Reliability Based Design Optimization with LS-OPT for a Metal Forming Application

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Summary:

The purpose of this paper is to account for uncertainties in the manufacturing processes of metal forming in order to evaluate the random variations with the aid of FE-simulations. Various parameters of the Finite-Element model describing the investigated structural model are affected by randomness. This, of course, leads to a variation of the considered simulation responses such as stresses, displacements, and thickness reductions. On this, for the simulation engineer basic questions arise regarding: (1) the dimension of the range of variation of the simulation responses (2) the significance/contribution of the (input) parameters with respect to specific responses and (3) the reliability of the process design with respect to constraints (failure, damage, requirements, ...). In order to find solutions to these questions several methodologies may be applied that are available in the commercial optimization software LS-OPT (Stander et al. [5]). Some of the methodologies, such as Monte Carlo simulation, meta-model based Monte Carlo simulation, stochastic fields, are discussed in this paper and are demonstrated by means of a metal forming problem. For this, a non-robust design with respect to the specified constraints has been detected. By utilizing reliability based design optimization (RBDO) through LS-OPT, the failure probability (violation of constraints) could be reduced significantly.

Keywords:

Metal Forming, Robustness, Stochastic Analysis, Uncertainties, Monte Carlo Simulation, Meta Models, Reliability based Optimization, Stochastic Fields

1 Introduction

The design of a metal forming process is focused on the accuracy of products and the minimization of forming failure such as fracture, wrinkling and excessive thickness reduction. Metal forming processes are highly non-linear applications and the results are strongly influenced by various parameters, e.g., the anisotropic material behavior of the supplied steel or manufacturing process parameters such as friction, draw bead geometry or binder forces. In order to perform a realistic analysis of the metal forming process the uncertainty of those parameters must be appropriately considered within a FE-simulation. A proper consideration and treatment of uncertainty basically enable a reliability assessment and ensure the subsequent quality of the product.
The uncertainty of the parameters is conventionally considered with the uncertainty model randomness and modeled with the aid of probability distribution functions. The type of the probability distribution function and the distribution parameters are assumed by engineering knowledge and by quality requirements specified by the DaimlerChrysler AG for the steel suppliers. Statistics of the uncertainties based on measurements are not available for this study. The subjectively assumed stochastic parameters are processed with a Monte Carlo simulation based stochastic FE-analysis. The obtained simulation results are randomly distributed respectively. In conjunction with further evaluations conclusions could be drawn regarding (1) the dimension of the range of variation of the simulation responses, (2) the significance/contribution of the parameters with respect to specific responses and (3) the reliability of the design with respect to constraints.
Basic concepts of stochastic investigations are discussed. A brief introduction in the reliability-based design concept is provided. The standard approach to simulate stochastic variations is the Monte Carlo method, usually by using a structured sampling as Latin Hypercube. For very expensive simulations meta-models are applied to preserve the practical applicability of the stochastic analysis. The number of required FE-simulations is reduced significantly. Meta-models are established on the basis of interpolation points. The stochastic simulation with the aid of the Monte Carlo simulation is then performed with the meta-model exclusively – additional FE-simulations are not required. Apart from polynomials, non-linear approximation schemes, such as Neural Networks can be used (Stander et al. [5], Liebscher et al. [7]) to form meta-models that might be suitable to replace the expensive FE-simulation within a stochastic simulation.
The considered metal forming application is introduced and the assumed probabilistic models of uncertain process parameters are discussed in detail. Results of the stochastic analysis for a metal forming application are presented. Finally, a brief conclusion and an outlook on future investigations are provided.

2 Methodologies for Stochastic Investigations

2.1 Goals of Stochastic Investigations

The stochastic investigations are performed to obtain information on the

(1) Variation of the simulation output (responses) due to variation of input (variables, parameters).
(2) Significance/Contribution of the parameters with respect to specific responses.
(3) Reliability with respect to constraints (failure, damage, requirements, ...).

2.2 Simulation of Stochastic Variations

The Monte Carlo method is widely used because it is robust and easy to implement. The method may be understood as a numerical experiment that produces a sequence of numerical results (pseudo-outcomes) similar to the results (outcomes) expected in the actual use of the product. These numerical obtained results (pseudo-outcomes) are then examined using statistical techniques to predict the future properties of the product. For computing the mean and variance of the process variation only, it is probably the best known method. Given that the results from the Monte Carlo analysis are unbiased, we compute the confidence bounds similar as for any other statistic. These confidence intervals are tabulated in the standard books [4]. The number of simulations required depends on the statistical properties being computed. The properties are the mean and standard deviation of the processes as well as the probability of rare events (outliers). If the mean or the standard deviation is required, then the number of simulations can be computed considering the desired accuracy and by manipulating the formulas for computing the confidence bounds. For this, prerequisite is to guess the expected variance. Usually a structured Monte Carlo sampling as the Latin Hypercube method is used in order to improve the accuracy for a given number of simulations.

