INTERRELATION ANALYSIS FOR METAL FORMING PROCESSES WITH LS-OPT AND LS-DYNA

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ABSTRACT: The aim of this paper is to investigate the evaluation of process sensitivities for metal forming applications. The Finite-Element software LS-DYNA is a suitable tool for the simulation of complex metal forming processes. For the forming engineer it is of interest how individual process parameters contribute to output quantities typically by means of quality measures. Three different approaches will be examined in this study. Firstly, standard methods such as correlation and linear regression analysis are discussed. As an extension of those linear approaches, in LS-OPT there is the possibility for non-linear sensitivity analysis according to Sobol's principle. The second part of the paper deals with the capability of fringing statistical results on the FE-model in order to visualize contributions of variables to specific responses in space. Statistical information is plotted on the part geometry (FE-mesh) and supports the engineer to detect critical regions. Lastly a methodology is introduced to evaluate feasible design spaces (parameter ranges) by solving an inverse problem. The feasible design spaces are described by means of hyper cuboids and are analyzed by the application of cluster analysis.

KEYWORDS: FE-Simulation, Forming Processes, LS-DYNA, LS-OPT, Sensitivity Analysis, Inverse Problem, Stochastic Fields, Cluster Analysis

1 INTRODUCTION

Within the manufacturing process of sheet metal parts, it is of interest how process parameters contribute to the quality performance of the finally produced parts. There are process parameters which can be controlled by the engineer and knowledge of effects of parameter changes with respect to quality performance is of great interest. On the other hand there are process parameters which cannot be directly controlled by the engineer, such as scatter in material properties, blank thickness, friction, temperature, etc. Here it is of interest how such uncertainties affect the reliability of the quality performance.
In LS-OPT several methodologies are implemented to address these questions [1]. In this paper the methodologies are introduced and illustrated by means of examples. In addition a new approach on the detection of feasible parameter regions is introduced.

2 Sensitivity Analysis

In general sensitivity analysis is performed in order to evaluate relations between design parameters and single value responses. On this several methods are available in LS-OPT.

2.1 Correlation Analysis

Evaluation of correlation coefficients is performed by dividing the covariance of two random values by the product of their standard deviations:

$$\rho_{\mathrm{x\,y}} = \frac{\sigma_{\mathrm{x\,y}}}{\sigma_{\mathrm{x}}\sigma_{\mathrm{y}}} = \frac{\sum_{i=1}^{N}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{N}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{N}(Y_i - \overline{Y})^2}}$$

In case X is a process parameter (e.g. binder force) and Y a quality performance value (e.g. thinning), the correlation coefficient $\rho_{X,Y}$ gives an indication of the relation between these two values.
The values of the correlation coefficients are within the interval $[-1, 1]$. Values close to 0 indicate a

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weak (linear) relationship and values close to -1/1 a strong (linear) relationship between the investigated random variables *X* and *Y*.

An example of a display of correlation coefficients in LS-OPT for a metal forming example is given in Fig. 1.

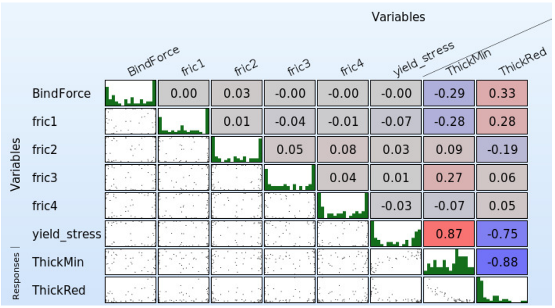

Fig. 1 *Correlation matrix*

For instance, the plot in Fig. 1 tells the user that the yield stress has a significant positive correlation with respect to the minimum thickness (ThickMin) and the friction coefficient “fric4” is almost insignificant with respect to thickness reduction (ThickRed) and minimum thickness (ThickMin).

