Forming Technology Forum 2007 – Application of Stochastics and Optimization Methods
14th – 15th March 2007, IVP, ETH Zurich, Switzerland

USING ROBUSTNESS AND SENSITIVITY EVALUATION FOR SETTING UP A RELIABLE BASEMENT FOR ROBUST DESIGN OPTIMIZATION

Dr.-Ing. Johannes Will*, Dipl.-Ing. Kathrin Grossenbacher**

*Dynardo GmbH
Luthergasse 1C, 99423 Weimar, Germany
Johannes.will@dynardo.de
**BMW Group, München, Germany

ABSTRACT

For a few years, FE-methods are used in industrial applications for simulating the forming process. In the beginning, the computations took a great amount of time and the results often were unsatisfactory. Today, the simulation has become an integral part for assessing and evaluating forming processes.

The optimization, i.e. improvement of product characteristics, has been an integral part of forming simulation based virtual product development for several years now. On the other hand, the robustness of forming processes is becoming more and more focused on recently. In fact, robustness is an additional demand on optimized forming processes. Therefore; a process is necessary of optimizing and at the same time securing the robustness. That process is called Robust Design Optimization (RDO). The optimization and robustness evaluation are either performed consecutively or simultaneously, and several methods are available for this. In the following, existing methods shall shortly be introduced and discussed from a practical point of view regarding their appliance.

From our experience of introducing optimization and robustness evaluation methodology in virtual product development processes, it is absolutely necessary to understand booth domains, the design space of optimization as well as the reliability space to be able to formulate a successive RDO problem. Therefore, starting with a consecutive approach of using sensitivity analysis, robustness evaluation and deterministic optimization is recommended for achieving that knowledge to iterate to an optimized robust design. This procedure will be demonstrated at a practical application.

Of course, the final dream of virtual product development is an automatic Robust Design Optimization procedure with dealing simultaneously with optimization and reliability domain. Therefore, methods for a simultaneous performance of the optimization and the robustness evaluation will be introduced and their potentials will be discussed.

For the forming simulation, LSDYNA is used. For the sensitivity study, the robustness evaluation and the optimization optiSLang, a general purpose parametric optimization and reliability software package [1] is used. At this the CAE-based forming process, the mapping and the result extraction is automated and integrated in optiSLang. After that, optiSLang is performing sensitivity analysis, robustness evaluation and optimization.

Especially for forming simulation, Dynardo developed Statistics_on_Structure (SoS), a statistical post processor with interfaces to the BMW forming simulation meta format, to optiSLang and to LSDYNA. A visualisation of statistical measures on the FE-mesh facilitates considerably the engineering evaluation of robustness since the result values of a forming simulation which are to evaluate are generally spatial correlated values. The statistical measures on the FE structures serve as discussion basis for the identification of critical areas and as a basis for evaluating the robustness. In addition, this type of representation leads to a high acceptance of the results in the production departments.

The practical application of robust design optimization in forming simulation shows a high degree of nonlinearity in the optimization domain. To ensure robustness it was not possible to identify a constant safety distance which means a deterministic design with a maximum FLD_crack value of 0.7 could be robust or have a failure rate of 50%. Finally, it was necessary to check the robustness explicitly for all optima candidates. Therefore is seems mandatory to implement robustness evaluation to forming simulations in virtual product development processes.

Keywords: Sensitivity Study, Robustness Evaluation, Statistics, Robust Design Optimization, optiSLang, SOS

1. INTRODUCTION

For a few years, FE-methods are used in industrial applications for simulating the forming process. In the beginning the computations took a great amount of time and the results often were unsatisfactory. Today, the simulation has become an integral part for assessing and evaluating forming processes.

The optimization, i.e. improvement of product characteristics, has been an integral part of forming simulation based virtual product development for several years now. On the other hand, the robustness of the forming processes is becoming more and more focused on recently. In fact, robustness is an additional demand on optimized forming processes. Therefore, a process is necessary of optimizing and at the same time securing the robustness. That process is called Robust Design Optimization (RDO). The optimization and robustness evaluation are either performed consecutively or simultaneously, and several methods are available for this. In the following, existing methods shall shortly be introduced and discussed from a practical point of view regarding their appliance.

From our experience of introducing optimization and robustness evaluation methodology in virtual product development processes, it is absolutely necessary to understand booth domains the design space of optimization as well as the reliability space to be able to formulate a successive RDO problem. Therefore, starting with a consecutive approach of using sensitivity analysis, robustness evaluation and deterministic optimization is recommended for achieving that knowledge to iterate to an optimized robust design. This procedure will be demonstrated at a practical application.

Of course, the final dream of virtual product development is an automatic Robust Design Optimization procedure with dealing simultaneously with optimization and reliability domain. Therefore methods for a simultaneous performance of the optimization and the robustness evaluation will be introduced and their potentials will be discussed.

At the beginning of an optimization process, a sensitivity study is recommended. Here within the design space, defined by the optimization variables, the sensitivity of the optimization variables due to important results, objectives, terms of objectives and constraints is investigated. As a result, design space reduction, adjustments of design boundaries and selection of appropriate result values for objective definition can be investigated. Therefore with a sensitivity study, the base for a successful optimization is set up.

In general, three optimization method classes are available in optiSLang to solve the optimization problem. These are: mathematical optimization methods using gradients, response surface methods, and stochastic search algorithms. Multi objective (Pareto) optimization will be mentioned shortly.

Within the robustness analysis, the sensitivity of the unavoidable scatter of environmental conditions and their impact on the forming results is evaluated using stochastic analysis methodology. In contrast to the sensitivity study, the robustness evaluation is performed in the reliability space defined by the naturally given scatter of the forming material, the forming process or the forming tools. As a result the scatter of important forming results and their correlation to the input scatter can be investigated. Therefore, the robustness evaluation generates the information how large a safety distance from critical forming results needs to be to generate a robust product. Additionally, at the end of the optimization process the robustness evaluation quantifies and secures the robustness.

For industrial application of robust design optimization in forming processes, the design space for optimization and the reliability space are usually different. That means not all scattering variables are allowed to vary for optimization and not all optimization variables have a scatter that significantly influences the results. Therefore, recycling of robustness information from optimization runs and vice versa is very limited. That has the consequence that robust design optimization using statistical measurements or probabilities to quantify robustness usually needs significantly more effort than pure deterministic optimization procedures.