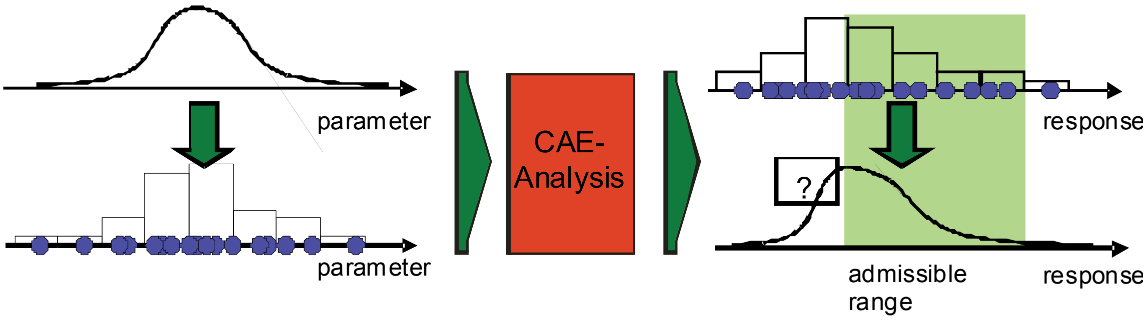

Fig. 1: Scheme of stochastic analysis

2.3 Reliability-based Design

The reliability of a given design may by assessed by comparing a numerically determined failure probability P_f with a given target probability P_t. Reliability of a specific design is achieved if

$$P_f < P_t \qquad (1)$$

is satisfied. The selection of the target probability P_t is problem dependent and often orientated to the desired product quality vs. production costs. On the basis of this definition of reliability a safety distance

$$d_s = P_t - P_f \qquad (2)$$

is defined. Positive values d_s indicate a permissible design, whereby higher positive values stand for a more reliable design.
The objective p of the reliability based design optimization (RBDO, Jensen [10]) may be formulated regarding two different aspects. In order to achieve a maximum reliability of an investigated subject with respect to a set R of problem dependent constraints, the objective p is given by

$$p : \max(d_s) \mid \mathbf{c}(\mathbf{x}) > 0 \qquad (3)$$

where $\mathbf{c}(\mathbf{x}) > 0$ indicates that the set of constraints R is satisfied. The safety level d_s is maximized under the condition that all constraints are met. Conventional objectives q concern with e. g. the reduction of cost due to minimization of the mass. In order to combine these optimization goals with the idea of a reliable design, the objective p of the reliability based design may also be reformulated as

$$p : \min(q) \mid d_s, \mathbf{c}(\mathbf{x}) > 0 \qquad (4)$$

The safety distance d_s is additionally considered as constraint of an actual optimization problem. In most cases the objective Eq. (4) is suitable for practical relevant questions. Sometimes the term reliability-based optimization (RBO) is used instead of RBDO with the same meaning.
The optimization problem given with Eq. (3) or (4) may be solved by any appropriate optimization scheme. A First Order Second Moment (FOSM) approach is implemented in LS-OPT (Stander et al. [5]). In the FOSM method, the reliability of a structure is assessed by evaluating the standard deviation of a response, which is similar to the determination safety distance. The standard deviation is computed using the meta model gradients and the variable standard deviations; no additional computational cost is therefore incurred to compute the reliability information. The application of FOSM is reasonable for moderately small values of P_f.
In the general case the failure probability P_f has to be computed by numerical evaluation of the integral

$$P_f = P\left(\mathbf{x} \mid g\left(\mathbf{x}\right) \leq 0\right) = \int_{\mathbf{x}|g(\mathbf{x})\leq 0} f\left(\mathbf{x}\right)\, d\mathbf{x} \qquad (5)$$

in order to determine the safety distance d_s within the optimization procedure Eq. (3) or (4). In Eq. (5) $\mathbf{x}$ is the vector of random parameters, $f(\mathbf{x})$ denotes the joint probability density function of the random quantities $\mathbf{x}$, and $g(\mathbf{x})$ represents the limit state function. The limit state function is usually highly non-linear and given only in a non closed form. The design space is divided in the safety region $g(\mathbf{x}) > 0$ and the failure region $g(\mathbf{x}) \leq 0$. Generally, Eq. (5) is reformulated with the aid of the indicator function

$$I_f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{x} \in F \\ 0 & \text{if } \mathbf{x} \notin F \end{cases} \qquad \text{with } F = \{\mathbf{x} \mid \mathbf{x} \leq g(\mathbf{x})\} \ . \quad (6)$$

Specifically,

$$P_f = \int_{\mathbf{x}} I_f(\mathbf{x}) \cdot f(\mathbf{x}) \, d\mathbf{x} = E[I_f(\mathbf{x})] \ . \quad (7)$$

This enables the point estimation of the failure probability based on the sampling results of a Monte Carlo simulation according to

$$\hat{P}_f = \frac{1}{N} \sum_{k=1}^{N} I_f(\mathbf{x}_k) \ , \quad (8)$$

with *N* as sample size. This estimator is unbiased and efficient. A minimum sample size is estimated by

$$N \geq \frac{1-P_f}{P_f \cdot \delta_{P_f}^2} \qquad (9)$$

in dependence on a reasonable level of precision prescribed via the coefficient of variation δ_{P_f} of P_f . It becomes obvious that the computational effort becomes tremendous for small values of the failure probability P_f. On this account it is advisable to apply meta-model based stochastic simulation techniques that preserve the practical applicability of the reliability based design.

2.4 Meta-model Based Methods

The finite element evaluations of metal forming problems can be extremely expensive (100+ CPU hours). Meta-models — approximations to the structural performance, built using FEA evaluations of a selected set of designs — are commonly used to reduce costs.
Consider a scalar response *y* dependent on the variable vector $\boldsymbol{x}$ through the relationship $y(\boldsymbol{x})$ including potential bifurcations, noise, and errors. We have

$$y = y(\boldsymbol{x}) \ , \qquad (10)$$

where we want to approximate the relationship y using a polynomial response surface (Myers & Montgomery [6]) $f(\boldsymbol{x})$ as

$$f(\boldsymbol{x}) = \sum_{i=0}^{p} a_i \varphi_i(\boldsymbol{x}) \ , \qquad (11)$$

with a_i the coefficient for the basis function φ_i , and using *p* basis functions. The basis functions form a basis space for the changes in response that can be ascribed to the design variables, and are frequently chosen as the monomials $(1, x_1, \ldots, x_m, x_1^2, x_1 x_2, \ldots, x_1 x_m, \ldots, x_m^2)$ for the quadratic approximation using *m* variables. The coefficients $\boldsymbol{a}$ are computed as

$$\boldsymbol{a} = \left(\boldsymbol{X}^T \boldsymbol{X}\right)^{-1} \boldsymbol{X}^T \boldsymbol{y} \ , \qquad (12)$$

which minimizes $\boldsymbol{r}^T \boldsymbol{r}$, the square of the residuals. The basis function matrix is

$$X = [X_{i\alpha}] = [\varphi_\alpha(x_i)] \ , \qquad (13)$$

where the response is evaluated at $\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_n$ for a total of *n* experiments. The points in the design space where the response must be evaluated in order to create the response surface are selected using design of experiment techniques. For this, a number of experimental design methods are available; see Myers & Montgomery [6].

