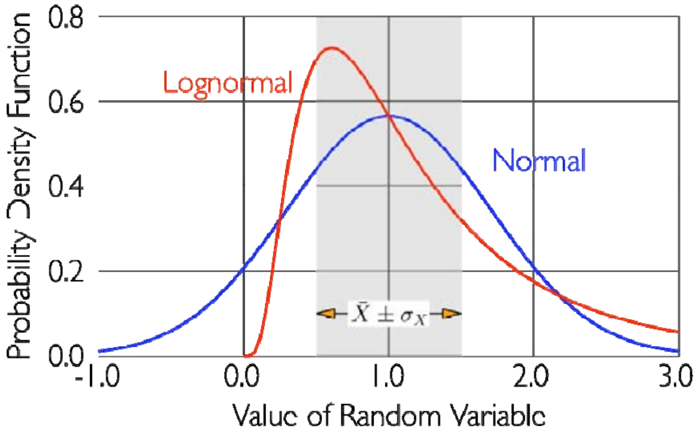


Figure 1: Normal versus Lognormal distribution, the figure visualizes that both distributions may have the same mean and standard variation but very different probability in the tails

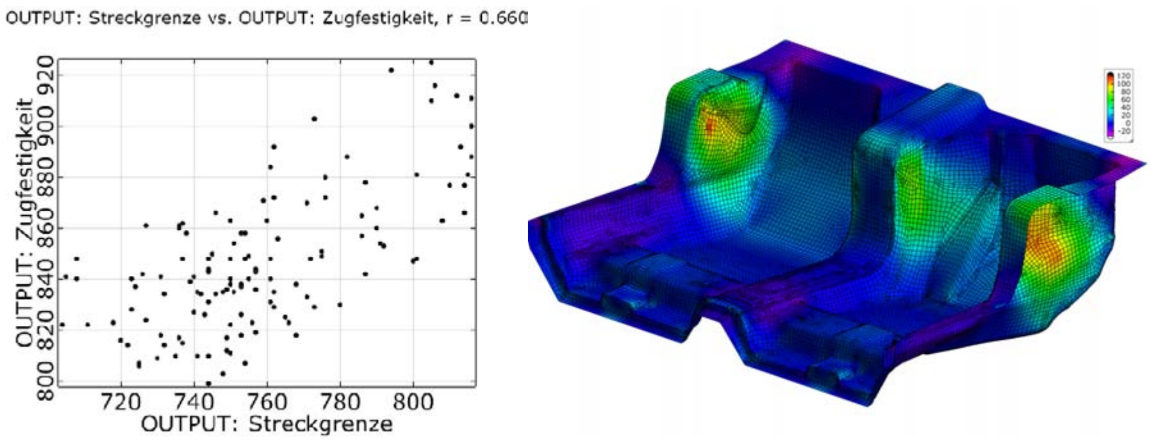
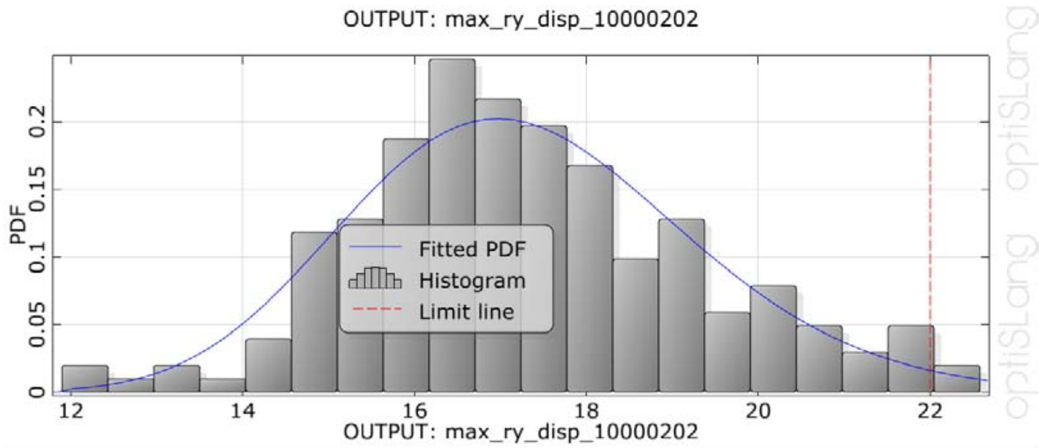


Figure 2: Example of correlations, left: correlation of scattering material parameter right: random field of initial stresses after forming process

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 error. Latin Hypercube Sampling methods are to be preferably used when creating samples to keep this error as small as possible. Research regarding the estimation of linear correlation coefficients [3], has shown that for the same expected statistical error, optimized Latin Hypercube Samplings are more than ten times more efficient than Monte Carlo samplings. Same trends are expected for nonlinear correlation measurements.



Statistic data			
Min:	11.9	Max:	22.58
Mean:	17.31	Sigma:	2.006
CV:	0.1159		
Skewness:	0.264	Kurtosis:	3.115
Fitted PDF: Log-Normal			
Mean:	17.31	Sigma:	2.006
Limit x = 22			
P_rel:	0.989474	1 - P_rel:	0.0105263
P_fit:	0.98349	1 - P_fit:	0.0165101
Sigma-Level:	2.33581		

Figure 3: Histogram for Robustness evaluation; the violation probability of the limit 22 is estimated at 1 to 2%

Statistical measures from the histogram form the base for the estimation of robustness measurements of response variability. Important measures of variation are coefficient of variation, standard deviation, min/max values or Sigma Level. In practical applications, the robustness of result values is often determined by examining if certain boundaries are exceeded. Figure 3 shows an example of reliable estimation of probability of overstepping limits. The probability of overstepping the limit of 22 is estimated by counting designs having response values larger than 20 to 1% (1-P_rel=0.01=1%) as well as calculated using a fitted distribution function to 1.6%. (1-P_fit=0.016=1.6%). Using two procedure of estimating, we can state that the probability is between 1 to 2%.

If the scatter of output variables is not tolerable, it is searched for apparent correlations between the variation of input variables and the variation of individual output variables. The simplest and most widely used correlation measurement is the pairwise linear correlation coefficients. The correlation coefficients form the base of measures of determination. Measures of coefficients of determination (CoD) are percent-wise estimates, where ratio of variation of an output variable to the variation of individual input variables can be explained by using the correlation hypothesis.

