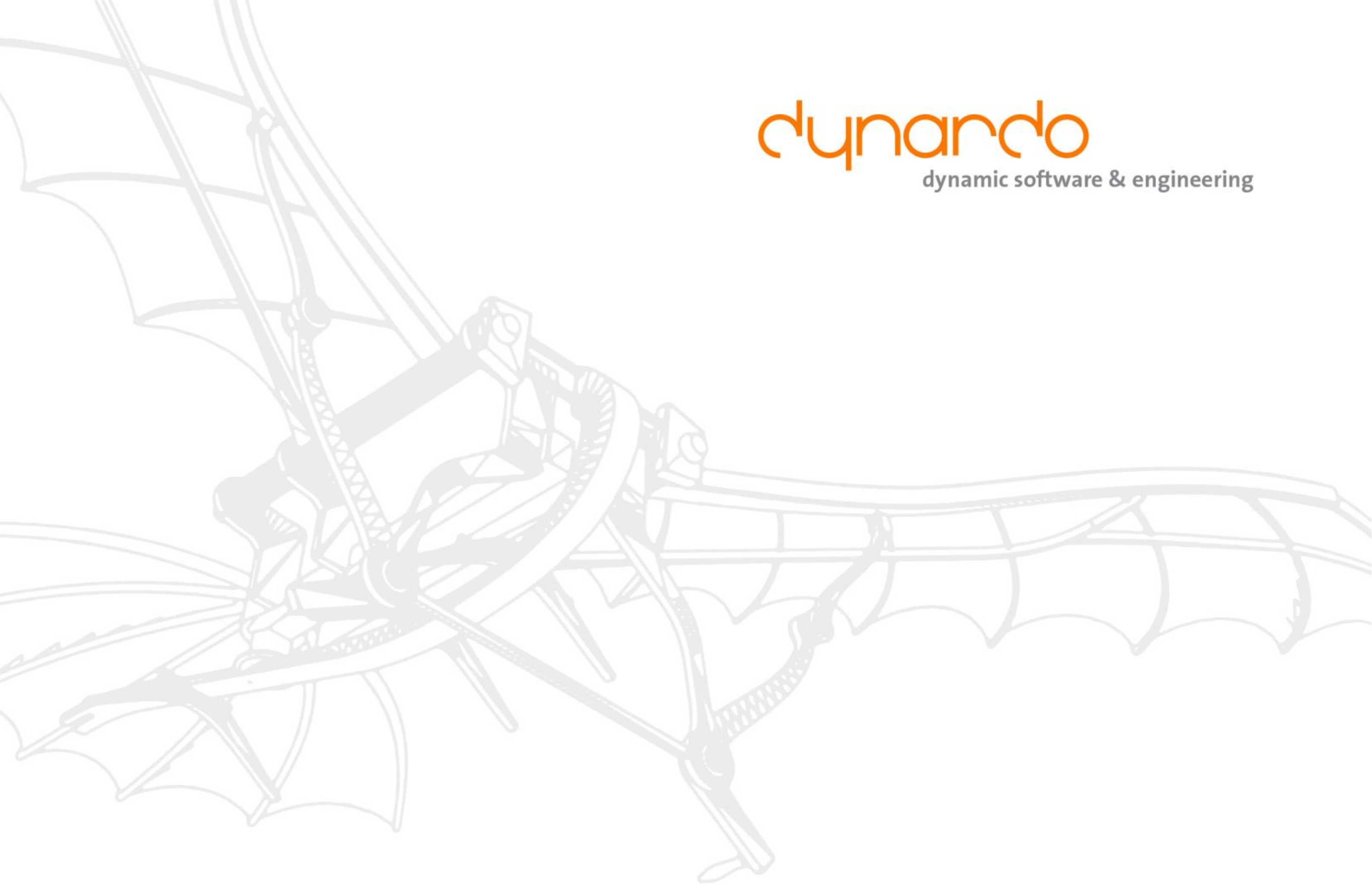

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Lectures

Robustness analysis of metal forming simulation – state of the art in practice

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Robustness analysis of metal forming simulation – state of the art in practice