Variation in the responses, such as buckling, that cannot be described by this basis function space will be residuals, $\boldsymbol{r}(\boldsymbol{x})$. We have therefore

$$y(\boldsymbol{x}) = f(\boldsymbol{x}) + r(\boldsymbol{x}) = P(y(\boldsymbol{x})) + R(y(\boldsymbol{x})) \qquad (14)$$

with $\boldsymbol{f}^T \boldsymbol{r} = 0$, $P(y(\boldsymbol{x}))$ the projection of the response onto the predictable space, and $R(y(\boldsymbol{x})) = R(P(y(\boldsymbol{x})))$ the projection onto the one-dimensional residual space.
The response variation and probabilities of events can be computed cheaply doing a Monte Carlo analysis considering the response surface $f(\boldsymbol{x})$, the variation of the variables, and the process variation as

$$y = f(\boldsymbol{x}) + N(0, s^2)\,, \qquad (15)$$

where the process variation (noise) is approximated as the normal distribution *N* with a zero mean and variance s^2. Therefore, it is assumed that the response surface capture the deterministic response variation - the bias error is neglected.
The predicted values of the response are

$$\hat{\boldsymbol{y}} = \boldsymbol{X}\left(\boldsymbol{X}^T\boldsymbol{X}\right)^{-1}\boldsymbol{X}^T\boldsymbol{y} = \boldsymbol{H}\boldsymbol{y}\,, \qquad (16)$$

from which the residuals can be computed, using the hat matrix **H**, as

$$\boldsymbol{r} = \boldsymbol{y} - \hat{\boldsymbol{y}} = (\boldsymbol{I} - \boldsymbol{H})\boldsymbol{y}\,. \qquad (17)$$

The process variation (noise) is estimated from the sum of the residual mean squares as

$$s^2 = \frac{\sum_i^n r_i^2}{n-p}\,, \qquad (18)$$

with *n* the number of sampling points and *p* the number of basis functions. The process variation can be accumulated to the response variation to receive the total variation. A detailed discussion of this approach can be found in Roux et al. [1]. As afore mentioned the methodology is not restricted to polynomial response surfaces, but any non-linear approximation scheme, such as Neural Networks or Radial Basis Functions can be used (Stander et al. [5], Liebscher et al. [7], Simpson et al. [9]).

3 Example – Metal Forming Application

The influence of the random variation of material and manufacturing parameters on the forming process of an automotive deck lid outer panel is investigated in this study. The geometry of the forming die is shown in Figure 2. The material used for the part is the steel grade DCO6 (1.0873), a typical mild steel used for complex outer panels.

Fig. 2: Die geometry of the deck lid forming tool (Courtesy of DaimlerChrysler AG)

3.1 Considered Uncertainties

3.1.1 Material Properties

The base material parameters for the study are given by DaimlerChrysler. The ranges and lower bounds for typical material parameters of the used steel grade are listed in Table 1. These are quality requirements specified by DaimlerChrysler for the steel suppliers.

Rp	120 … 160 MPa	Yield strength
Rm	> 270 MPa	Ultimate tensile strength (engineering stress)
n	> 0.23	Hardening exponent
A_g	> 24%	Uniform elongation (engineering strain)
r_m	> 2.20	Mean anisotropy coefficient

Table 1: Quality requirements for steel grade DC06

In real sheet metal forming processes the material properties of the blank material may vary within a specific range depending on the used steel grade. According to Table 2 the yield strength vary between a minimum and a maximum tolerance limit. The uniform elongation and the ultimate tensile strength must be above a minimum value. Within this ranges the mechanical properties of the blank material are afflicted with an uncertainty, which can partially cause failures in a real forming process. In almost the same manner the anisotropy coefficients *r0*, *r45* and *r90* may underlie variation within a certain range and thus probably also impact the forming results.

Yield Strength / Elasto-Plastic Hardening

The first variation taken into account is the use of different hardening curves. In the used LS-DYNA material model *MAT_3-PARAMETER_BARLAT the hardening curves are described in analytical form with the Swift law

$$\sigma = K \cdot \left(\varepsilon_0 + \varepsilon\right)^n \quad (19)$$

with the strength coefficient *K,* the strain parameter ε_0, the true strain ε and the hardening exponent *n*. The parameters for the base simulation are listed in Table 2.

K	ε_0	n
550	6.90e-03	0.275

Table 2: Base Parameters of Swift Law

As an example, the variation of the hardening exponent *n* between 0.25 and 0.30 leads approximately to a variation of *Rp* between 120 and 160 MPa for constant values of ε_0 and *K*. The corresponding hardening curves are shown in Figure 3.