Of course a robust product can be achieved by deterministic optimization with applying safety factors, but in practice applying “safe” safety factors often leads to very conservative designs and it may contradict the optimization idea. Therefore, introduction of stochastic analysis to quantify robustness will become necessary.

2. SENSITIVITY STUDIE

Sensitivity studies are recommended in order to investigate the design space chosen for optimization. For that purpose, parameter studies which are the variation of single parameters belong to the everyday life of an engineer for a long time now. In analogy, the design of experiment methods which systematically calculate single parameters and combinations of parameters, can be used in small parameter spaces. If the dimension or the nonlinearity of the parameter space increases, stochastic sampling strategies are to be favoured for scanning the design space.

A further advantage of stochastic sampling strategies compared to design of experiments is that they furthermore permit a statistical evaluation of sensitivities via correlation analysis, variation analysis and statistical measurements of determination. For description of the sampling methodology for scanning the optimization design space and the statistical measurements refer to Chapter 3.

Sensitivity studies may enable an adjustment and reduction of the parameter space for subsequent optimization problems. The previous knowledge obtained from the sensitivity studies about sensitivities and coefficients of determination of important results is very helpful for an adequate formulation of the objective function. Finally, from the computation of the sensitivity studies design areas of admissible designs can be identified and adequate starting points for optimization can be obtained.

3. ROBUSTNESS EVALUATION

Based on a forming 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 that deterministic design regarding the naturally given input scatter. To generate the sample set, stochastic analysis methodology is used. Based on the robustness definition, we classify variance based robustness evaluation or reliability based robustness evaluation (reliability analysis). Because the main focuses of the robustness evaluation in the forming simulation are statistical variation and correlation measurements and not rarely event probabilities, we restrict our self in that paper to a discussion of variance based robustness evaluation. For a reliability analysis or discussion of reliability based robust design optimization, we refer to the literature [2].

The definition of the uncertainties forms the base for stochastic generation of the sampling set. Typical scattering input variables of forming simulations are for example material values like yield strength, tensile strength, R-values, friction values, sheet-thickness or position of blank and tool.

The characteristic of input scatter is described by using statistical distribution functions and it defines the probability space of possible realizations. In practical applications, existing knowledge of scatter is translated to 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 that correlations of single scattering input variables or of partially correlated stochastic fields can be considered. The necessity of this shall be illustrated using the example of material formulation of steel. Commonly the flow curve for the forming simulation is described with a set of scattering parameters with significant correlation for example between yield stress and tensile strength. Only consideration of the complete statistical information of 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 which the scatter of the input variables depends. Therefore, if only raw 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 [3], shows that for the same expected statistical error Latin Hypercube Samplings are ten times more efficient than Monte Carlo samplings. Thereby, the required amount of computations for securing a certain confidence interval 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 convincing result values is considered when doing robustness evaluations [4]. When doing robustness evaluations of forming simulations, the necessity arises to visualize the spatially highly correlated statistic measures on the FE-structure and therefore a high number of correlation coefficients needs to be estimated. Projection methods [5] 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 or 3-sigma values. In practical applications, the robustness of result values is often determined by examining if certain boundaries are exceeded. The boundary values thereby often are compared with the Min/Max values or the 3-sigma-values. A so called 3-sigma-value is actually a value with a probability of exceedance of 0.0013. When doing robustness evaluation, sigma-values can generally be estimated from the sample set or under assumption of distribution hypothesis computed from mean value and standard deviation. When doing robustness evaluation, one can assume that for estimations from the sample set to a few existing supporting points, a determination of the fractal values via normalized distribution functions is to be preferred [5].

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.

Specific requirements for visualising statistical measures on forming simulations

A visualisation of statistical measures on the FE-mesh facilitates considerably the engineering evaluation of robustness evaluation since the result values of a forming simulation which are to evaluate are generally spatial correlated values. The statistical measures on the FE structures serve as discussion basis for the identification of critical areas and as a basis for evaluating the robustness. In addition, this type of visualisatioin leads to a high acceptance of the results in the production departments. Therefore, it is important to visualize the statistic measures directly on the component and respectively on the corresponding reference mesh and to communicate them in the design process. Mean value, variation coefficient, standard deviation and min/max values should be determined in the FE discretisation and displayed on the FE structure [5].

Beginning with the linear correlation hypotheses and its measures of coefficients of determination as well as measures of variation, represented on the FE-structure, a first evaluation of robustness is performed. The found “hot” spots are then statistically secured on local level with optiSLang. Should small measures of coefficient of determination be found in areas of decisive scatter on the FE-structure, further statistic measures (quadratic correlation hypotheses and anthill-plots for nonlinearities in the transmission behaviour) become necessary. If robustness cannot be reached with adjustments in the reliability domain like reducing input scatter or moving mean values for material parameters, a new constraint for the optimization is born. Usually a larger safety distance against critical results has to be achieved by an optimization step.

4. DETERMINISTIC OPTIMIZATION

Basically, at least three categories of algorithms are available for solving the optimization problem: mathematical methods of optimization using gradients (gradient method), response surface methods (RSM) and stochastic search strategies.

Mathematical Optimization Methods using Gradient Information

Mathematical optimization methods [6], which determine the search direction by using gradient information, offer the best convergence behaviour of the above mentioned methods. But they also have the greatest requirements on the mathematical composition of the numerical problem formulation, on continuity, differentiability, smoothness, scalability as well as the accuracy of the gradient determination. Because the forming simulation within this paper is performed by explicit dynamic solvers, it is knowsn that the explicit time integration procedure has too much numerical noise to determine values gradient information and therefore gradient optimization methodology is not recommended for that example.

Response Surface Methods or Meta Models

If the amount of optimization variables is limited to a few variables (5 to 15), then response surface methods [7] offer attractive possibilities of optimization. These methods create an approximation of the design space by using an approximation function on a suitable set of supporting points. The support points should be determined by using an optimised support point pattern (D-optimal Design of Experiments –DOE) for the approximation function. The approximation function usually has smooth mathematical properties and it can be used for the search for the optimum in the subspace mathematical methods of optimization.. Weak point of the response surface method is the proof that the approximation at points of interest in the design space is sufficient and respectively accurate enough for the optimization. To secure the approximation quality adaptation, Response Surface schemes are used. Hereby, adaptive response surface methods (ARSM) which zoom and scroll the approximation space until the optimum converges on the response surface, are the most successful [8]. The critical value from practical view, is first of all the number of optimization variables. Therefore, response surface methods are used in small dimension of the most sensitive optimization variables which have been determined before using sensitivity studies. Designs which have been pre-optimized in such a manner can be used as starting point for evolutionary search strategies.