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Abstract

Robustness analysis is the evaluation and analysis of product performance or structural behavior with respect to design variations, typically being random variations. Simple approaches are based on load case models, where pre-defined combinations of load cases are evaluated and verified for safety. A more comprehensive approach to verify robustness is based on numerical stochastic modelling. Using stochastic concepts one is able to predict the robustness regarding statistical properties like failure probabilities, quantile values or QCS (quality capability statistics) through simulation. One further can systematically identify variables being responsible for critical variations through nonlinear sensitivity analysis. 3D visualization of statistical results helps to identify hot spots and to improve confidence. 3D visualization of sensitivity measures improves model understanding. The decomposition into scattering shapes allows the identification and further analysis of spatially distributed effects (e.g. nonlinear buckling). When considering uncertain process parameters in terms of spatially distributed quantities (e.g. when analyzing the influence of geometric perturbations onto robustness), one can represent them as random fields and include them into sensitivity and robustness analysis.

This article explains the methodological approaches to stochastic modelling and how they are implemented in commercial software like *optiSLang* and *Statistics on Structures*.

1 Introduction

Manufacturing tolerances, material scatter, random load or other stochastic effects cause scattering properties of components or structures that are usually of spatial distribution. To ensure product quality, to avoid recalls or to fulfill safety requirements, one can consider these random effects by using appropriate statistical models and methods already in the design phase.

In particular, the process of sheet metal forming has been deeply investigated using stochastic methods in the past years. This became possible due to more powerful computer hardware and CAE software allowing the simulation of highly nonlinear mechanical processes. Further, traditional quasi-deterministic approaches (e.g. the usage of safety-factors applied to individual load case scenarios) frequently lead to too conservative designs or even fail to predict failure when using nonlinear mechanical models.

The design, simulation and optimization of deep drawing processes require a deep understanding of the governing mechanisms. Statistical analysis can help to answer some leading questions: Primarily, it helps to identify potential failure locations and to quantify the probability of exceeding critical thresholds. Further, it provides non-linear sensitivity analysis based on surrogate modeling that allows the identification of sources of failure. Visualization of sensitivity indices on the FEM mesh allows a greater understanding of the deep drawing process and easily helps to identify modeling errors. Random fields allow the identification of distributed scatter (e.g. non-linear buckling shapes) and their causes. Further, random fields can also be used to generate random (perturbed) designs, e.g. geometries with random perturbations due to manufacturing. This article will present an overview of state-of-the-art methods for robustness analysis. Most of them are already available in today's commercial software packages.

2 *Robustness analysis based on scalar parameters*

2.1 Tolerance analysis

Aim of a tolerance (or robustness) evaluation is the analysis of the effect of uncertainties on a model and its response. Typically, a CAE model of a manufacturing process, of a product in operation or of any structural device under certain loading conditions is considered. The response of such a model is, generally, uncertain. The origin of the uncertainty lies in manufacturing tolerances, varying material parameters (e.g. strength), uncertainties in loading and pre-damage etc. Even when deterministic CAE simulations predicted a robust model behaviour, uncertainties in the model response may lead to high failure rates.

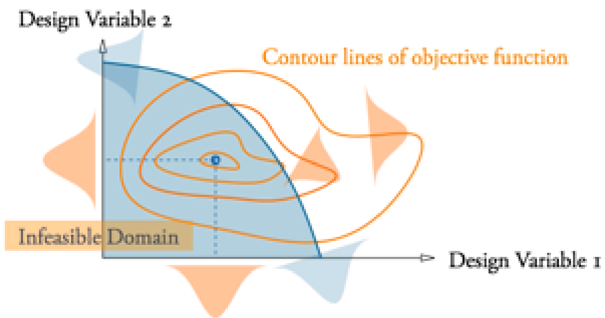

Fig. 1 Uncertainties in design optimization: Random variations in objective function and in constraints, source: [XXX]

There are various ways to deal with these uncertainties in the engineering design process:

- **Deterministic approach**, testing the exceedance of a critical threshold for a single design.
  This usually involves (partial) safety factors and often leads to robust, but not necessarily optimal designs.
- **Random numbers**, considering uncertainties in terms of single random parameters in a probabilistic model.