2.2 Linear Regression Analysis

Linear polynomial approximations can be used to evaluate indicators for the significance of parameters as well. The indicators are analysed by interpretation of the slope of the linear approximation as a measure for the significance of the respective parameter, see Fig. 2

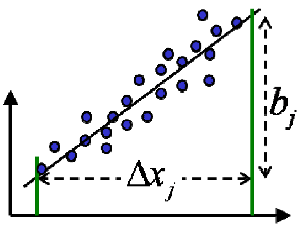

Fig. 2 *Regression coefficient b_j as an indicator for the significance of parameter x_j*

Scatter (deviation) with respect to the linear approximation is considered by the evaluation of confidence intervals for the sensitivity predication. Detailed information is available in [1].
An example of an evaluation of linear regression analysis is displayed in Fig. 3. Yield stress is the dominating parameter and has a positive influence on the minimum thickness. This means, increase of yield stress leads to an increase of the value for the minimum sheet thickness.

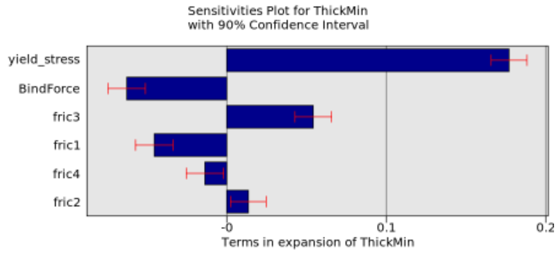

Fig. 3 *Evaluation of linear sensitivities from regression analysis with confidence interval (red bars)*

2.3 Global Sensitivity Analysis according to Sobol

The Sobol’ indices are sensitivity measures for arbitrary complex computational models. They estimate the contribution of individual input parameters in the process simulation on the variance of model response values such as e.g. quality performance. This section just provides a short introduction.

The models under investigation are described by a function $\underline{Y} = f(\underline{X})$, where $\underline{X} = (X_1, X_2, ..., X_n)$ is the random input vector consisting of *n* random variables (i.e. process parameters) and where $\underline{Y} = (Y_1, Y_2, ..., Y_m)$ denotes the random output vector consisting of *m* random values (i.e. quality performance).

Each random model response Y_j $(j = 1, 2, ..., m)$ is characterized by its variance D^j. It is possible to decompose each variance D^j into partial variances associated with the single random input variables $X_1, X_2, ..., X_n$ as follows:

$$D^j = \sum_{i=1}^{n} D_i^j + \sum_{1 \le i < k \le n} D_{i,k}^j + \cdots + D_{1,2,...,n}^j$$

and to relate each partial variance to one Sobol’ index

$$S_{i_1,...,i_s} = \frac{D^j_{i_1,...,i_s}}{D^j} \quad \text{with} \quad 1 \le i_1 < \cdots < i_s \le n,$$

$s = 1,2,\ldots,n$

Each of the Sobol’ indices $S_{i_1,...,i_s}$ represent a sensitivity measure that describes which amount of each variance D^j is caused due to the variation of the single random input variables and its mapping onto the output values. More information on global sensitivity analysis with Sobol’ indices is available in [3], [5], and [6].

The Sobol’ indices are practically computed using Monte Carlo simulations [4], this means that for computationally demanding models, e.g. finite element models in engineering mechanics, practical application is only possible with the usage of efficient meta models (approximations).

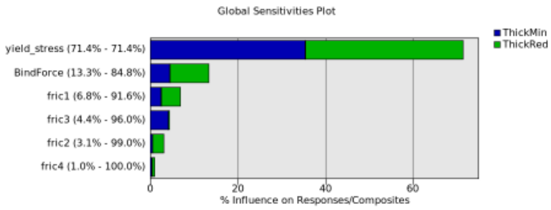

Fig. 4 *Contribution of process and material parameters on variation of thickness changes*

In Fig. 4 the percentage contribution (Sobol' indices) of each parameter on the variation of minimum sheet thickness (ThickMin) and on sheet thickness reduction (ThickRed) is displayed. The evaluation of Sobol' indices are based on a FFNN (feed forward neural network) meta model [1].