Evolutionary Search strategies

If the before mentioned algorithms do not lead to the desired goal stochastic search methods, of which the evolutionary algorithms with the subdivisions genetic algorithms [9] and evolutionary strategies [10] are the most successful, are used for solving the problem. The term stochastic search method is used as “random” event lead to the change in design. Important differentiating factor between genetic algorithms and evolutionary strategies is the method of evolutionary development of the optimization variables. The most important evolutionary process of the genetic algorithms is the random substitution of genes (optimization variables) between two parent designs to produce a descendant. The most important evolutionary process of evolutionary search strategies is the mutation (random change) of single genes of a parental design to produce a descendant.

Genetic algorithms are thereby especially useful for a relatively wide-ranged search in the design space. Therefore, they are often used as a “global” search strategy. Evolutionary strategies are especially useful, if a proper previous knowledge is available in the starting generation. Starting with the best designs from the sensitivity study, evolutionary strategies can be used for local optimization on admissible design islands.

Single and multi objective (Pareto) optimization

If all optimization terms form only one objective function, a single objective optimization problem has to be solved. But of course, different weights on the objective terms may influence the definition of the optimal design for several reasons. As long as the different optimization terms are not in conflict or the conflict can be solved within the design space, the single objective optimization procedure is recommended.

If a set of Pareto optimal solutions from conflicting objectives should be determined, the multi objective optimization is necessary. By definition, a design point x is said to be Pareto optimal if no objective function criterion can be improved without worsening at least one other objective criterion. The set of all Pareto Optimal solutions is the so called Pareto Frontier or Functional Efficient Boundary.

For multi objective optimization, an optimization task with more than one objective and arbitrary constraints are formulated.

It should be mentioned that only in case of conflicting objectives a Pareto frontier of compromise solutions exists. Because Pareto optimization increases significantly the effort to obtain the Pareto frontier (compared with the effort to obtain one optimum), the user should have a good understanding of conflicting objectives before starting a Pareto optimization to resolve that conflict.

In general, again the three main different optimization strategies (gradient based, RSM, EA) can be used.

Gradient based Pareto optimization strategies are recommended for smooth (differentiable) problems and they are not suitable for explicit time integration. For problems with a small set of optimization variables (< 5..10), global Response Surface Approximations can be used to identify conflicting objectives and to approximate the Pareto frontier. In all other cases, Evolutionary based Pareto algorithms like Strength Pareto Evolutionary Algorithm [11] are recommended.

5. ROBUST DESIGN OPTIMIZATION

As pointed out in the introduction, the paper follows for the application example a consecutively approach of robustness evaluation and deterministic optimization and calls that a robust design optimization procedure.

An automatic procedure has to combine the two disciplines and has to introduce explicit robustness measurements into the objective function. The crucial question is how to come to a meaningful estimate of robustness measurements without to much additional effort. Looking to our example, it is obvious that the effort to measure robustness with 50 to 100 Latin Hypercube samples per optimization candidate will result in a very large number of external solver calls.

To avoid this reducing, the number of Latin Hypercube samples per optimization candidate could be tested. But then, the variability measurements will have lower confidence and the probability of missing nonlinear effects will increase. Because the FLD_crack values show distinct nonlinearity, a too high reducing of the sample size will not be successful.

A common approach for reducing the number of solver calls is the use of Response Surface Approximation. In the past, there was the limitation that global polynomial response surface often results in poor approximations of the reliability domain and could only be used for a very small number of optimization and reliability variables (5..7). But for some years, there are significant improvements in developing meta models for reliability analysis using Kriging [17,18], Neuronal Networks [14,15,16] or advanced Moving Least Square Approximations [2]. There is the hope that for robust design optimization tasks with less than 15 important optimization and reliability variables these models work in combination with adaptive D-optimal design of experiments and that the effort to create sufficient support point sets is not too high. However, our small example already has 13 optimization variables and at least 3 additional important reliability variables and it tends to become to large for meta model methodology.

Often in literature [19,20,21], a procedure of introducing some scatter to the optimization variables can be found. Then the robustness of the optimization domain regarding optimization variable scattering can be investigated without spending significant additional computation compared to a deterministic optimization procedure. But that procedure obviously implies that the reliability domain is part of the optimization domain and that no non-optimization variable has significant impact on result variability. Even for our little example, the procedure would miss the most important result scatter sources and therefore will not be successful.

Summarising that a short and not complete discussion a step by step approach to identify important optimization and reliability variables using sensitivity analysis and robustness evaluation is recommended. If enough knowledge about the design space as well the reliability space is identified to reduce the set of important optimization and reliability parameters to less than 10..15 advanced Meta models suitable for robustness evaluation promise to offers attractive possibilities which complete the state of the art RDO methodology. Especially in the reliability domain, reducing the variables should be based on a safe knowledge about importance and a final robustness evaluation after automatic RDO is recommended.

6. APPLICATION

For the demonstration of a consecutive approach of using sensitivity analysis, robustness evaluation and optimization for achieving an optimized and robust design, a relatively fast running forming simulation (approximately 1 hour per run) of a small car body part of BMW was taken. For the forming simulation, the explicit FE-solver LS-DYNA was used. Because mesh refinement is used, the resulting finite element meshes of variants are different. To generate a common evaluation base for optimization and reliability, all results are mapped to a reference FE-mesh.

Figure 1: left – mesh adter forming simulation right – reference mesh

Figure 1 shows a final mesh of forming simulation using three steps of mesh refinement and the reference mesh were all results are mapped. Figure 2 shows the FLD plot and the FLD diagram of the start design. The parameters to optimise the problem are 12 bead forces varying from 0 to 350 N and the tool binder force is varying from 50 to 300 KN. Figure 3 shows the location of the beads.Within that design space, an optimal and robust forming process is aimed. Main evaluation criteria are cracks (red colour at FLD plots) or risk of cracks (yellow colour at FLD plots). The cracking value is defined as the major strain of the considered strain state, normalized with the forming limit curve (FLC).To ensure sufficient hardening, an additional constraint of 2% thickness change as minima in the whole stamping part i aimed.