This involves a stochastic description of the model input parameters (mean, standard deviation, probability distribution function, correlation among parameters) or at least knowledge on the interval bounds in which an input parameter can vary. The response can then be evaluated in terms of statistical quantities (e.g. scatter ranges, quantile values, event probabilities, safety margins ("sigma levels"), other robustness measures like QCS (DIN 55319-3)).
Such probabilistic models can be easily solved with simplifying assumptions (linearization etc.) using e.g. fault tree analysis, failure mode and effects analysis or reliability block diagrams. Sampling strategies (design of experiments with Monte Carlo-like methods), on the other hand, allow engineers to analyse linear and nonlinear models.

- **Random fields**, considering random effects being distributed in space or time.

Tolerance studies can be easily carried out with software packages developed by DYNARDO [1], i.e. *optiSLang* (for random numbers) and *Statistics on Structures* ("*SoS"*, for random fields) [3].

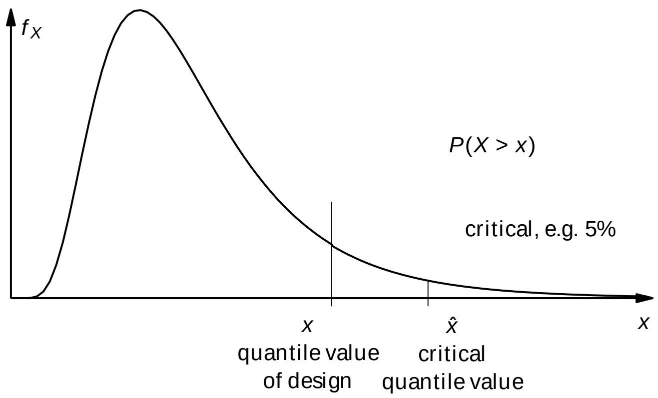

Fig. 2 Robustness with respect to a critical threshold by exceedance probability (for example)

A schematic flow of a robustness analysis is illustrated in figure 3: First one needs to define statistical properties oft he input parameters of a CAE process, for example statistical distribution types, mean value, standard deviation, value bounds, correlations of material parameters, loads or geometric parameters (unless not available). These inputs may also be random fields, for example in case of random geometric perturbations, pre-damage or load distribution. Software packages like *optiSLang* then create a Design of Experiments (DoE) that scans the random variable space and evaluates the responses of a CAE process, e.g. a metal forming simulation. The response fields (for example the plastic strain, stress or thinning) can then be imported into *SoS*. In there one can evaluate the robustness with respect to quantile values, exceedance probabilities or QCS statistics. Critical locations can be visualized on the FEM mesh. Once a critical locations has been identified, one can perform a nonlinear sensitivity analysis to identify the input parameters whose variations influence the response scatter at most.