2.4 Design Exploration using Meta Models

Meta models are created on the basis of multiple simulations with different parameter combinations (Design of Experiments (DOE)). Meta models provide a functional relationship between process or material parameters and response values of the simulations. In LS-OPT there are capabilities to visualize meta models and to use them as a tool for exploring interrelations between parameters and simulation responses, see Fig. 5.

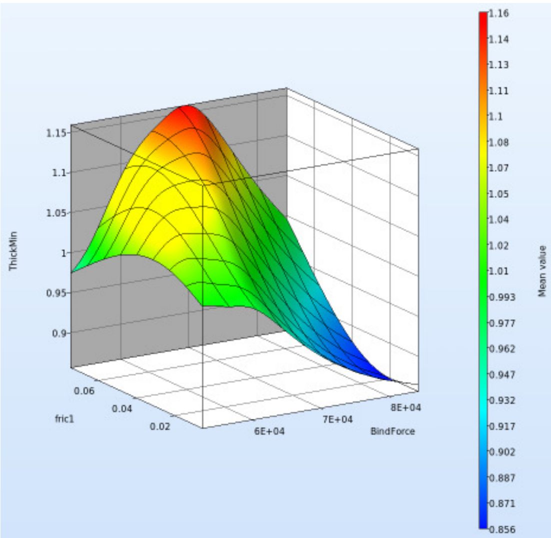

Fig. 5 *Meta model displays the interrelation between the process parameters binder force and draw bead friction with respect to minimum sheet thickness after forming*

3 Fringe of Statistical Results on FE-Model

Variation of node and element results due to changes/uncertainties in process parameters can be displayed on the FE-model by colours. Such plots can give an indication where large scatter in the results occur. It can also show mean values of specific responses or minimum and maximum values of all applied simulations. For more information on the possibilities of fringing statistical results on the FE-model in LS-OPT it is referred to [1].

The latest versions of LS-OPT provide the capability of fringing statistical results also on the basis of mesh adaptive simulations. For this, mapping of element and node results of multiple runs onto a reference mesh is performed.

Example (Courtesy Daimler AG):

In the manufacturing process of a deck lid uncertainties are considered by introducing scatter on several process and material parameters. Scatter is applied by probability distribution functions for the respective parameters. On this, multiple simulations are performed with perturbations of the original process and material parameters. For more information on this example it is referred to [2].

In Fig. 6 the standard deviation of the percentage thickness reduction due to the applied uncertainties is plotted. The maximum standard deviation in this plot is 18.9%. This means, at this point there is a variation with a standard deviation of 18.9% considering all applied simulation runs under consideration of uncertainties for process and material parameters.

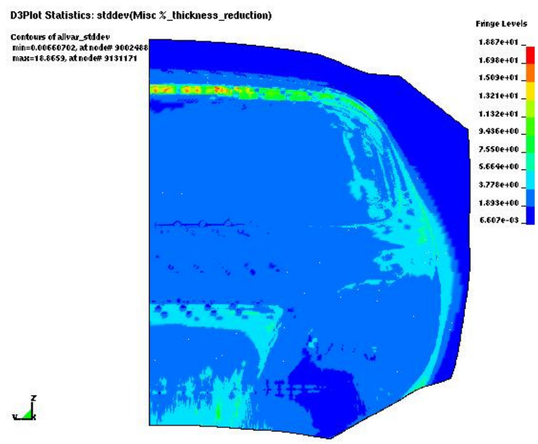

Fig. 6 *Standard deviation of sheet thickness reduction. Red spots indicate high variation of percentage thickness reduction.*

In addition, contribution of single process or material parameters to the variation of the simulation results can be displayed in colours on the FE-model. On this, sources of scatter in the quality of a product can be detected and quantified. An example is given in Fig. 7.