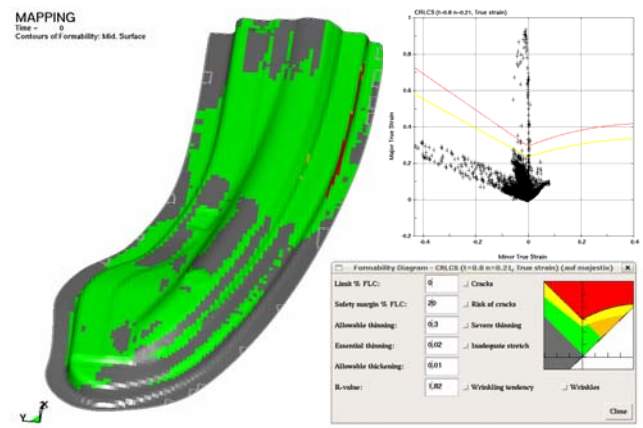

Figure 2: FLD plot and diagram of the start design

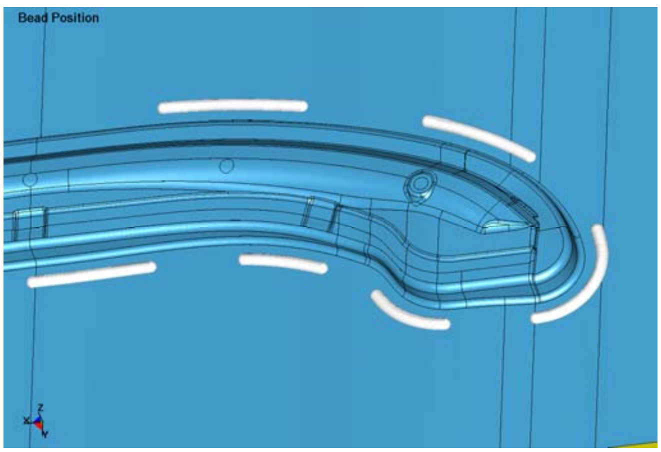

Figure 3: Positioning of the beads
bead, 1,3,5,7,9,11 are shown, beginning lower left

Sensitivity Study

Using 100 optiSLang Latin Hypercube Samples in the 13-dimesional design space of optimization, a sensitivity study is performed. From the 100 designs only 2 did not show cracks or risk of cracks, therefore it is assumed that the design space has very limited islands of admissible design. The best design from the sensitivity study is the design_78 (figure 4) with a maxima FLD_crack value of 0.73 and a hardening violation of 60 (sum of violation of thickness change from all elements). The other admissible design is the design_54 (figure 5) with a maxima FLD_crack value of 0.96 and a sum of hardening violation of 55. Looking to the design vectors (Figure 6), they are obviously very different mechanisms to avoid cracking.