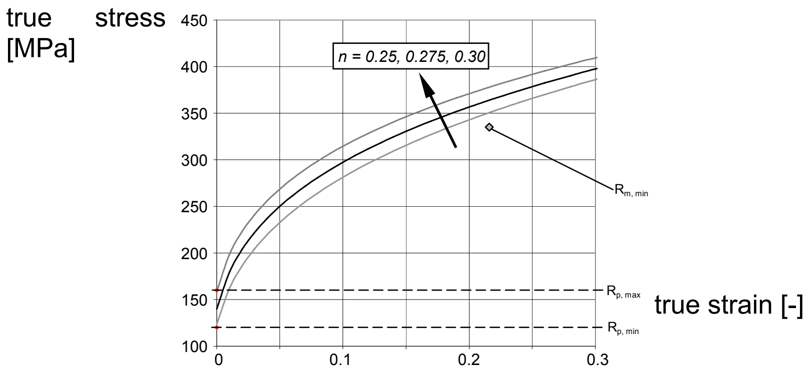

Fig. 3: Hardening curves for varying hardening exponent n (Swift Law)

The values for the lower and upper hardening exponent let the corresponding hardening curves start at the minimum and the maximum allowed yield strength (see Table 1) respectively. In Figure 3 the point $R_{m,min}$ corresponds to the minimum tensile strength reached at the minimum uniform elongation A_g, whereby the engineering strain A_g is converted to true (logarithmic) strain and the tensile strength $R_{m,min}$ is displayed as true stress.
Finally for the robustness study, in consideration of not violating the quality requirements in Table 1, the variation of the parameters of the swift law is applied by a uniform distribution within the ranges displayed in Table 3:

Rp [MPa]	*K* [MPa]	*n* [-]
120-160	440-660	0.23-0.3

Table 3: Lower and upper bounds for the Swift Law parameters

Anisotropy Coefficients

For metal stamping simulations it is common practice to consider anisotropic effects of the sheet metal blank. These effects originate from the rolling process in manufacturing the metal coils. To account for the anisotropic properties, the material model `*MAT_3-PARAMETER_BARLAT` for the LS-DYNA simulations is used (Hallquist [8]). The initial values for the anisotropy coefficients are listed in Table 4.

	r_0	r_{45}	r_{90}	r_m	Δr
Base values	2.1	1.8	2.7	2.1	0.6

Table 4: Base Values for `*MAT_3-PARAMETER_BARLAT`

Beside the uncertainty of the hardening behavior the uncertainty of varying anisotropy coefficients *r0*, *r45* and *r90* is investigated. For this, uniform distributions are applied as well with the ranges listed in Table 5.

	r_0	r_{45}	r_{90}
Range	2.0-2.5	1.4-2.0	2.5-3.2

Table 5: Lower/Upper limits of uniform distributions for anisotropy coefficients

3.1.2 Manufacturing Process Parameters

Variation of Friction Coefficient

The friction between punch and blank and in the draw beads depend on the applied lubrication (usually oil) and on the surface properties. To account for this a uniform distribution of the static friction coefficient within 0.05 and 0.10 is assumed.

Binder Force

A possible variation of the binder force in the manufacturing process is considered by a uniform distribution with a lower bound of 1720 kN and an upper bound of 2100 kN.

Draw Bead Forces

In the FE-simulation the resistance of the blank while passing through the draw bead is approximated by a corresponding load (draw bead force). The draw bead properties may vary during manufacturing due to variation in lubrication and possibly due to mechanical wear. For this study a normal distribution with a standard deviation of 10% with respect to the mean value is assume

Blank Sheet Thickness

Blanks for sheet metal forming are commonly manufactured by cold rolling. In this process the mills are charged by high forces and rolling speed can be fairly high. Many times this leads to an effect, called mill chatter, which causes a variation in the sheet thickness in longitudinal (rolling) direction with a specific frequency. A reason for “mill chatter” can be slight excentric suspension of the mill or slight deviation of the desired circular shape of the mill, see Figure 4.

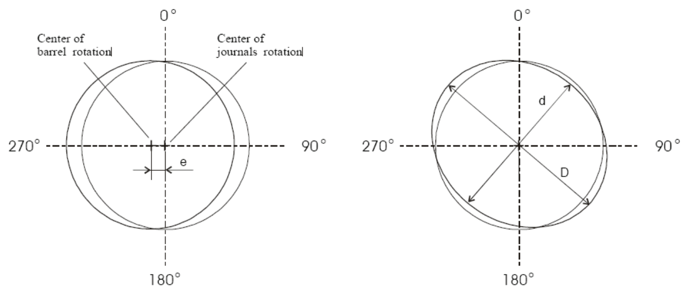

Fig. 4: Example of an Excentric mill (Source: Rolling Automation, Gerhard Rath, © 2003)

In addition, in lateral direction thickness variations may occur due to non-uniform down forces of the mill. The most likely case is displayed in Figure 5.

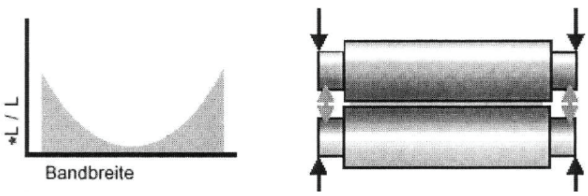

Fig. 5: Non-uniform contact forces (Source: Rolling Automation, Gerhard Rath, © 2003)

Due to these effects for the numerical stochastic investigations a harmonic perturbation is applied in longitudinal as well as in lateral direction. The variation of the amplitude in both directions is assumed to be normal distributed with a mean of 0mm and a standard deviation of 0.01mm. The total target thickness is 0.8mm.
Figure 6 shows a plot of a possible total shell thickness perturbation (superposition in both directions) displayed on the FE-model of the blank. This is realized by the LS-DYNA Keyword `*PERTURBATION`.