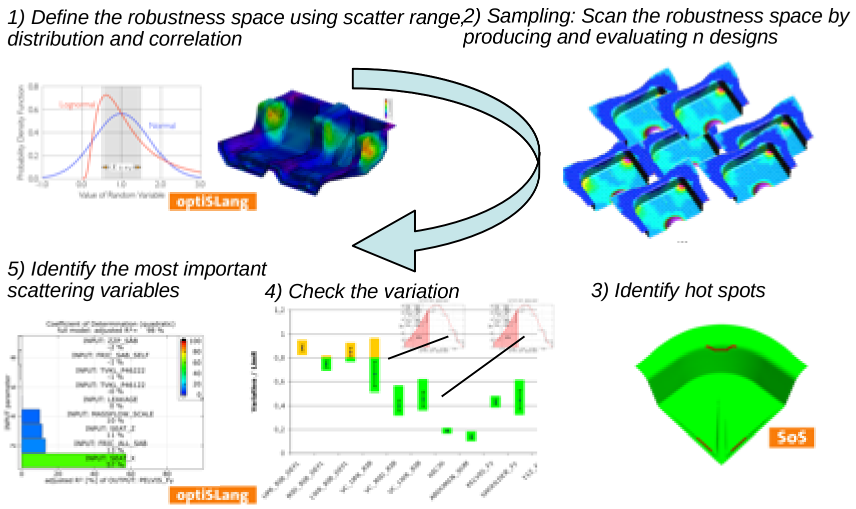

Fig. 3 Schematic flow of a robustness analysis in CAE

2.2 Identification of failure sources

If critical tolerances are violated by the model, engineers must find out the sources for the failure. A mathematically founded approach is to carry out a sensitivity analysis. This analysis aims to identify the subset of uncertain input parameters with significant impact on the explainable variation of the model response. The software *optiSLang* can be used to identify this subset using the Metamodel of Optimal Prognosis (MOP) [2]. The individual CoP values of each parameter represent the amount of variation of the model response that can be explained by the variations of the respective input parameter, see figure 4.

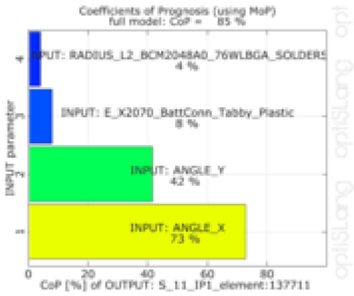

Fig. 4 Sensitivity analysis using 30 random input parameters: Identified 4 important input scatter parameters.

In sensitivity analysis, one first locates the finite element node or finite element of interest (e.g. with largest failure probability) or takes extremal values (e.g. the maximum plastic strain of each design).
An important issue of spatially local sensitivity analysis is the nonlinear character of the varying location of extremal points (like maximum stresses or strains). Hence, the sensitivity analysis

- may present an incomplete picture since it ignores the correlation between neighbouring points,
- may fail because the degree of nonlinearity is too large (too small CoP values).

The issue of varying positions can be considered by random field models, like available in *Statistics on Structures*.

3 Robustness analysis based on field quantities

3.1 Motivation

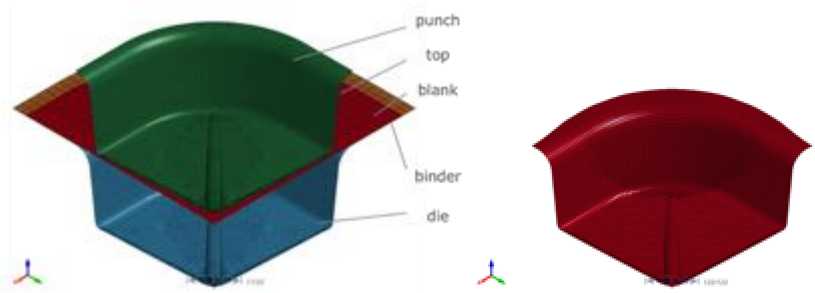

Fig. 5 Setup (left) and resulting sheet after rebound (right) of a deep drawing process simulation

Consider, for example, the deep drawing production process as illustrated in figure 5: Therein, material properties, surface friction, sheet thickness or positions and geometry of the production tools (punch, die, etc.) are typically uncertain. These random deviations are investigated using a DoE with 100 designs. Here, one may often be interested in the maximum values of thickness reduction and plastic strain of the forming sheet. In order to ensure the robustness of the production process, one may use e.g. as robustness goal the exceedance probability of exceeding a critical threshold for the maximum plastic strain and the thickness reduction.