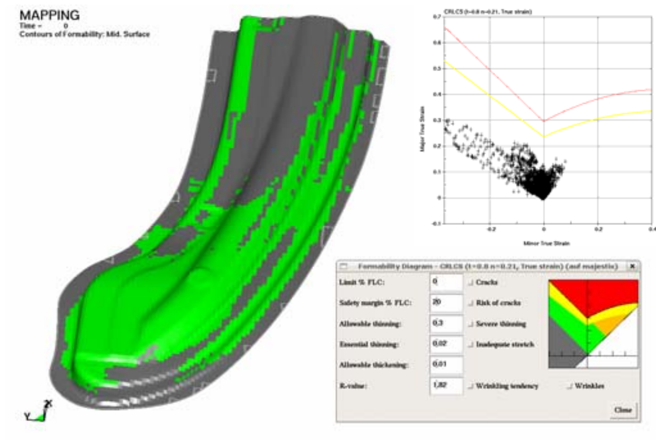

Figure 4: design_78 of Sensitivity study

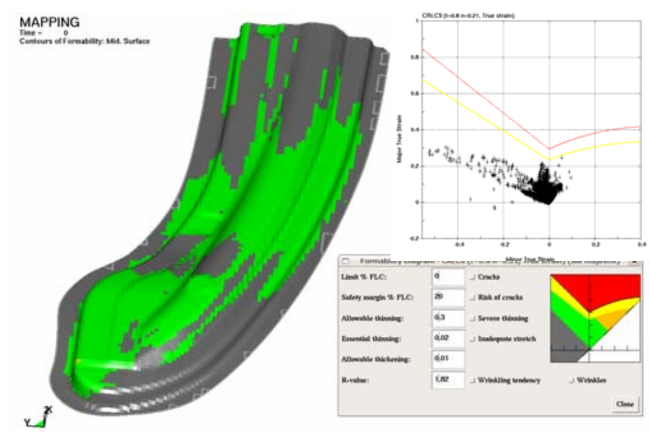

Figure 5: design_54 of Sensitivity study

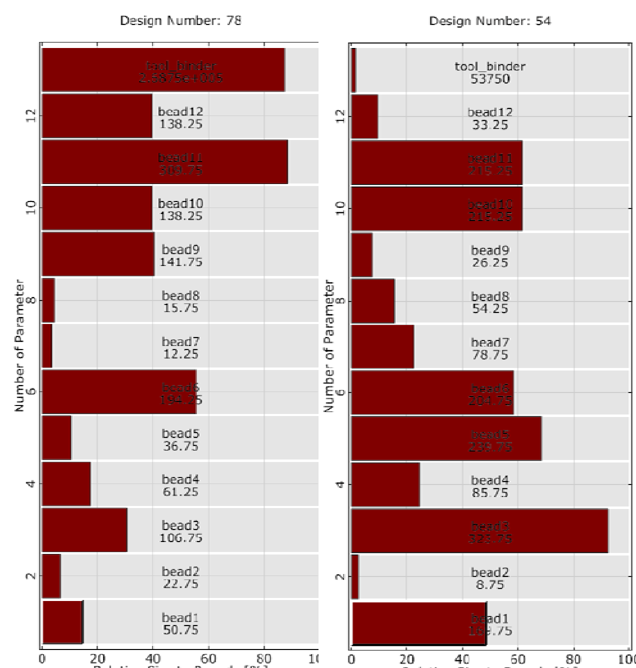

Figure 6: design vector of design_78 and design_54

Figure 7 shows a projection of the coefficient of determination (COD) of linear correlation between all input variation and FLD_crack variation. The element based CoD is varying between 60 and 85%. Figure 8 shows the coefficients of variation to the sum of FLD_crack violating elements. Taking into account linear and quadratic correlation between all optimization parameter variation and violating sum of FLD_crack, the variation of a CoD is calculated by 65%. Therefore, a significant amount of FLD_crack variation comes from a higher order nonlinearity, result value generation or numerical noise. From our experience, in other areas of virtual product development using explicit dynamic solver [13] is recommended to ensure a high coefficient of determination for result values used for the optimization. If a large part of the result variation cannot be explained, that part may be just stochastic itself and then this result may confuse the optimizer more than it gives a direction.

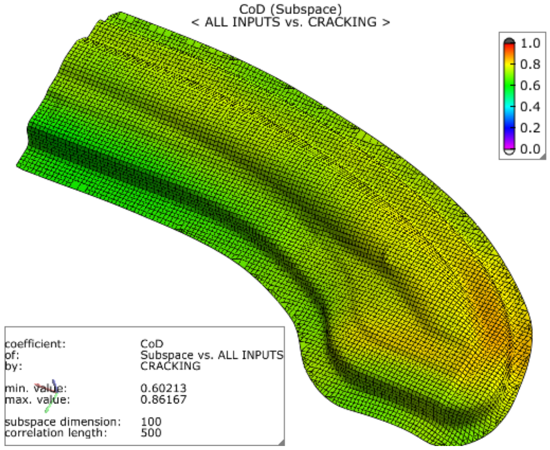

Figure 7: CoD of all inputs to FLD_cracking criteria

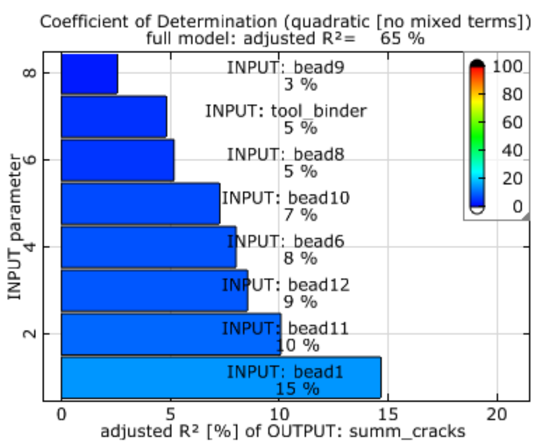

Figure 8: CoD for the sum of violating cracks

Figure 8 shows no significant ranking of the importance of the optimization parameter. Therefore, a reduction of the design space is not recommended at that time. Of course one reason for that effect is that all the bead force variation show high correlation near the bead position (see for example Figure 9) and all act together with the tool binder force. To avoid cracking and to secure sufficient hardening, everywhere all beads may be necessary to be adjusted. Summarising the sensitivity study, two admissible design island were found and no reduction of the optimization problem is recommended. Because the largest part of the design space is violating the cracking criteria and seems to be very nonlinear with pure coefficients of determination, evolutionary optimization strategies from the two admissible design islands seem to be suitable.

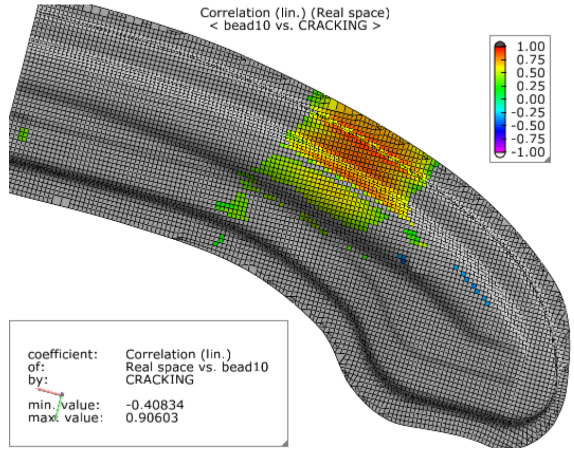

Figure 9: coefficient of correlation of force bead 10 to FLD cracking criteria

Robustness Evaluation

Using a consecutive approach for the robustness evaluation and deterministic optimization, the introduction of a safety distance in the deterministic optimization is necessary. That safety distance should ensure that the stamping process is robust against given uncertainties. Therefore, the reliability space is investigated by using optiSLang variance based on robustness evaluation. Of course, the definition of robustness needs a kind of reliability level which defines a probability of violating the crack criteria that it should not exceed. A common quality criteria is the 3-sigma bound that correlates to a failure probability of 0.0013 (1.3 out of thousand).

For robustness evaluation, scatters of all bead forces as well tool binder force, scatter of friction value, sheet metal thickness, yield stress and R-Value are taken into account. The uncertainty of forces, friction, yield stress and R-Value are defined with normal distribution functions and a coefficient of variation (CoV) of 0.05. The uncertainty of sheet metal thickness is defined with normal distribution functions and a CoV of 0.03.

A robustness evaluation for design_78 from the sensitivity study is performed by using a sample set of 50 optiSLang Latin Hypercube samplings. The Robustness evaluation of Design_78 shows 3 violating designs that correspond to a failure rate of app. 5%. The cracking or the risk of cracks occur in the influence area of bead 5 to 7 (see figure 12).

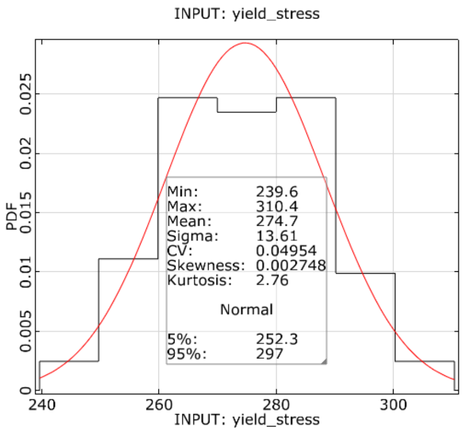

Figure 10: Histogram yield stress

Figure 10 and 11 show histograms of 100 optiSLang Latin Hypercube realizations of yield stress and sheet metal thickness input scatter.