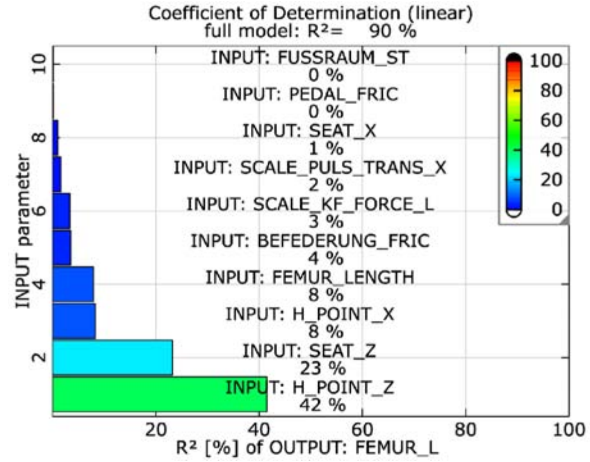


Figure 4: Coefficient of Determination of Femur Force, shows that 90 % can be explained with identified linear correlations, the variation of vertical seat position (H_POINT_Z) result is 42% of total variation of femur force

Having significant multidimensional or non-linear effects on the response identification and quantification of pairwise linear correlation is not good enough anymore. In this case, the application of methods to identify and quantify multidimensional nonlinear correlations becomes urgent. In order to avoid the “curse of dimensionality” in applying multidimensional nonlinear correlations in large dimensions of scattering variables, Dynardo has developed the Meta-model of Optimal Prognosis (MOP) algorithms [4] and invented the measurement of forecast quality [4] (Coefficient of Prognosis-CoP) of the correlation model. This approach provides automatic reduction of the dimensionality to the most important parameter combined with automatic identification of the meta-model which shows the best forecast quality of variation for every important response value. At the same time, the amount of necessary CAE-solver calls to reach a certain forecast quality can be minimized. This technology allows successful application of CAE-based robustness evaluation as a standard process to CPU-intensive applications of automotive industry.

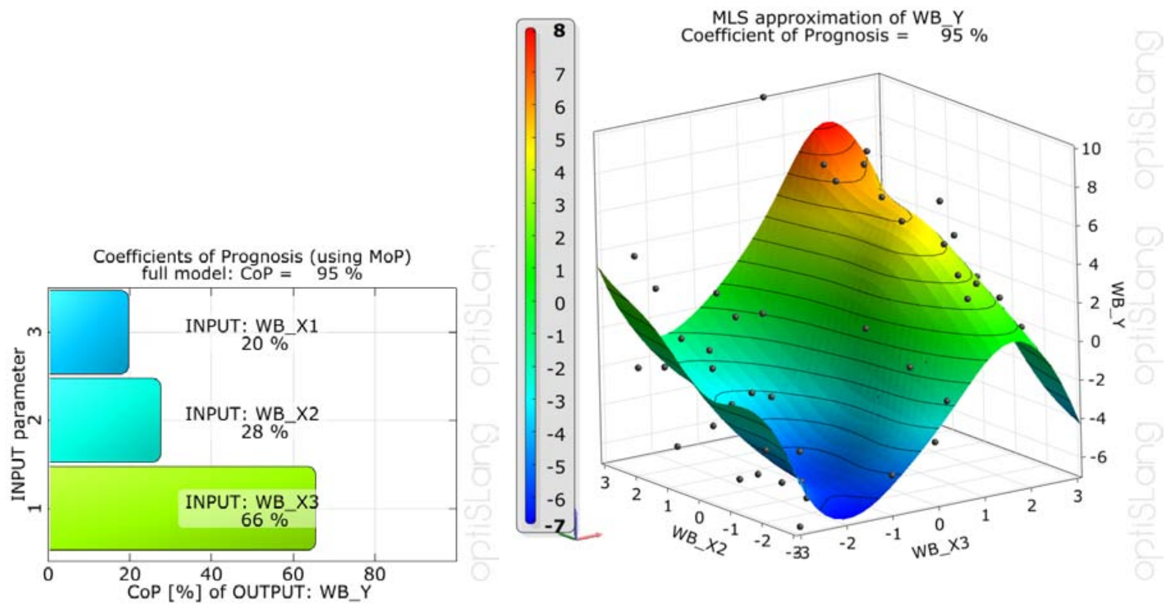


Figure 5: Coefficient of Prognosis (CoP) using the Meta-model of optimal Prognosis (MoP) to quantify the input variable contribution to the response variable variation

Figure 5 shows an example. The identified correlation model (MoP) reaches a forecast quality of 95% of the total variation of the response value. Variables 1 to 3 are identified to have significant contributions.

Introducing robustness evaluation into regular virtual product development cycles needs an automatic and standardized post processing process. The enormous amount of statistical data has to be reduced to some significant result values which answer the primary questions. Of course the post processing procedure may vary depending on the different application areas. An example of the procedure of passive safety is illustrated in figures 13, 14 and 15. First the variation is summarized in one graph as the primary result of robustness evaluation. The range of scatter is normalized to legal limit values and different colors show exceedance of internal or legal limits. From the base of this summary, the engineer can look closer to single result values by evaluating the coefficient of determination and the correlation structure between this response and input scatter. That information forms the base to point out necessary modifications of the system or to point out necessary improvements of numerical modeling or result extraction.

3 NVH APPLICATIONS

Dynardo started in 2002 with the integration of robustness evaluation for NVH applications [5]. The main motivation was to investigate how tire, body in white and suspension system scatter influence the NVH performance. Therefore, consideration of stiffness scatter (sheet metal thickness, suspension system stiffness scatter, tire stiffness scatter) is investigated. The evaluation of variation as well as correlation between input and output variation solved the task of robustness evaluation of driving comfort criteria. Because FEM is implicitly used for the numerical simulation, the numerical noise does have no influence on the statistical measurements. Since 2003, we are in the productive level of FE-based NVH application.