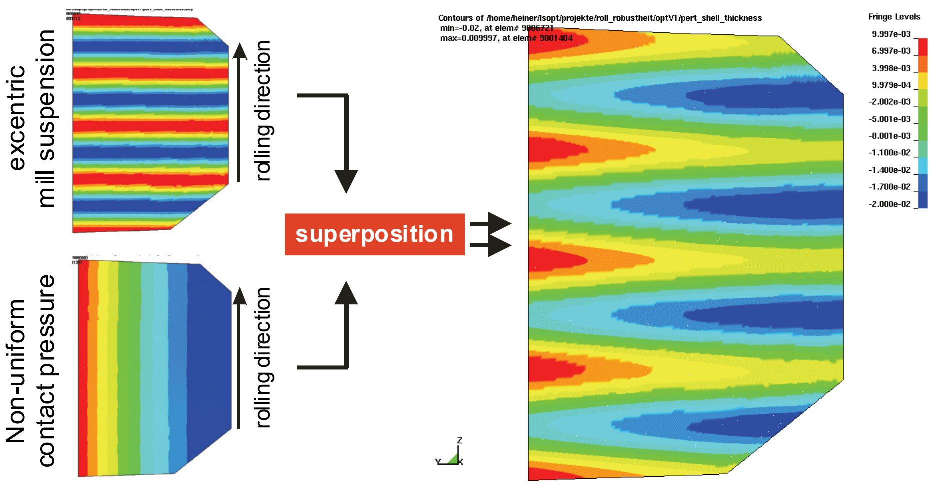

Fig. 6: Random field capturing thickness perturbation due to the manufacturing process of rolling

3.2 Results of Random Variation

For this, in total only 21 simulations are performed. The wall clock simulation time on 2 CPUs is about 10h per run. It turned out, that although the baseline run is a feasible design (Figure 7), the perturbations due to the considered uncertainties leads in 15 runs to an infeasible design. The main criteria for the feasibility of the design are the minimum shell thickness after the forming process and the performance with respect to the FLC-diagram. In 15 runs localization occurs and the minimum sheet thickness becomes very low, see Figure 8. Consequently the FLC requirement is also violated (Figure 9).

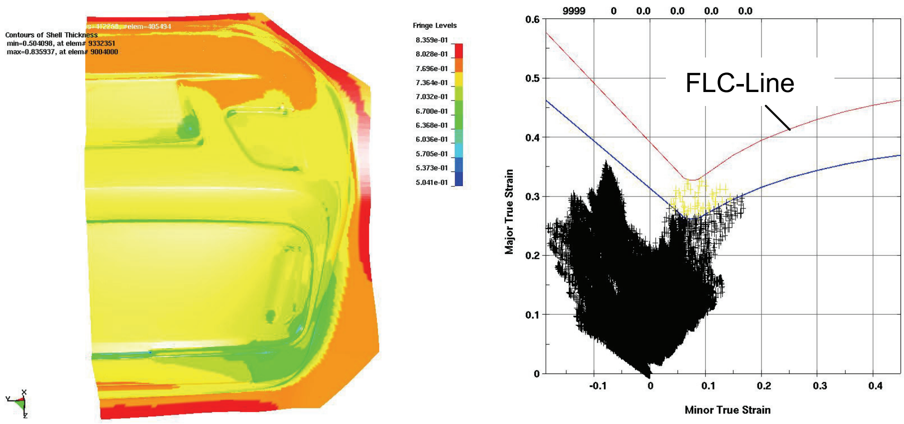

Fig. 7: Left - Final shell thickness distribution of the baseline run (minimum shell thickness ~0.51mm) Right – FLC-Diagram for the baseline run, no points above the FLC-Curve

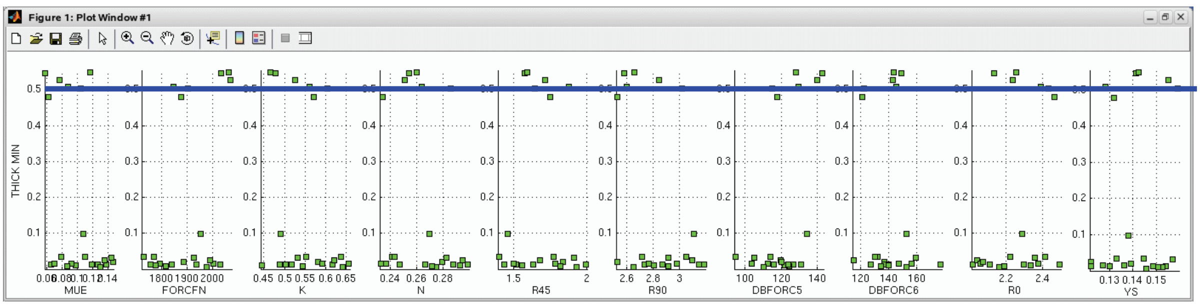

Fig. 8: Minimum sheet thickness of the blank (THICK_MIN) vs. considered parameter variations. Initial target value of sheet thickness is 0.8mm.

A similar behavior is observed for the distance of the strain-ratios to the FLC-Curve. A positive value indicates the maximal perpendicular distance of a point above the FLC-Curve (infeasible), a negative value indicates the minimum distance below the FLC-Curve (feasible), see Figure 9.