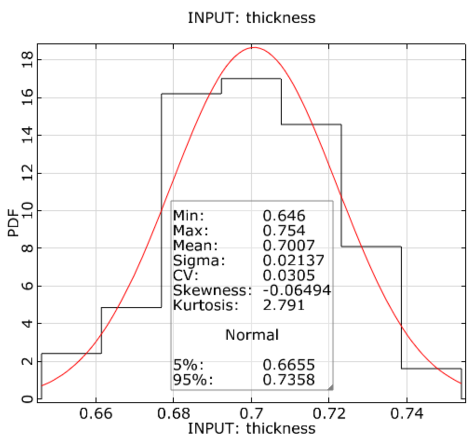

Figure 11: Histogram sheet metal thickness

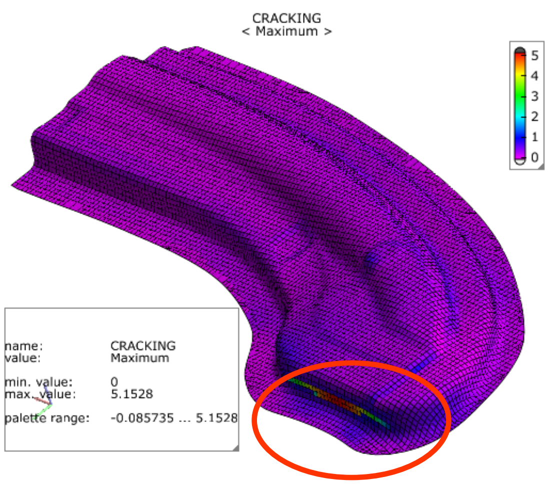

Figure 12: maxima per element FLD_crack value robustness evaluation design_78

The coefficients of determination on finite element level (figure 13) as well as for the maximum FLD_Crack value (figure 14) are much higher than for the sensitivity analysis. That indicates that the local (compared to the huge design space of optimization) sensitivities for the robustness have less nonlinearity and the numerical noise does not influence the result values significantly. Also in contrast to the sensitivity study in the optimization design space, figure 14 shows a clear ranking of importance. Main source of the variation in the FLD_crack value is the uncertainty in yield stress, followed by scatter from bead force 6. Summarising the robustness evaluation of design_78, FLD_crack value of 0.73 for the deterministic forming simulation does not ensure robustness. The FLD_crack variation is mostly correlated to the material scatter and shows a high coefficient of determination.

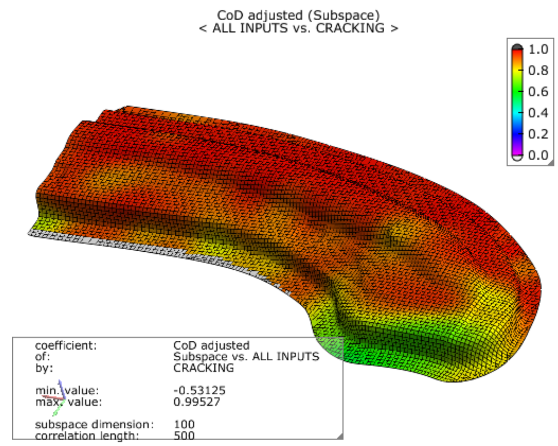

Figure 13: coefficient of determination of all uncertainties to FLD_cracking criteria

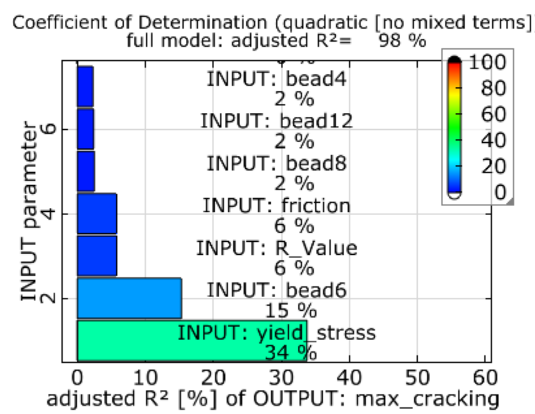

Figure 14: CoD to maximum FLD_cracking value

Optimization step

One outcome of the sensitivity study was the decision to use evolutionary optimization algorithms to improve the two admissible designs. One outcome of the robustness evaluation was that FLD_crack value of 0.73 is not sufficient to ensure robustness. Therefore, the safety distance to limit the FLD_crack value is increased and a maximal FLD_crack Value of 0.68 is aimed. At the same time, the hardening violation should be minimised. It is known from the sensitivity study that the two objectives are in conflict, but the robustness against cracks is much more important.

Therefore, a weighted single objective function with a weight of 1000 at the maximum FLD_crack value and a weight of 1 at the hardening violation is used. For optimization default optiSLang evolutionary local design improvement (1 design start population, 5 new designs per generation, adaptive mutation as main evolution factor) is used.

After both evolutionary strategies reach FLD_crack values closed to 0.68 the optimization was stopped. For Design 78_68 (figure 15) with a FLD_crack value of 0.679 and a Hardening violation of 57 and for Design 54_58 (figure 16) with a FLD_crack value of 0.685 and a Hardening violation of 61 was reached. Compared to design_78 the evolutionary algorithm increased in design 78_68 moderately the forces of bead 3,4,5,6 and 8,9,10.

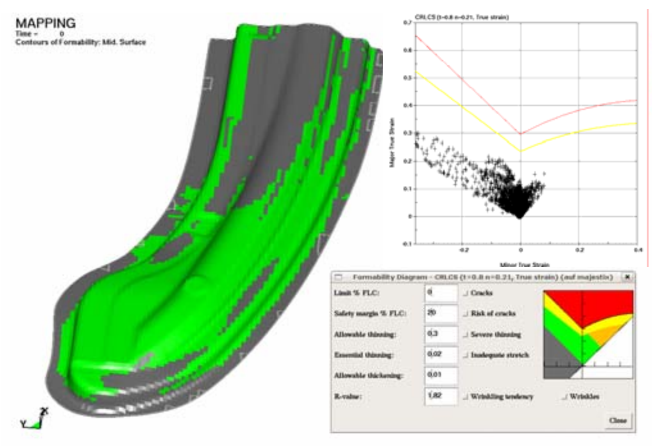

Figure 15: Design 78_68 evolutionary improvement

Compared to design_54 the evolutionary algorithm increased in design 54_58 moderately the forces of bead 1,4,6 and decrease the forces of bead 10 and 11.