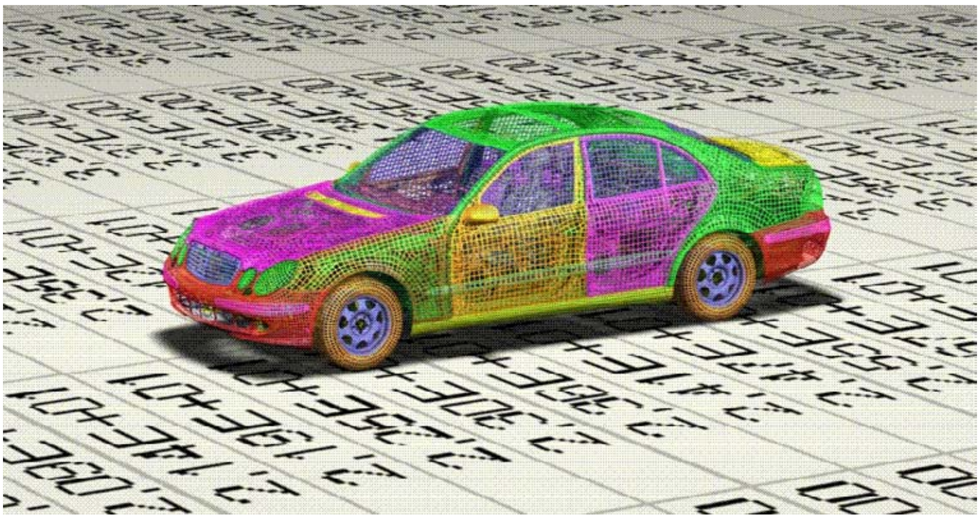


Figure 6: The Robustness of NVH performance of new C-Class was investigated for several NVH load cases

The challenge for NVH applications is the continuously increasing number of scattering variables (now up to 600). Therefore, we developed a significance filter for output correlations using the confidence intervals of the known correlation coefficients of the sampling.

That procedure allows calculating the CoD even if the number of sample points is much less than the number of scattering input variables. After Implementation of the MOP procedure, the reduction to important variables is even more efficient and reliable.

Besides plots of variation and correlation of single peaks usually extracted from windows in the frequency or time domain, important post processing capabilities are plots of the scatter bands in the frequency and time domain. From that plots the user can extract information, at which frequencies engineering tasks concerning suspension or body in white will significantly influence the NVH performance.

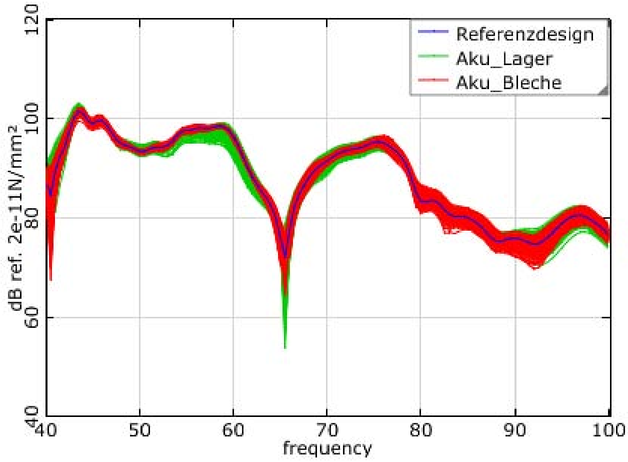


Figure 7: Plot of scatter bands in the frequency domain, Blue: reference design; Red: scatter due to sheet metal uncertainties; Green: scatter due to suspension system uncertainties

4 FORMING APPLICATIONS

The robustness of the **forming processes** is becoming more and more important to quantify the quality and robustness of the formed parts. In addition, if spatially scattering thickness or material (hardening) of formed parts is significantly influencing the robustness of **crashworthiness** applications (refer to the example in the section crashworthiness), the robustness evaluation of the forming process may become a necessary step to generate reliable information about spatially correlated scatter of formed parts.

Typical scattering input variables of forming simulations are material parameters like yield strength, tensile strength, R-values, anisotropy values, friction values, sheet-thickness or position of blank and tool. In forming simulations, the definition of robust processes is often based on bounds representing 3-sigma values. A so called 3-sigma-value is actually a value with a probability of exceedance of 0.0013 (1 out of 1000). Besides the calculation of sigma values, evaluating the related probabilities using histogram and fitted distribution functions (fig 3) is recommended.

The visualization and analysis of statistical values on the FE-mesh are important during the engineering evaluation of robustness evaluation since the result values of a forming simulation, which are to evaluate, are generally spatial correlated values. Therefore, the statistical measures on the FE structures serve as basis for the identification of critical areas. Because local element correlation analysis suffer on the “patchwork” character, Dynardo is using Random Field technology to decompose the spatially correlated variation [8]. The resulting scatter shapes are sorted by their contribution to the total variation. Usually the majority of variation is defined with a handful of scatter shapes, which correlates to the main mechanisms of scatter in the forming process. From our experience, this type of visualization and scatter decomposition leads to better understanding of the mechanisms of scatter and higher acceptance of the results in the production departments.

The following pictures show an example of visualization of the variation of thinning at the FE-structure using value of standard variation. Two hot spots of variation can be identified (fig 8).

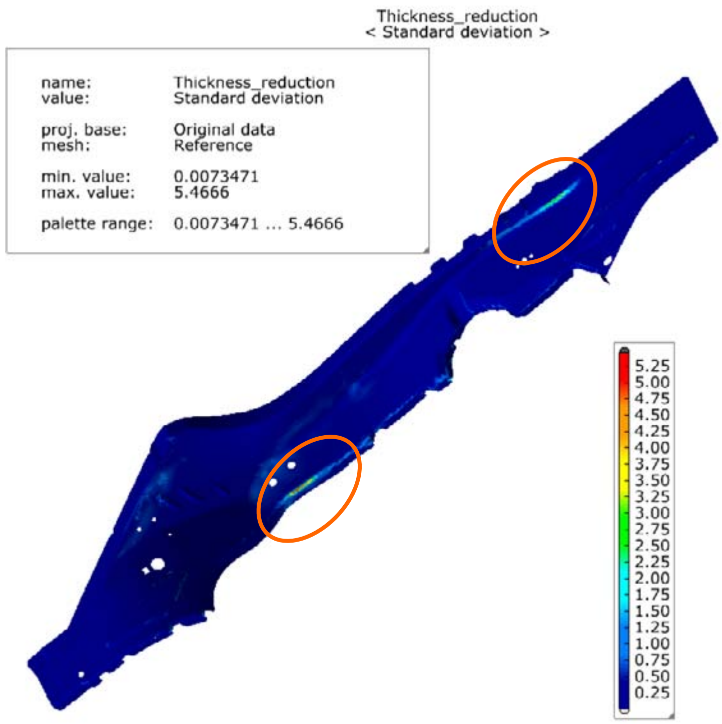


Figure 8: standard deviation per element shows the two hot spots of variation: here limits of thinning are violated