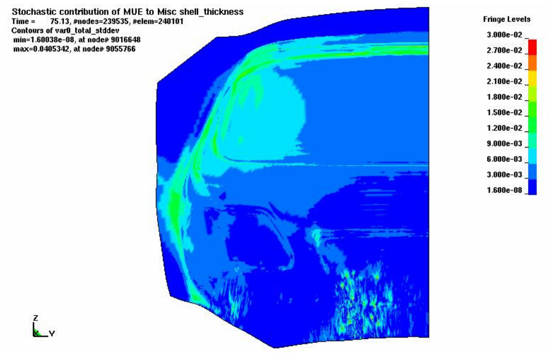

Fig. 7 *Contribution of friction parameter to variation of final sheet thickness. Red spots indicate a standard deviation of 0.03mm for variation of sheet thickness due to variation of μ [0.05;0.1]*

4 Detection of Feasible Regions

Apart from evaluation of a single combination of optimal process parameters, it might be of interest to detect parameter ranges which lead to feasible product requirements. On this, the engineer is able to assess changes in the manufacturing process or in material properties within the development process.

4.1 Analysis of feasible parameter ranges

The scheme in Fig. 8 illustrates an approach for detection of feasible parameter ranges. Based on parameter samples in the input space (Design of experiments (DoE)), corresponding simulation results in the response space can be assigned, compare Fig. 8-(1). Constraints, e.g. thickness reduction less than 20%, are usually applied in the response space, see Fig. 8-(2). For non-linear relations between input and output space, borderlines of feasible/infeasible parameter regions are not easy to determine. Feasible regions can even be disjoint as displayed in Fig. 8-(2). With the aid of cluster analysis technologies ([9],[10]) joint regions in the input space might be detected, see Fig. 8-(3).

The cluster analysis approach is a data mining method with the objective to determine interrelated points within general point sets. The problem of detecting interrelated points can be solved for low dimensions (up to three) by using 3D-scatterplots relatively easy. But for higher dimensions, the characterization of clustered points by means of graphical tools is cumbersome or just impossible. Therefore, numerical approaches for cluster analysis are required.

The results of a cluster analysis are point sets with any amount of spreading. There is no information about a continuous borderline that separates feasible and infeasible parameter regions. Therefore it is proposed to adapt hyperrectangles to the detected point clusters, see Fig. 8-(4). Hyperrectangles are cuboids with the dimension of the number of parameters. The advantage of rectangles is that there is no interaction (dependency) between parameters in the definition of the feasible regions. More detailed information on the described procedure can be found in [8].

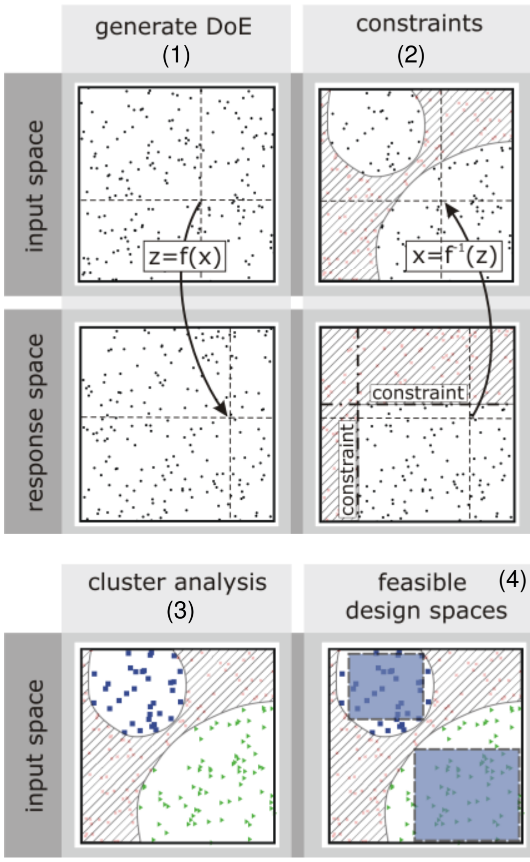

Fig. 8 *Scheme for detection of feasible design spaces (parameter ranges).*

4.2 Example: Design of a deep drawing process (Courtesy BMW AG)

The considered example consists of 4 tubes, which represent the punch and the die. Some line forces are to represent the draw beads, see Fig. 9. In total 28 input parameters are introduced. These are the radius of the two dies, 22 draw bead forces, shell thickness, binder force and the initial positioning of the blank in both directions.