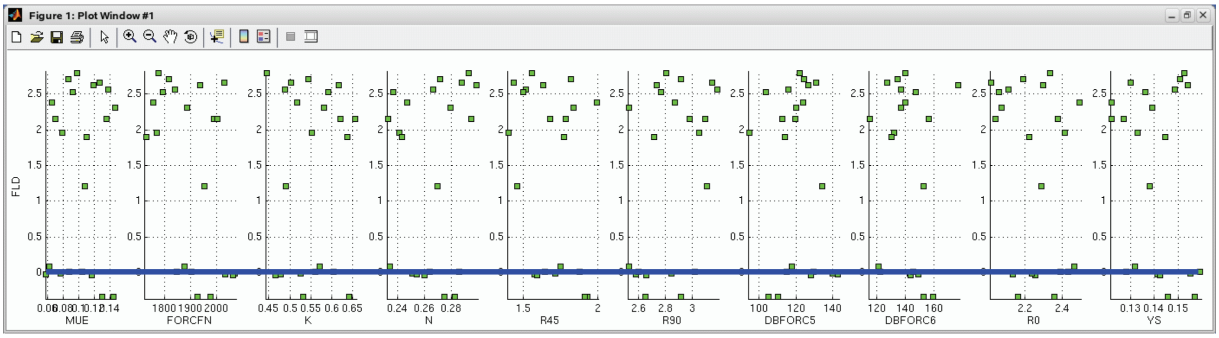

Fig. 9: Points indicate the distance to the FLC-Curve, positive – infeasible, negative - feasible

Conclusions after Random Latin Hypercube Simulations

Considering the chosen baseline design, the FE-simulation is very sensitive regarding the assumed variations of the uncertain process parameters. The failure probability is very high and the baseline configuration must be declared as non-robust. Consequently, the next step has to be the improvement and optimization of the robustness of the model. Therefore, reliability based design optimization is investigated. Approach and results are discussed in the next section.

3.3 Reliability Based Design Optimization (RBDO)

The methodology of the applied RBDO study is FOSM (First Order Second Moment) in combination with the successive response surface scheme. FOSM is based on the assumption of normal distributed probability density function. The representation of the distribution function is just by the mean and the standard deviation. For the meta-model, which is adapted sequentially through the successive scheme iterations, a neural network approach is used, see Fig. 11. Details regarding the RBDO approach and the successive response surface scheme with neural networks are discussed in the LS-OPT Users Manual [5].

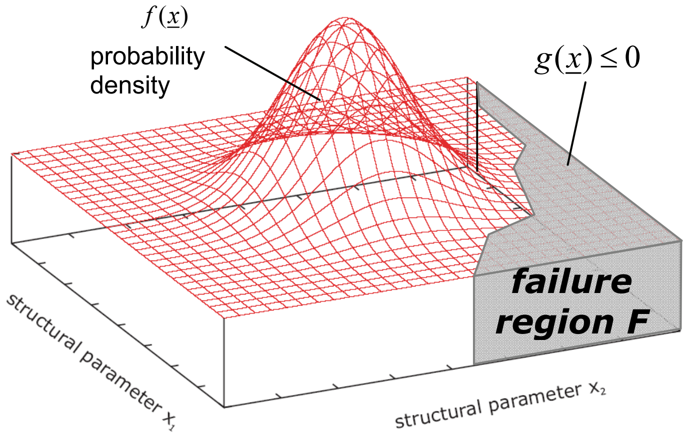

Fig. 10: Goal of RBDO is to minimize the failure probability of the design

Definition of the Optimization Problem

Here, the objective of the RBDO is to minimize the failure probability under consideration of the uncertainties described in Section 3.1. Failure is defined by exceeding a threshold for the minimum shell thickness and for the violation of the FLC-Line.
For the RBDO in total 17 variables are considered. Thereof, 10 variables are pure “noise variables” which take into account the uncertainties. To drive the optimization process 7 “control variables” are

introduced (see Table 6), simultaneously these variables operate as noise variables with specific probability distributions.

Variable	Description	Distribution "noise variable"			Range "control variable"	
		Type	mean	std	min	max
DBF1	Draw Bead Force #1	normal	70	5 kN	20 kN	200 kN
DBF2	Draw Bead Force #2	normal	20	5 kN	20 kN	200 kN
DBF3	Draw Bead Force #3	normal	80	5 kN	50 kN	120 kN
DBF4	Draw Bead Force #4	normal	90	5 kN	60 kN	120 kN
DBF5	Draw Bead Force #5	normal	100	5 kN	70 kN	130 kN
DBF6	Draw Bead Force #6	normal	140	5 kN	20 kN	200 kN
FORCFN	Binder Force	normal	1910	50 kN	1400 kN	2400 kN

Table 6: Seven variables are defined as control ***and*** *noise variables. Control variables drive the optimization process, noise variables are to consider uncertainties.*

Meta-Model Based RBDO

For the successive surface scheme 26 runs were performed per iteration. The density of the sampling points increases towards the optimium. The neural network is updated with additional training points after each iteration (see Fig. 11).

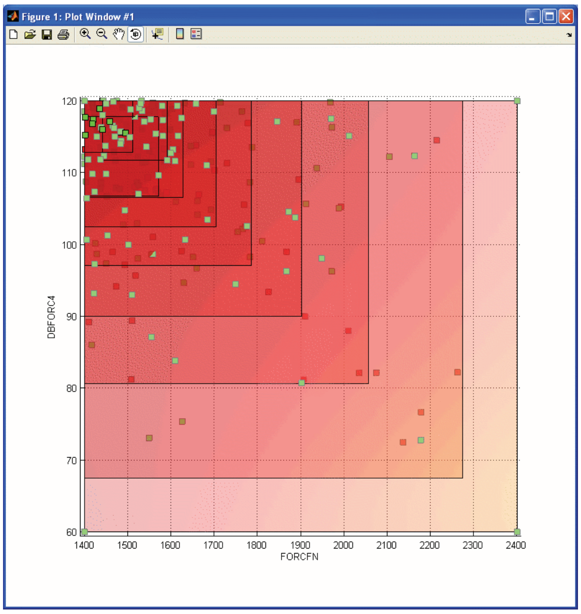

Fig. 11: Successive Response Surface Scheme with Neural Nets after 10 iterations

Fig. 12 displays a global approximation of the entire design space after the 10th iteration for the variables DBFORC4, FORCFN and the response THICK_MIN. It shows a D-SPEX window where the Meta-Model can be explored by rotating, zooming, visualization of analysis results, residuals, etc. Especially useful is the fact that the visualized constraints do not only consist of constraints of the displayed response, but of the other response describing the violation of the FLC-line.
For the 15 not displayed remaining variables, D-SPEX offers the possibility to vary these variables through sliders in an additional control panel window. For more information regarding D-SPEX it is refered to [11].