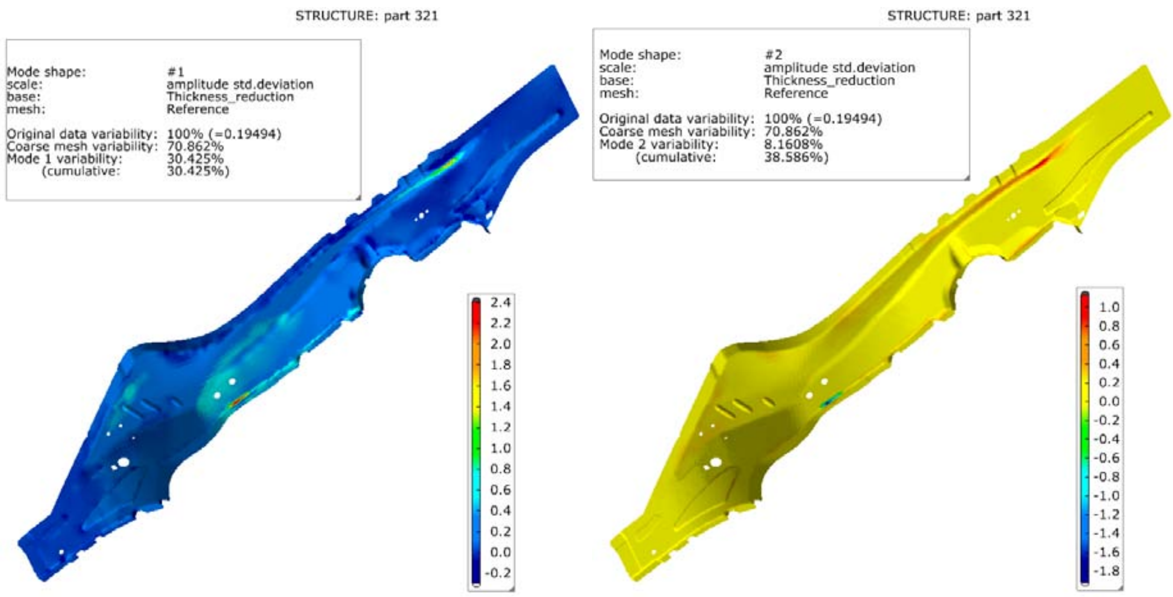


Figure 9: The first two scatter shapes, both have contributed to the hot spots

Using Random field decomposition, the two main shapes of total variation are calculated (fig 9). Both shapes have contributed to the two hot spots of variation. Using correlation analysis between the scatter shapes of the result values and the input scatter, it can be clearly seen that the first shape of variation is resulting from the scatter of (coil) sheet thickness and the second scatter shape is resulting from the material anisotropy and process friction scatter (fig 10).

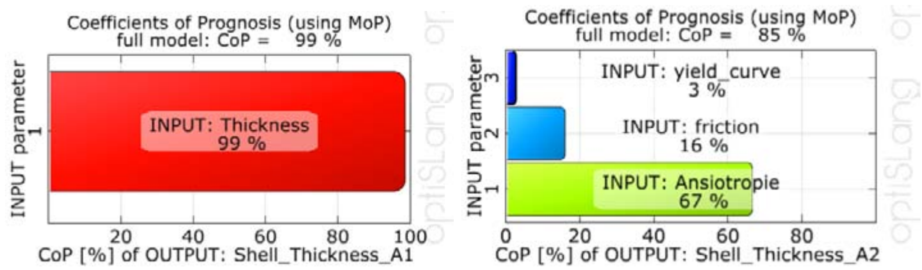


Figure 10: Coefficient of Prognosis (COP) measurements show the contribution of input scatter to the two main scatter shapes

The permanent process of automation and standardization in serial production requires especially the handling of different forming solvers. Therefore, extracting reliable and unique quality criteria of the formed parts is essential. The development and integration of a statistical FE-based post processor into the CAE-process are important boundary conditions for a successful integration of robustness evaluation into forming simulation.

5 CRASHWORTHINESS AND PASSIVE SAFETY APPLICATIONS

5.1 Notes on Numerical Robustness of Crashworthiness and Passive Safety Applications

The inspection of numerical robustness of FE-based crash test computation results from the experience that small parameter variation or the variation of demonstrable insignificant physical parameters can lead to large scattering of the result variables or respectively lead to obviously unfeasible results. If n-designs are to be computed and their variation and correlation is to be evaluated statistically, the question of which proportion of the resulting variation results from numerical noise arises. Therefore, successful application of robustness evaluation to passive safety crashworthiness application needs reliable quantification of the resulting response variation.

In the beginning of robustness evaluations at passive safety in 2004, we performed in parallel “physical” robustness evaluations of physically scattering parameters (scattering in reality) and “numerical” robustness evaluations regarding variation of numerical parameters or small perturbations of physical 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 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 noise within a physical robustness evaluation.

Starting with measurements of pairwise correlations (Coefficient of Determination) improving to measurements of multidimensional correlation (Coefficient of Importance), we finally converged to quantify the “with the best possible correlation model explainable” amount of output variation by using the Coefficient of Importance CoI) [4].

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 identified correlations have 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. Realizing that measurements of determination based on correlation coefficients, as well as based on meta-models suffer on large statistical errors with increase of dimensions and nonlinearities, the introduction of measurements of forecast quality (CoP) became very important.

From our experience, we selected the rule of thumb that for “numerically” robust models, measures of determination using CoP of over 80% should be determined. If the measures of determination in practical applications decreased significantly below 80%, it was very often identified that the corresponding result variable shows a significant amount of numerical noise. A reason, therefore, may be insufficiencies in the result extraction, or more frequently insufficiencies of the FE-modeling interacting with the approximation methods, like noise resulting from contact treatment. After improving the modeling or the result extraction, the measure of determination usually increased up to over 80%.

It shall be stated that in theory, it is impossible to determine exactly the proportion of numerical noise. Also, the diagnosis of forecast quality of variation 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. Besides numerical noise, an important motivation of aiming at high coefficients of determination for robust designs is that the correlations between input variation and output variation should be identifiable. These correlations finally may be used as possibilities of influencing the result scatter. In order to improve robustness, 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.

The subject of bifurcation points is surely to be discussed separately. For the purpose of robust designs, one would want to vastly avoid systems with uncontrolled bifurcation points, which can be traversed in multiple ways within the scatter range of input variables and then lead to significantly different system responses. As a matter of principle, one would have to be able to find correlations between indicators of bifurcation or results heavily influenced by bifurcation and the input scatter. Otherwise the bifurcation occurs randomly which implies that we are dealing with a very sensitive, most likely not robust dynamic system.