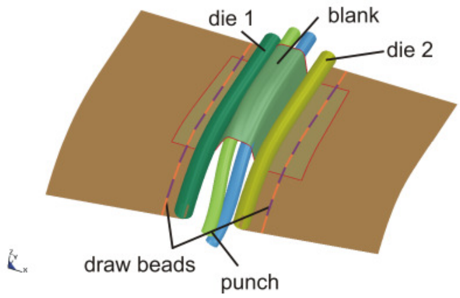

Fig. 9 *FE-Model of deep drawing process*

Within pre-defined parameter ranges, 232 experimental design points (DoE) are simulated.
Several constraints are introduced to ensure a reliable manufacturing process without violating FLC and cracking criteria. In addition, it has to be ensured, that the edge of the blank does not pass the draw beads. And furthermore, a criterion for the blank geometry after springback by comparing the actual geometry with the desired geometry is introduced. On this, for the sum of the difference a threshold is defined.

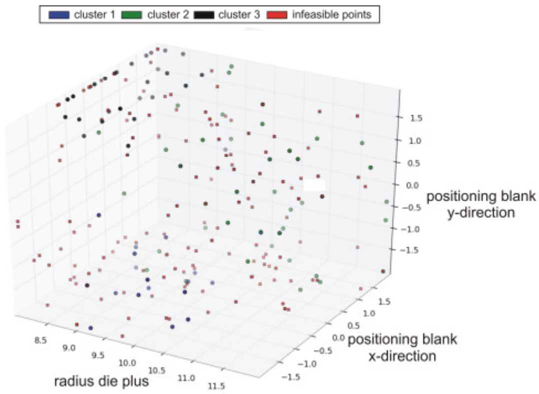

Fig. 10 *Result of cluster analysis and display of infeasible analysis results*

In Fig. 10 the result of a cluster analysis is displayed in three dimensions with respect to parameters on blank position in x/y-direction and on die radius. Three clusters of interrelated feasible analysis points are detected. In Fig. 10 the coherence of the points of a cluster is not obvious. The reason is, because the points include 28 dimensions (parameters), but the view in Fig. 10 is only in three dimensions. Red (infeasible) points have violated any of the above mentioned constraints.

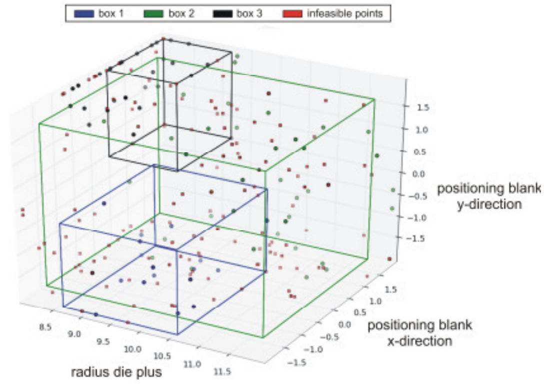

Fig. 11 *Adapted hyperrectangles as borderlines for feasible parameter regions*

Hyperrectangles are assigned to the respective clusters to enable a proper description of the feasible parameter regions. The result is visualized in Fig. 11 for the cluster configuration depicted in Fig. 10. For more detailed information on this example it is referred to [8].

5 CONCLUSIONS

Different approaches for the evaluation of interrelations between process and material parameters are demonstrated. Analysis of correlation coefficients and of sensitivities from linear regression models reveal the drawback, that they do not capture non-linear relations between parameters and system responses. Evaluation of global sensitivities by Sobol' indices consider such nonlinearities, but require more simulation calls, even in case meta models are used. Particularly for high dimensional problems (many parameters) this is a major issue.

In the second part of the paper it is shown how variations of system responses and interrelations between process or material parameters and system responses can be displayed in LS-OPT on the FE-model.

In the last part a methodology is introduced to evaluate feasible parameter ranges. This seems to be a promising new approach. Nevertheless, a lot of research work has to be done, particularly in improvement of algorithms for cluster analysis and determination of best suitable hyperrectangles.

6 ACKNOWLEDGEMENT

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