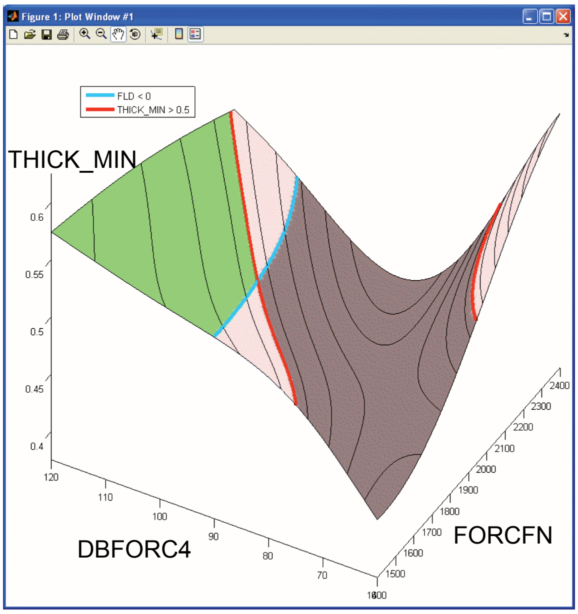

Fig. 12: Global approximation of the Design Space with a Neural Network Meta-Model

Optimization History for the Responses THICK_MIN and FLD

Fig. 13 shows the optimization history of exceeding the lower bound for the minimum sheet thickness THICK_MIN. The probability of failure drops down from about 55% for the base line design to 3.3515e-4 after 10 iterations. The “computed” value at the optimum is fairly close to the “predicted” value. “Computed” means the simulation value for the optimum parameter combination and “predicted” means the approximated value of the meta-model for this parameter combination.

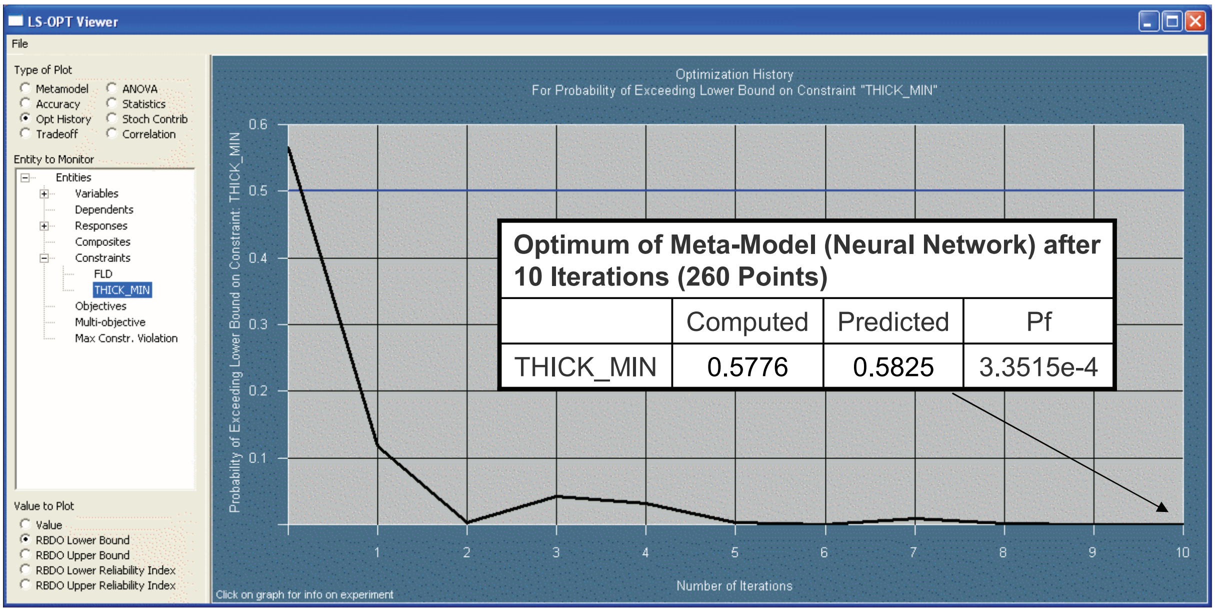

Fig. 13: Optimization history of the probability of exceeding the bound for THICK_MIN

Fig. 14 shows the optimization history of exceeding the upper bound for the FLD criterion. Finally the probability of failure could be reduced to 0.01191. This means, approximately 1 of 100 designs will exceed the FLC-line.