5.2 Passive Safety Applications

In 2004, we started with the integration of robustness evaluation into passive safety applications [6]. The goal of robustness evaluations is to investigate and improve the robustness of the restraint systems of fulfilling consumer ratings and legal regulations at the crash tests. Fig 12 shows an example how a restraint system was improved by improving FE-modeling and physical modifications of the restraint system to move the mean value and to reduce the response scatter.

In passive safety applications using MKS or FE-models, the quantification of numerical noise became an important part of robustness evaluation. In other word by checking the quantity of numerical noise, we check the model quality. By developing a reliable quantitative estimation of numerical noise robustness, evaluation of passive safety applications became accepted for regular procedures in virtual prototyping [6]. In 2005, we started to implement robustness evaluations of FE-based crash analysis for passive safety applications. Today, at productive level of FE-based passive safety application (side crash, head impact) using CoP measurements, we can reduce the number of necessary solver runs as much as possible.

Consideration of the test setup (dummy positioning, crash puls), airbag (mass flow, venting, permeability), sensors, belt system, door/interior stiffness and scatter of friction is state-of-the-art in robustness evaluation of passive safety (fig 11). Besides consideration of the influence of dummy scatter also the influence of geometric scatter of the body in white became a topic of interest.

Automation of post processing is a key feature for productive serial use. Starting from one variation overview, the engineer can identify the critical response values regarding variation (fig 13). Using plots of scatter bands in the time domain, the characteristic of the response scatter is evaluated (fig 14). Using the coefficients of determination of the extracted performance values possible, influence of bifurcation, numerical noise or extraction problems are investigated and quantified (fig 15).

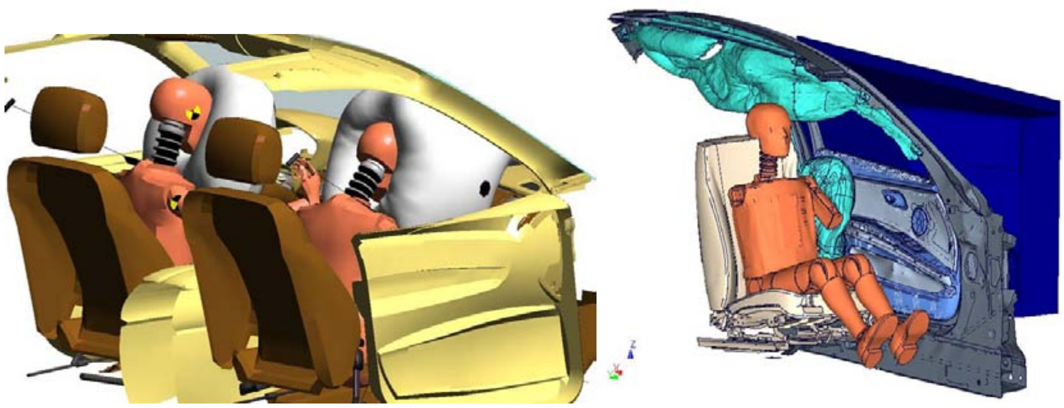


Figure 11: For passive safety applications multi body as well finite element models are used in robustness evaluations

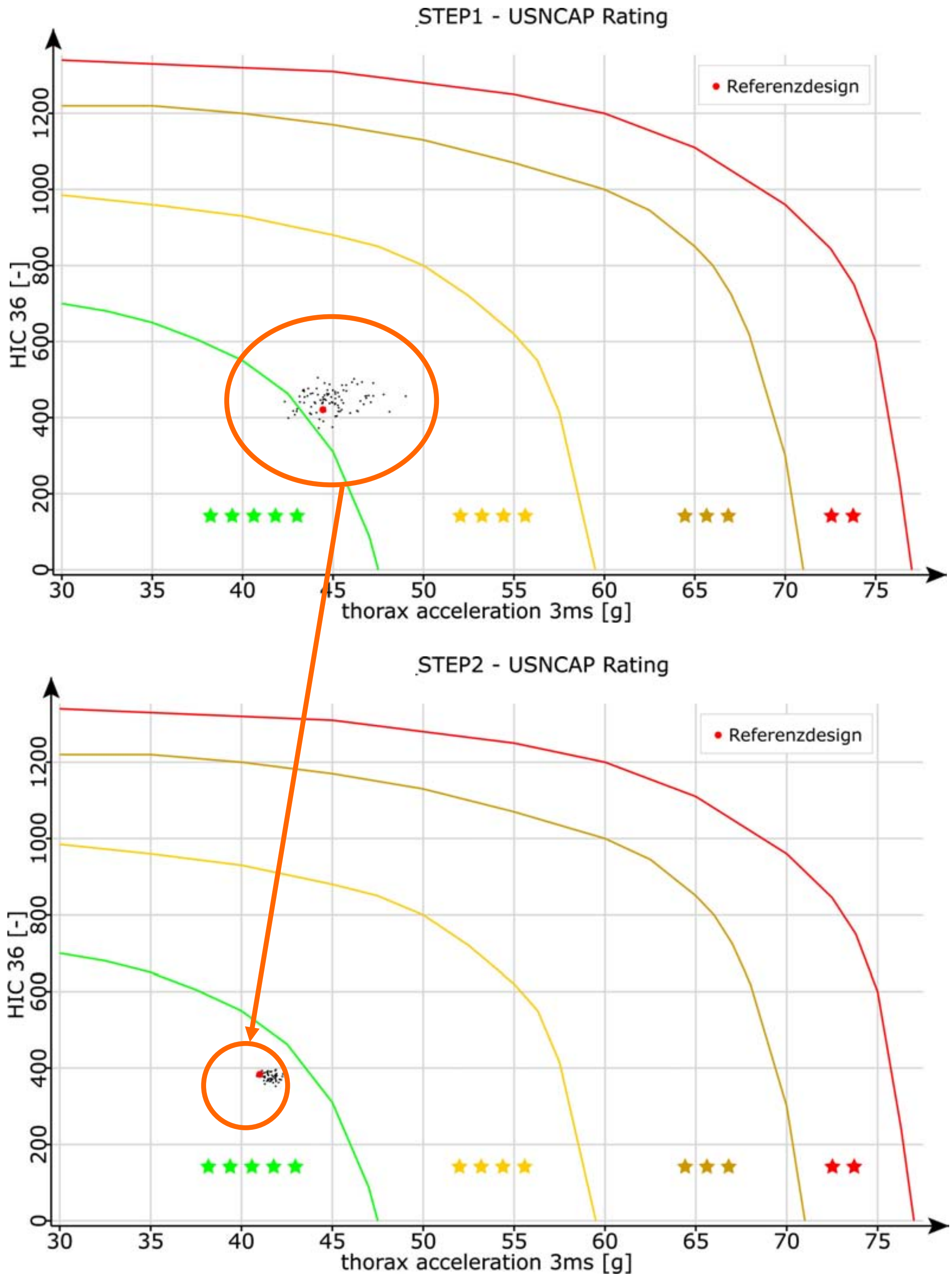


Figure 12: Visualization of robustness improvement of passive safety performance: upper diagram shows the scatter at milestone 1; lower diagram shows the scatter at mile stone three of the virtual product development process