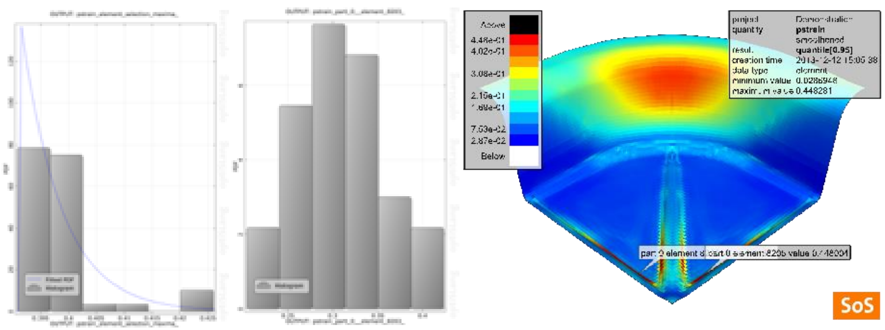

Fig. 6 Comparison of histograms of the maximum plastic strain for each design (left) and the plastic strain at the most critical hot spot (middle) at element 8203. The positions of the 2 hot spots were identified using the quantile value of the plastic strain for an exceedance probability of 5% (right).

Figure 6 demonstrates a typical problem when analyzing the statistics of extremal values. The histogram of the maximum plastic strain is not a copula model anymore – it is quite difficult to fit an appropriate distribution function and estimate statistical properties. Furthermore, when applying sensitivity analysis (e.g. MOP in *optiSLang*), the amount of explainable variation may be too low (here: CoP[Total]=86%). The reason is that the position of the maximum is changing with each change of the input parameters. The degree of nonlinearity can be reduced by considering individual “statistical hot spots”, i.e. a small set of fixed positions for which the plastic strain violates the robustness criteria. For example, the histogram of the plastic strain in element 8203 is a copula model for which a distribution function can be identified with high accuracy. Furthermore, also the total CoP has improved to 98%.

Generally, CAE solutions being distributed on FEM meshes (but also being distributed in time or in frequency domain) should be treated comprehensively by considering both, the location and the actual value, individually at the same time. This approach is not limited to robustness analysis, but can be extended to many optimization problems. Several strategies were developed in statistical analysis, namely the identification of statistical hot spots as well as the modeling in terms of random fields [3,4] and field meta models [7]. The two strategies will be sketched in this section.

3.2 Hot spot detection and robustness evaluation

An intuitive approach for improving the results of a variation study is to change the interpretation of the task: Instead of measuring the exceedance probability of the maximum plastic strain (as seen in the introductory example) one could consider the exceedance probabilities of the most likely failure points individually and combine those later. The same applies to sensitivity analysis, where one could create the MOP for those points being frequently the maximum in the DoE instead of creating the MOP for the maximum value.

The post processing of *SoS* (figure 7) plots statistical properties directly on the FEM mesh. It further can highlight regions violating critical limits and identifies nodes and elements with extremal statistical values. One can chose from a great variety of statistical properties to be visualized and analysed for nearly any kind of physical quantity.

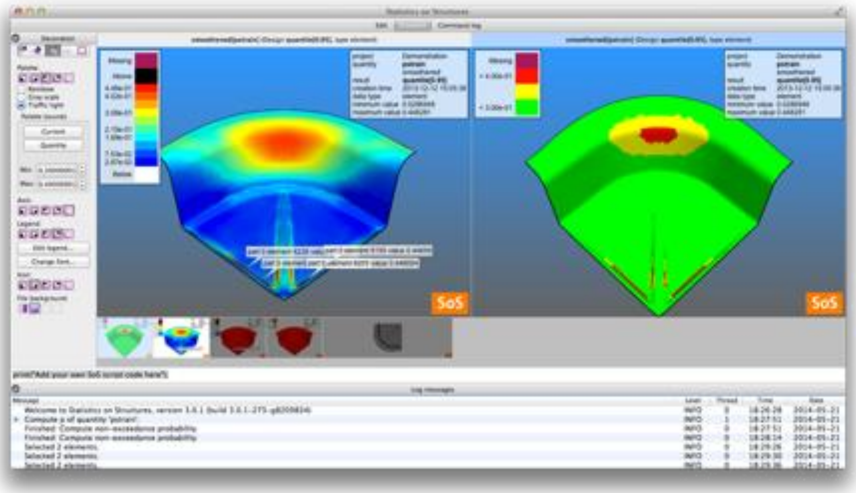

Fig. 7 Robustness evaluation based on quantile values: Left: Plot of all values of plastic strain that are exceeded with a probability of 5%, selected elements are the maxima. Right: Traffic light plot of the same quantile values (green: plastic strain <0.3, yellow: 0.3<pstrain<0.4, red: >0.4)