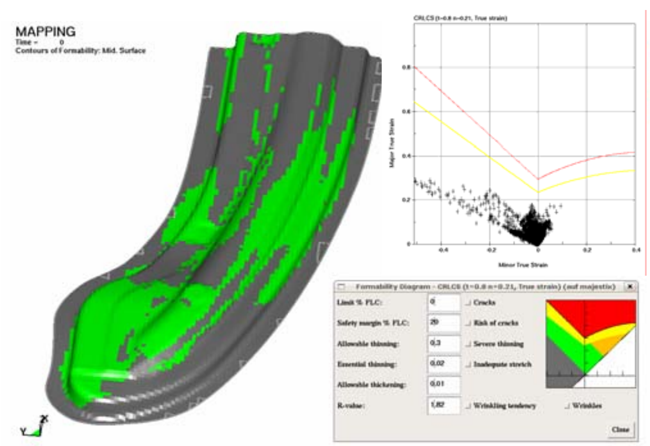

Figure 16: Design 54_58 evolutionary improvement

Robustness Check

To check the robustness of the optimized design with a deterministic FLD_crack value of 0.68, the robustness evaluation is repeated by using a sample set of 50 optiSLang Latin Hypercube samplings around design_78_68. Within the 50 forming process realizations for design_78_68, maximal FLD_crack value of 0.79 (see figure 17) is calculated. With fitting of distribution functions, a maximal 3-sigma-value of 0.88 (figure 19) is prognosed; therefore the design fulfils the defined quality criteria of robustness.

Again, the reliability domain shows a high coefficient of determination and uncertainties in yield stress and friction are responsible for more than 50% of the calculated FLD_crack scatter (see figure 18). But with the adjustments of beat forces the sensitivity of bead and tool binder force scatter has changed (compare figure 14 und 18).

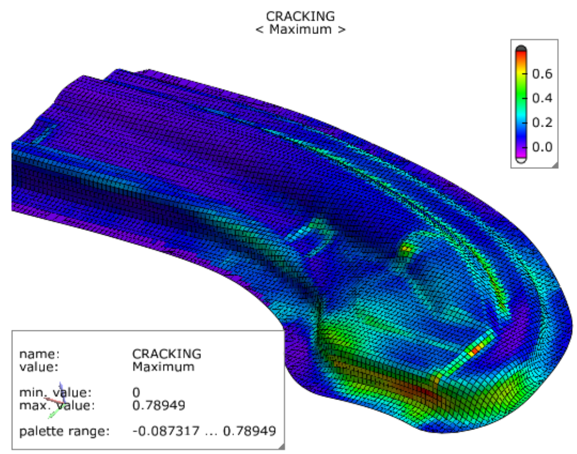

Figure 17: maxima per element FLD_cracking value robustness evaluation design_78_68

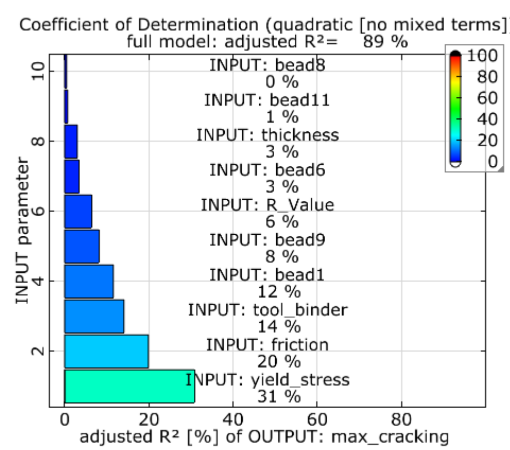

Figure 18: CoD to maximum FLD_cracking value

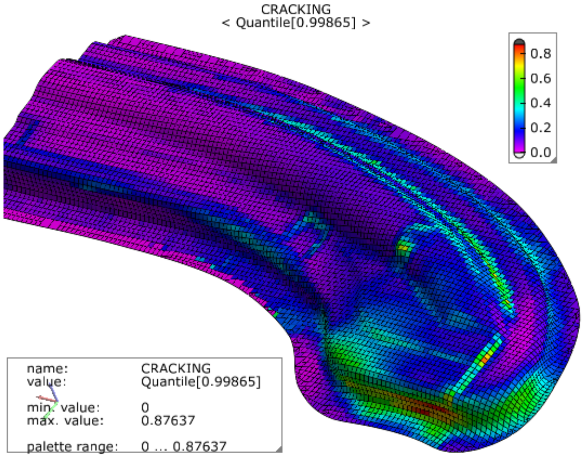

Figure 19: 3-sigma-value per element FLD_cracking value robustness evaluation design_78_68

The Robustness on the second admissible design island was also checked by using a sample set of 50 optiSLang Latin Hypercube samplings around design_54_58. Because of a high failure rate, this evaluation was stopped after 21 simulations. More than 50% of the forming simulation exceeded the maximum FLD_crack values of 1.0 and the search of robust designs on that island was stopped.

Continuing the iterative approach of robustness evaluation and deterministic optimization, different optimization strategies and different safety distances were checked. Table 1 shows a summary.

Design	maximum FLD_crack optima candidate	Robustness evaluation FLD_crack value
78_sensitivity	0.73	6 % failure
78_68_EA	0.68	no failure at 50 designs max. FLD_crack=0.80 max. 3Sigma value=0.88
78_179_EA	0.70	19 % failure
78_200_ARSM	0.64	23 % failure
54_58_EA	0.685	50% failure

Table 1 Summary of optimization steps and robustness evaluations

Continuing the iterative approach of deterministic optimization and robustness evaluation optima candidates from different optimization strategies (Evolutionary Algorithms and adaptive Response Surface Methodology) with different safety distances were checked. Table 1 shows a summary. It is clearly to see that no constant safety distance was found.