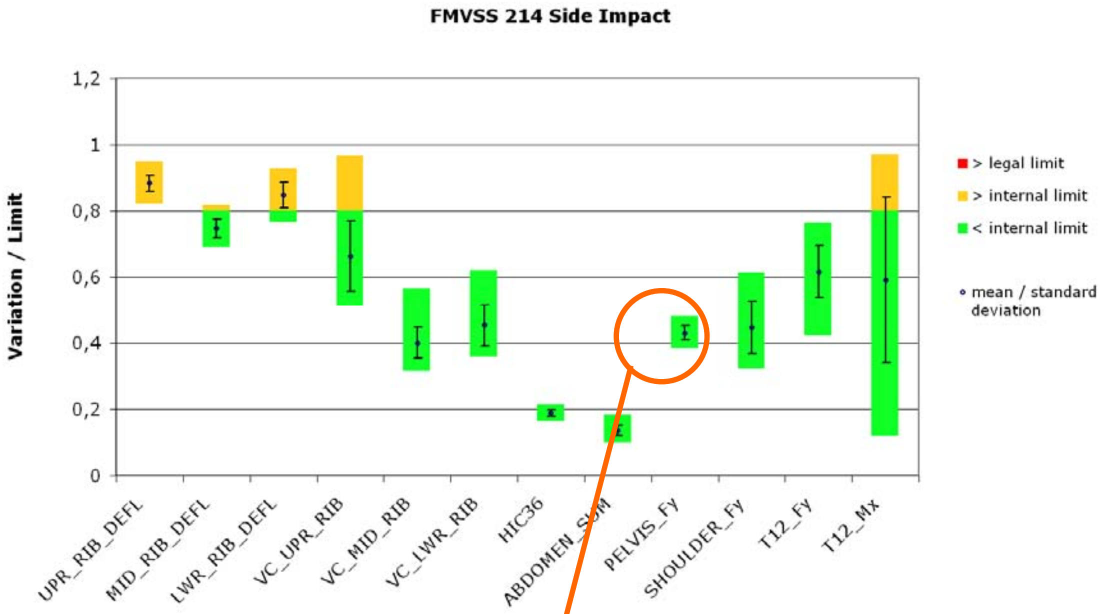


Figure 13: Summary of variation of all important responses for load case FMVSS 214

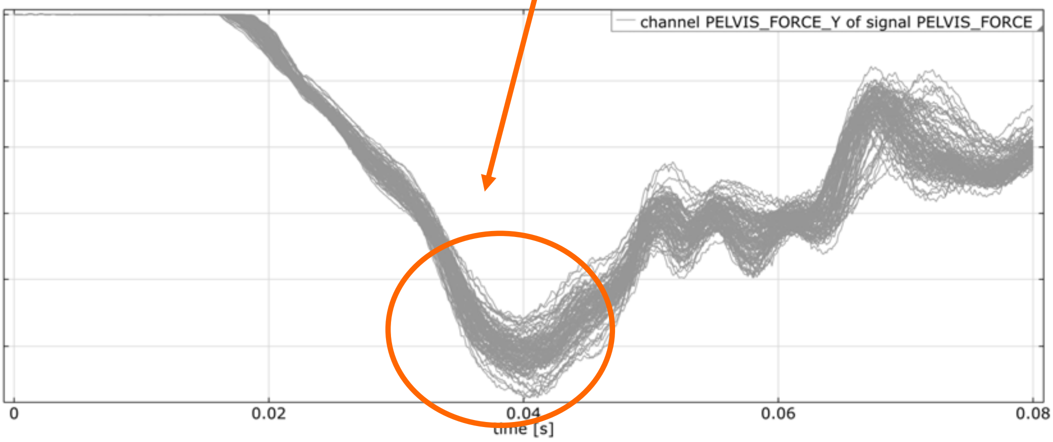


Figure 14: Scatter band of output signal pelvis force Y-direction

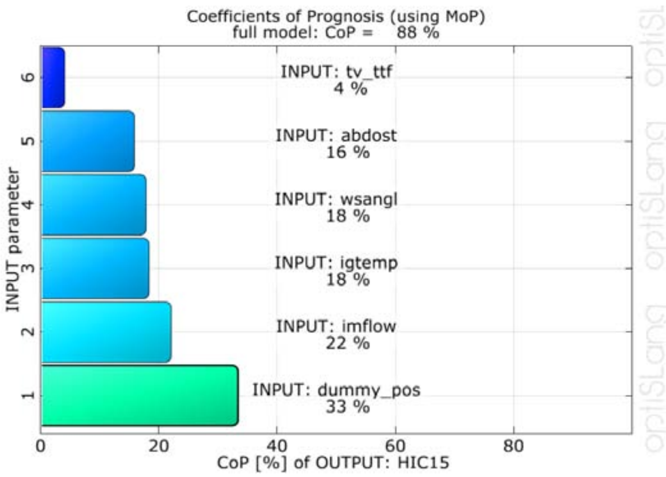


Figure 15: Coefficient of Prognosis for Variation of HIC15 values

Until 2007, more than 100 robustness evaluations were performed by Dynardo at the BMW virtual prototyping for passive safety systems. In the serial use, the following added value could be obtained concerning the dimensioning and increase of the robustness of restraint systems [6]:

A better understanding of the transmission mechanisms of input scatter on significant performance variables was developed.

Scattering input parameters were identified, which have significant contribution to important response scatter.

Model weaknesses were detected and numerical noise of significant vehicle performance variables was reduced. Thereby, the model robustness/stability and the quality of prognosis of crash-test computations were increased.