3.3 Random field modelling

Random fields denote random physical quantities which are distributed in space or time (e.g. on finite element meshes). They actually dominate mechanical CAE analysis since most parameters like

- **Geometric tolerances**: geometric perturbations, layer thicknesses, thickness of composite layers
- **Material parameters**: mortar and admixtures in concrete, porosity in ceramics, cast metal.
- **Damage**: plastic strain, cracks
- **Loading and state variables**: stresses, strains, displacements

are spatially distributed on a FEM mesh. There are many applications in sheet metal forming/deep drawing and other disciplines where the robustness analysis must be based on random fields in order to obtain meaningful results. Think of input parameters (e.g. random geometric perturbations) being modelled as random fields.

Further, many responses must be analysed in terms of a random field (compare for example extracting the maximum stress from FEM mesh as a single random parameter with the treatment of the whole stress field as a random field).

The main challenge of random fields is the stochastic description of the correlation between different points in space. Since FEM meshes may nowadays contain ten or hundred thousands of nodes and elements, one needs a sparse computer representation of the correlation. In *Statistics on Structures*, this is realized through a decomposition of the random field into deterministic *scatter shapes* (defining the spatial correlation) and a very small number of *amplitudes* (scalar random parameters) [3], see figure 8. Usually, only a very small number of amplitudes is required to represent most of the variation of the random field. Since the amplitudes are scalar random numbers, one can use *optiSLang* to analyse and simulate random fields through their amplitudes.

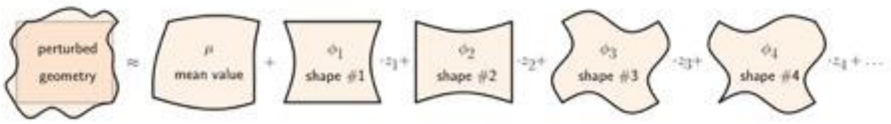

Fig. 8 Decomposition of a random field sample (here: a geometric perturbation) into deterministic scatter shapes (eigenvectors) and a small set of random amplitudes (variations in reduced space).

3.4 Sensitivity analysis

A spatially global sensitivity analysis can be carried out using the random field decomposition in *SoS* into scatter shapes and amplitudes and then analysing the amplitudes in *optiSLang*, see figure 9. Using this decomposition one can, e.g. separate buckling shapes and other spatially distributed effects on metal sheets.

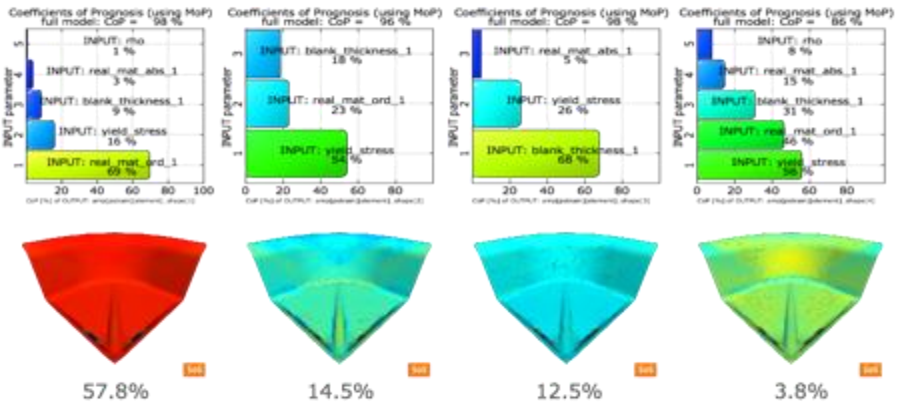

Fig. 9 Spatially global sensitivity analysis of plastic strain field. on top: CoP values for the first 4 amplitudes, below: the associated scatter shapes that associate the individual CoP values to the nodes of interest. Bottom: Amount of total variability in the model being explained by the respective amplitude.