7.SUMMARY AND OUTLOCK

A consecutive approach of using sensitivity analysis, robustness evaluation and deterministic optimization is demonstrated for achieving an optimized robust design. To meet the necessary requirements, Dynardo is continuously developing the software tool optiSLang and Statistics_on_structure. For robustness evaluation of forming simulation, especially the implementation of coefficient of determination for linear and quadratic correlation hypothesis and the projection of important statistical measurements on the FE-model create the breakthrough for practical applications.

For the iterative process of sensitivity, robustness and deterministic optimization between 300 and 1000 runs are necessay. For the example with 4 optimization cycles 600 runs were used.

The practical application shows a high degree of nonlinearity in the optimization and the reliability domain. To ensure robustness, it was not possible to identify a constant safety distance which means a deterministic design with a maximum FLD_crack value of 0.7 could be robust or have a failure rate of 50%. Finally, it was necessary to check explicitly the robustness for all optima candidates. Therefore, it seems mandatory to implement robustness evaluation for forming simulations in virtual product development processes.

If enough knowledge about the design space as well the reliability space is identified to reduce the set of important optimization and reliability parameters to less than 10..15 advanced Meta models promise to offers attractive RDO methodology.

In general there are three possibilities to improve the robustness, first limit the input scatter of important scattering input variables, second move the mean values of scattering input variables to move the correlated result scatter or third change the transfer behaviour of input scatter to output scatter. For successful improve of the robustness of the forming part finally the geometry and the forming process was redesign.

REFERENCES

[1] optiSLang - the Optimizing Structural Language Version 2.1, DYNARDO, Weimar, 2006, www.dynardo.de

[2] Roos, D.; Adam, U.; Bucher, C.: Robust Design Optimization; Proceedings. Weimarer Optimierung- und Stochastiktage 3.0, 2006, Weimar, Germany

[3] Will, J.: Bucher, C.: Statistische Maße für rechnerische Robustheitsbewertungen CAE-gestützter Berechnungsmodelle, Proceedings Weimarer Optimierungs- und Stochastiktage 3.0, 2006, Weimar, German

[4] Will, J.; Baldauf, H.: Integration rechnerischer Robustheitsbewertungen in die virtuelle Auslegung passiver Fahrzeugsicherheit bei der BMW AG, VDI-Berichte Nr. 1976, Berechnung und Simulation im Fahrzeugbau, 2006 Seite 851-873

[5] Will, J.; Bucher, C.; Ganser, M.; Grossenbacher, K.: Berechnung und Visualisierung statistischer Maße auf FE-Strukturen für Umformsimulationen; Proceedings Weimarer Optimierung- und Stochastiktage 2.0, 2005, Weimar, Germany

[6] K. Schittkowski, C. Zillober, R. Zotemantel: “Numerical comparison of nonlinear programming algorithms for structural optimization”; Structural Optimization, Vol.7, Nr.1, S. 1-28

[7] H. Myers, C. Montgomery: Response Surface Methodology: Process and Product Optimization Using Designed Experiments”, Wiley, New York, 1995

[8] N. Stander, K. Craig: “On The Robustness of a Simple Domain Reduction Scheme for Simulation-Based Optimization”, Int. Journal for Computer-Aided Engineering and Software, 2002

[9] D. E. Goldberg: „Evolution strategies ii: Theoretical aspects”; In Genetic Algorithms in Engineering and Computer Science, chapter 7; Wiley, Chichester, 1995

[10] I. Rechenberg: „Evolutionsstrategie '94“; Werkstatt Bionik und Evolutionstechnik Vol. 1; Frommann-Holzboog, Stuttgart, 1994

[11] E. Zitzler, L. Thiele:“ An Evolutionary Algorithm for Multiobjective Optimization: The Strength Pareto Approach”; Technical Report 43, Computer Engineering and Communication Networks Lab (TIK); Swiss Federal Institute of Technology (ETH), Zurich, Switzerland, May 1998

[12] I. Rechenberg: „Evolutionsstrategie '94“; Werkstatt Bionik und Evolutionstechnik Vol. 1; Frommann-Holzboog, Stuttgart, 1994

[13] Blum, S.; Will, J.: Combining Robustness Evaluation with Current Automotive MDO Application, Proceedings Weimarer Optimierungs- und Stochastiktage 3.0, 2006, Weimar, Germany

[14] Papadrakakis, M. ; Papadopoulos, V. ; Lagaros, N. D.: Structural reliability analysis of elastic-plastic structures using neural networks and Monte Carlo Simulation. In: Computer Methods in Applied Mechanics and Engineering 136 (1996), S. 145-163

[15] Hurtado, J. E. ; Alvarez, D. A.: Neural-network-based reliability analysis: a comparative study. In: Computer Methods in Applied Mechanics and Engineering 191 (2001), S. 113-132

[16] Schueremans, L. ; Van Gemert, D.: Benet of splines and neural networks in simulation based structural reliability analysis. In: Structural Safety 27 (2005), S. 246-261

[17] Simpson, T.W.; Mauery, T.M.; Korte, J.J.; Mistree, F.: Comparison of Response Surface and Kriging Models for Multidisciplinary Design Optimization. In: American Institute of Aeronautics and Astronautics 1998

[18] Martin, J.D.; Simpson, T.W.: A Study on the Use of Kriging Models to Approximate Deterministic Computer Models. In: Proceedings of DETC’03, ASME 2003 Design Engineering Technical Conference and Computers and Information in Engineering Conference Chicago, Illinois USA, September 2-6, 2003

[19] S.J. Abspoel, L.F.P. Etman, J. Vervoort, R.A. van Rooij, A.J.G Schoofs, and J.E. Rooda: Simulation based optimization of stochastic systems with integer design variables by sequential multipoint linear approximation. Structural and Multidisciplinary Optimization, 22:125-138, 1996

[20] Pictet, O. V., M. M. Dacorogna, R. D. Davé, BatienChopard, R. Schirru, and M. Tomassini: Genetic algorithms with collective sharing for robust optimization in financial applications. OVP.1995-02-06, http://www.olsen.ch/research/307_ga_pase95.pdf.

[21] Branke, J. (1998): Creating roubust solutions by means of an evolutionary algorithm. A.E. Eiben, T. Bäck, M. Schoenhauer, and H.-P. Schwefel, editors, Parallel Problem Solving from Nature 1498, 119-128.