Robustness problems of the restraint systems were recognized and in cases of high violation of limits solved or improved by re-design of components.

5.3 Crashworthiness Applications

In the virtual product development, crash analyses are an important part for the design of the car body. The minimization of weight and sometimes competing requirements from several load cases have to be adjusted as optimally as possible. Consequently, no high safety distances can be kept while maintaining all requirements. Therefore, the assurance of robustness of the optimized design against unavoidable scatters of crash test constraints, production constraints and material constraints in preferably early stages of product development becomes more and more important. Robustness analysis of structural crash load cases has high demands for numerical robustness evaluations. Reason for this are the complexity of modeling, long calculation times, high non-linearities and the influences of numerical noise. Starting in 2004, we could increase the efficiency of optiSLang [10] and the post processor Statistics on Structure [11] so that since 2007, we have been able to meet necessary conditions to run robustness analysis of structural crash load cases with LS-Dyna at serial process at Daimler AG [7]. Today, robustness evaluations are used to verify robustness on important mile stones of the virtual development process as well as to investigate phenomena, which are seen in real world tests but so far not forecasted by the virtual models.

In the following example the use of random fields for parameterization of forming scatter is introduced [7]. A hardware test within an insurance test case (fig 16) applied to an early car design state did show plastic phenomena on the stringer. These did not occur in the deterministic analysis results of the virtual product development. With the help of robustness analysis, it was finally proven, that the phenomena resulted from the scatter of thickness of a forming part. To identify the source of the phenomena, a very detailed discretization level of geometric scatter considering the local distribution of thickness scatter from the forming process was necessary. Sheet metal thickness scatters at the steel coils, which in measurements had normal distributions, show a variation coefficient of up to 0.02. Robustness analysis of forming simulations displayed an additional 2 or 3 times higher scatter than the initial coil scatters in ranges of high plastic forming grades.

Therefore, a robustness evaluation of the forming process of the critical part was performed resulting in the local distribution of thinning and plastic strain. To introduce the thickness scatter from the forming process in the robustness evaluation of the crash analysis, Random Field parametric [8] using the main shape of thickness scatter (Fig 17) was used.

In addition, for a total of 21 sheets in the load path, uniform scatters of sheet thickness, scatter of yield strength, as well as scatter of test constraints, scatters of velocity, scatter of friction and barrier position were considered.

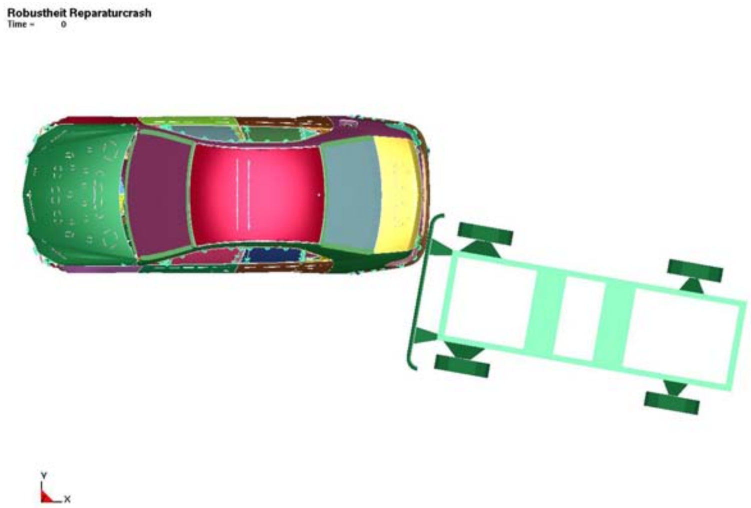


Figure 16: Load case repair crash, top view

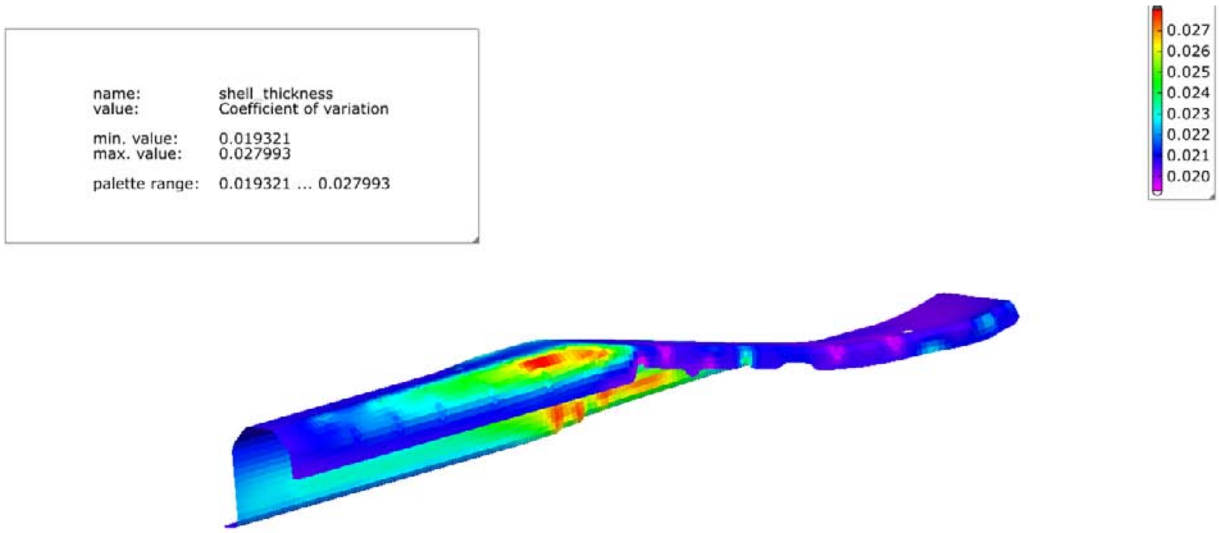


Figure 17: Variation coefficient of sheet thickness of the critical part in the robustness analysis of the crash calculation including the superposition of variation of coil sheet thickness and thinning from the forming simulation of the stringer

Within the variation space of 150 possible car configurations, the phenomena which was connected with high plastic strain and buckling of the stringer was found with a probability of 7%. The phenomenon is connected with high local plastic strains (fig 18) and high relative y-displacements (fig 19. Place and size of the plastic deformation correspond very well to the test.