One can also visualize the distribution of sensitivities of the individual input parameters directly on the FEM mesh. Using field meta models (e.g. F-MOP in *SoS*) one can visualize approximations of the CoP of the individual input parameters (and the whole meta model) for all locations on a FEM mesh, see figure 10.

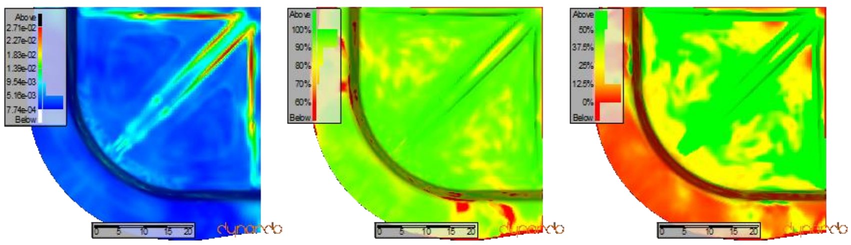

Fig. 10 F-CoP on a FEM mesh. Left: Standard deviation describing the amount of observed variation of the plastic strain field. Middle: Total F-CoP defining the amount of explainable variation (%). Right: F-CoP of the input parameter (vz-punch).

3.5 Generation of random designs

In robustness analysis one typically considers random tolerances of design parameters as inputs. Frequently, these are geometric parameters. Typically, one applies random variations to the parameters of a CAD model, for example support point coordinates of a B-Spline, radii and thicknesses of CSG models. Although this approach is very simple, it can obviously not represent realistic geometric random deviations. The space of possible deviations is still defined by the parameters of the CAD model.

Using random field models, however, one can easily generate quite realistic random deviations to any field quantity. Among these quantities, there are geometric deviations, but can also be deviations to material parameters, e.g. the spatial distribution of friction on a surface, pre-damage due to a previous manufacturing step, eigenstresses due to casting processes etc. There are, in principle, three types of random field models available in *SoS*:

- **Empirical random fields**: They are based on the analysis of many measurements (>40 samples) or on a DoE of simulated CAE solutions, see figure 11. They can represent anisotropic effects and are very accurate.
- **Synthetic random fields**: They can be used if no or very limited engineering knowledge is available (e.g. a single measurement). One can assume a numerical correlation model and constant values for mean and standard deviation.
- **Hybrid models**: If limited knowledge is avaiable, one can combine both model types. E.g. given 10 measurements one can estimate the spatial distribution of mean and standard deviation, but still needs to assume a numerical correlation model für the spatial relationships.

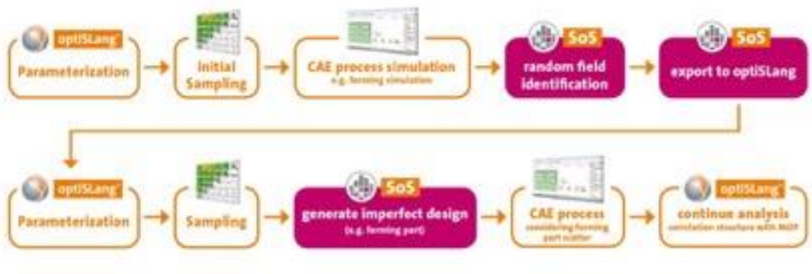

Fig. 11 Schematic flow for generating random designs. A first DoE is used to build an empirical random field. A second separate DoE uses the statistical random field model as input in a robustness study. These may be consecutive forming steps, e.g. 1st deep drawing, 2nd bending.

Figure 12 illustrates three realizations of a random field. This may be, for example, a coordinate deviation normal to the surface. Various random field models are implemented in *SoS*. Empirical random field models are very accurate statistical estimates that were from multiple measurements or from a DoE of CAE solutions. Synthetic random field models are typically based on engineering assumptions, if no or only little knowledge on the statistical properties of the considered field quantity is available.