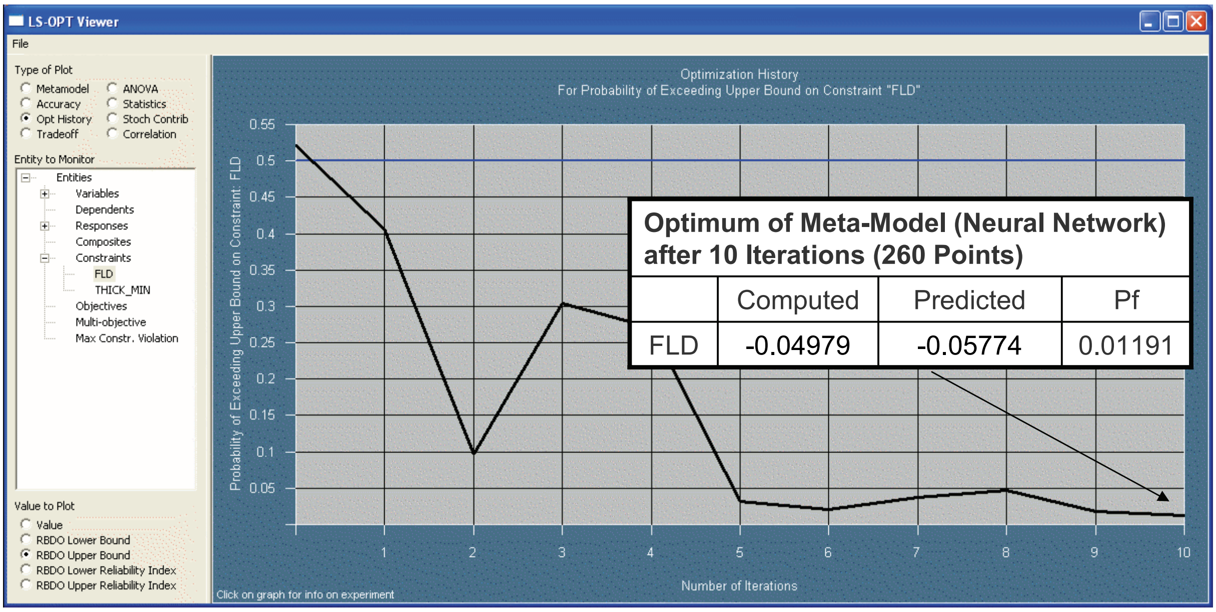

Fig. 14: Optimization history of the probability of exceeding the bound for the FLD criterion

Verification of Optimum with Direct Monte Carlo Simulations

The failure probabilities displayed in Figures 13 and 14 are estimated by the use of a Meta-Model. This means, the Monte Carlo evaluations are performed by the functional analysis of the meta-model. The number of Monte Carlo evaluations on the meta-model is in LS-OPT by default 100000, but of course there is an unknown approximation error of the meta-model. In order to verify the failure probability determined on the meta-model, 160 additional direct Monte Carlo simulations are applied. The mean values for the parameters are taken from the optimal design and the variance is applied according to the distribution functions described in Section 3.1.

Table 7 shows that the failure probabilities estimated by the use of Meta-Models are in the same order of magnitude as for the direct Monte Carlo simulation. Within the 160 Monte Carlo simulations no constraint violation could be observed, see Fig 15. The estimated failure probability in Table 7 is evaluated by the assumption of normal distributed responses THICK_MIN and FLD.

Failure Probability Meta-Model vs. direct Monte Carlo (normal distribution assumed)		
	Pf – Meta Model	Pf - Direct MC
THICK_MIN	3.35e-4	0.59e-4
FLD	0.0119	0.0103

Table 7: Comparison of the failure probability Pf determined by the use of Meta-Models and by the conventional Monte Carlo approach

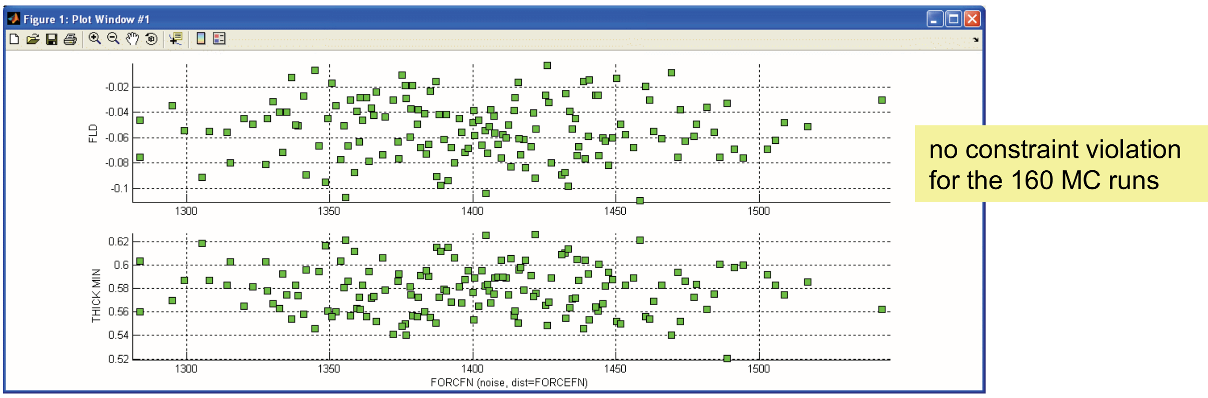

Fig. 15: Green colour of the points indicate feasible designs

4 Summary

For the metal forming study considering the chosen baseline design, the FE-simulation is very sensitive regarding the assumed variations of the uncertain process parameters. Frequently violation of the FLC requirements and under-run of the minimum sheet thickness appear. This represents a high probability of failure P_f. The design is thus referred as non reliable. Furthermore, it is considered as non robust due to assumed random variation of the input parameters (material properties, manufacturing process parameters) and their strong effects on the results.

In order to establish a feasible design the problem is reformulated in view of the reliability-based design concept. The objective of the RBDO is to minimize the probability of failure P_f and thus to maximize the reliability of the design. The limit state function $g(\mathbf{x})$ is formulated with respect to the failure criteria minimum shell thickness and distance of the strain-ratios to the FLC-Curve.

The reliability-based design optimization is investigated using LS-OPT. Due to the fact that the computational cost of the metal forming simulation is quite high, a meta-model based approach is applied. Utilizing RBDO leads to a design, which has a significantly improved failure probability. The verification of the optimum design by conventional Monte Carlo simulations justify the use of meta-models for reliability investigations for metal forming applications, at least for P_f values not less than 0.01.

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