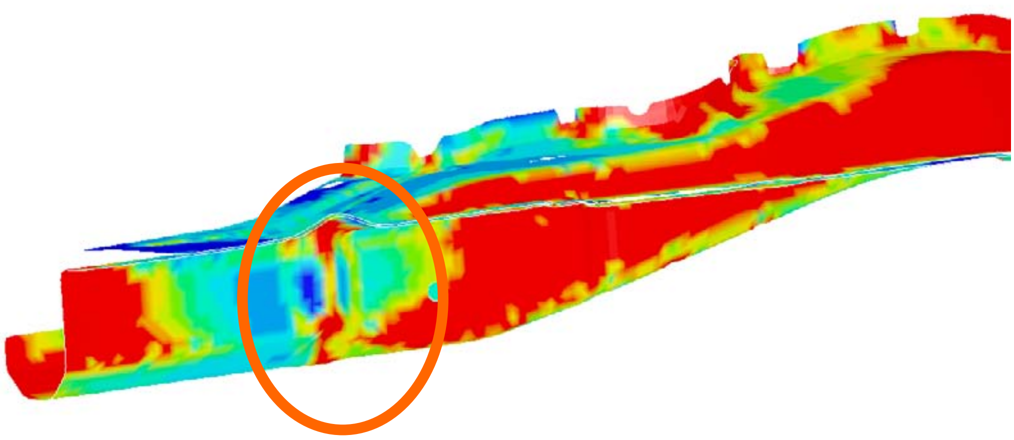


Figure 18: Buckling of the stringer

Correlation analysis confirmed that about 60% of deformation variation in buckling direction results from linear correlation. A great component of the remaining 40% comes from the nonlinear effect of buckling at small impact angles (red points in the Anthill plot). It was shown that the stringer is buckling if a high thinning coincides with small yield strength and small impact angle.

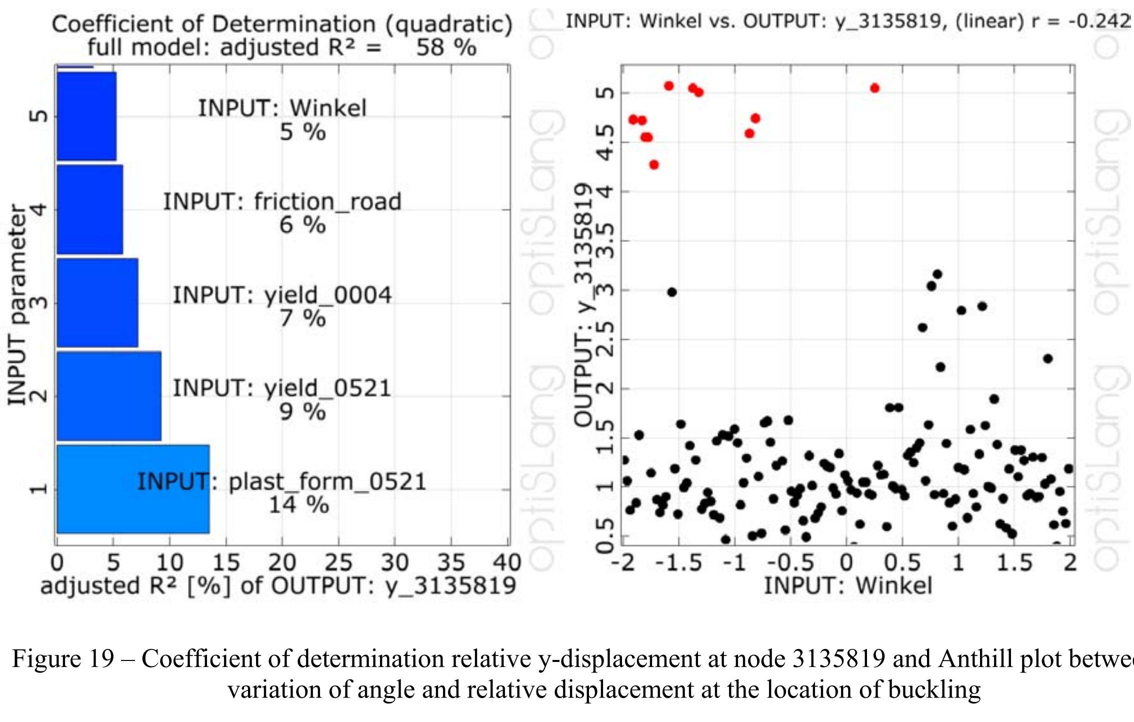


Figure 19 – Coefficient of determination relative y-displacement at node 3135819 and Anthill plot between the variation of angle and relative displacement at the location of buckling

To lower the sensitivity of the car design regarding scatters, certain actions were implemented on the stringer (overlapping sheets and additional joining techniques).

Robustness analysis of the improved structure could prove the improvement of robustness. Also, the next hardware test of the car did not show a complaint.

6 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, we can summarize that following boundary conditions have to be met:

Numerical model and simulation methods have to meet the fundamental ability of prognosis and therefore have to be able to show all significant physical phenomena and compare them to experience or experimental data.

Simulation processes often need to be improved regarding parametric, automatic repeatability and automatic result extraction to be ready for process integration.

The existing knowledge on input scatter and uncertainties, for example, in boundary conditions, material values or load characteristics, needs to be properly transferred to an appropriate statistical description. The know-how about the uncertainties needs to be continuously collected, updated and validated.

Correlation error minimized Latin Hypercube Sampling method is recommended 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 a reliable foundation of a robustness evaluation.

The statistical post processing needs to be standardized and automated. Standardization of parameterization, stochastic analysis and post processing of robustness evaluation is very important and 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 conservative assumptions.

A robustness evaluation of most important load cases, estimation of the variance of important performance variables and inspection if limit values are exceeded by the variation of the performance variables was conducted.

An 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 was exercised and an inspection of model robustness and stability by evaluation of coefficients of prognosis was carried out.

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 the numerical models show acceptable amount of numerical noise, the estimate of the scatter of important input variables is trustworthy.

7 CONCLUSIONS

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.

By using measures of determination and forecast quality of resulting variation, 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 from nonlinear correlations and the corresponding measures of determination and forecast quality using Dynardo's MOP approach. A second important step is the standardization of post processing by using projection of statistical measures on the finite element structure as well as by standardization and automation of robustness evaluation procedure.

Often, the productive use of stochastic analysis in virtual prototyping is associated with high requirements on CPU, on the parametric models and on the automation of the CAE-process as well as the 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 was one of the main topics of the optiSLang and SoS software development and will be further improved.

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