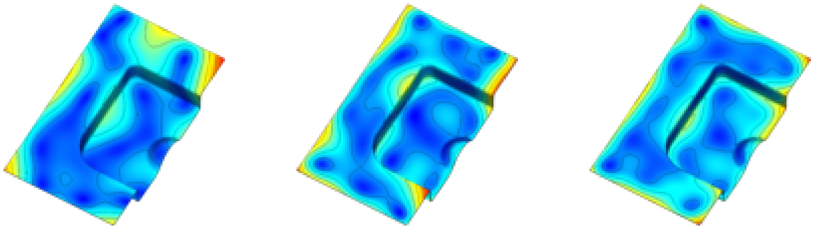

Fig. 12 Three realizations of a random geometric deviation.

4 Software

optiSLang (figure 13) is a software tool for process management, sensitivity analysis, meta modelling, optimization, robustness and reliability analysis. It is a general purpose suite for multidispliplinary multi-objective constrained nonlinear parameter-based robust-design optimization. Flows can be controlled through graphical programming. This leads to a very intuitive application even for very complex work flows.

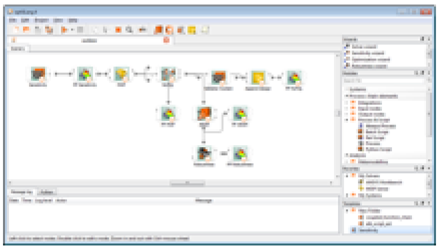

Fig.13 optiSLang GUI

Statistics on Structures (SoS) is a software that enhances optiSLang's capabilities to field data, i.e. data being distributed in one dimension (time or frequency domain), two dimensions (laser scans, photography) or three dimensions (FEM data, geometric measurements). It provides accurate and efficient algorithms and data structures for the analysis and generation of variations of large-scale data.

SoS (figure 14) was originally developed for the analysis of random scatter with specific effects arising in metal forming applications.

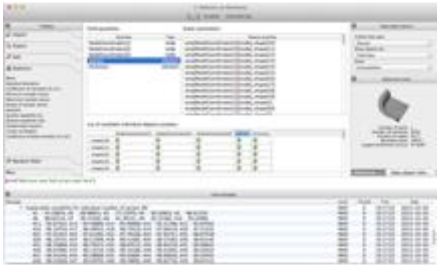

Fig.14 Statistics on Structures GUI

5 Summary

This article presented an overview on the state oft the art of numerical methods to evaluate robustness of metal forming and related processes. Typically they rely on statistical evaluation of structural robustness and nonlinear sensitivity analysis. Metal forming structures require special considerations that lead tot he application of random field models [5,6,7]:

- The visualization of statistical properties on the metal forming structure helps to provide confidence in the results.
- Statistical hot spot detection is an easy tool to improve the accuracy of the robustness analysis.
- Random field models allow the analysis and separation of spatially distributed effects like for example buckling.
- Random field models allow to generate random designs involving spatially distributed effects like geometric perturbations based on accurate anisotropic statistical models.
- Nonlinear field meta models allow to visualize the sensitivity factors of input parameters with respect to different locations on the FEM mesh. This helps to get a better model understanding.

- Field meta models enable engineers to predict the outcome of a CAE solution without extra solver run, for example in optimization.

The abilities of the presented numerical methods are not, however, limited to robustness analysis of metal forming processes. They can be used, e.g. to

- Analyse variations of signal data like history data in time or frequency domain.
- Generate random time histories or frequency domain variations.
- Analyse sensitivities of signal data.
- Calibrate model parameters o measured geometries or measured time histories.
- Identification of support parameters in spring back of forming structures.
- Establish statistical models of geometric perturbations based on measurements.
- Etc.

DYNARDO develops software for the specific needs arising in robustness evaluation and optimization of metal forming like *optiSLang* and *Statistics on Structures*.

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