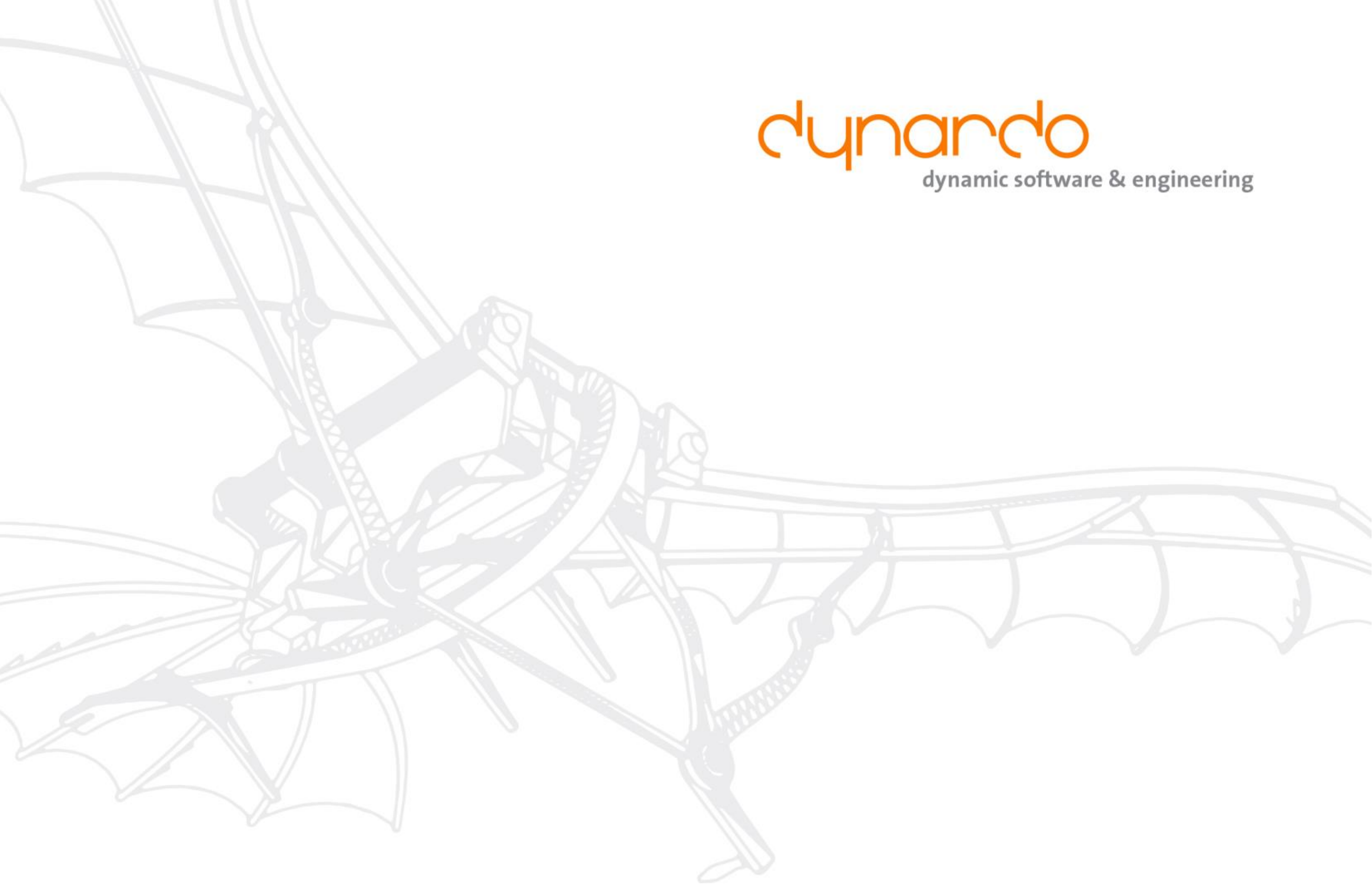

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Lectures

Robustness Evaluation in Sheet Metal Forming Using Statistics on Structures (SoS) and optiSLang

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Robustness Evaluation in Sheet Metal Forming Using Software Statistics on Structures (SoS) and optiSLang

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Summary

Some properties of engineering structures or structural parts are of random nature due to manufacturing tolerances, material scatter or random loads. For the assurance of product quality, avoidance of recalls and fulfillment of safety requirements, such randomness has to be taken into account by applying appropriate statistical modeling. Spatially distributed random properties are interpreted as random fields in this context.
DYNARDO develops the software Statistics on Structures (SoS) which is capable of decomposing random fields by Karhunen-Loeve expansion, visualizing the identified “scatter shapes”, analyzing random properties on FEM structures, locating “hot spots” of large variation or allowable limit exceedance, and investigating correlations.
SoS can be used as a “post processor” for statistics on FEM structures, i.e. for visualization of the descriptive statistics on the structure, visualization of correlations between random input and structural results as well as visualization of quality performance (QCS).
SoS can be coupled with optiSLang to investigate the nonlinear correlation structure between inputs and outputs of a previous simulation. It can read and write optiSLang binary files integrating optiSLang’s MOP solver easily into the analysis of correlation.
SoS can be further used together with optiSLang to simulate random fields within a numerical robustness evaluation, i.e. it generates spatially distributed fields (random geometry perturbations, shell thickness perturbations, pre-damage perturbations, loads etc.) to be used in a robustness study.

This presentation introduces the new software release SoS 3.0. SoS 3 comes with exciting new features, radically improved numerical efficiency and a new GUI. The abilities of the software are demonstrated through a robustness evaluation of an example application from sheet metal forming.

Keywords

Metal Forming, Robustness Evaluation, Random Fields, Statistics, SoS, optiSLang

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.

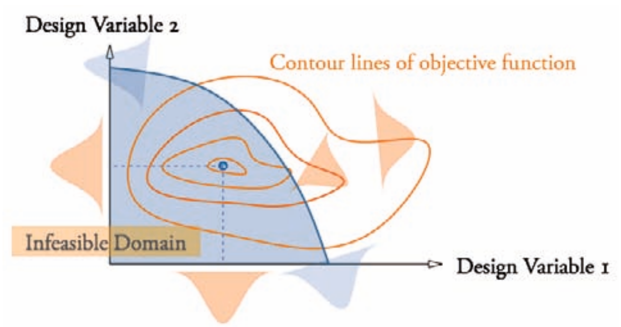

Fig. 1 Uncertainties in design optimization: Random variations in objective function and in constraints, source: [1]

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 [5], i.e. *optiSLang* (for random numbers) and *Statistics on Structures* ("*SoS*", for random fields).

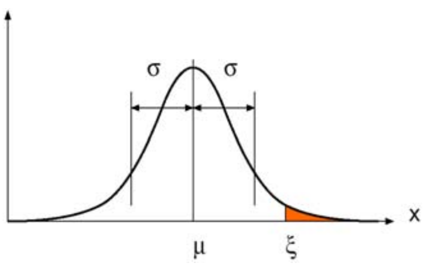

Fig. 2 Robustness with respect to a critical threshold (xi): Variance based analysis („sigma level" as distance from mean mu +/- k*sigma) vs. exceedance probability (highlighted area)

2. Random fields

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) [2], see figure 3. 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.

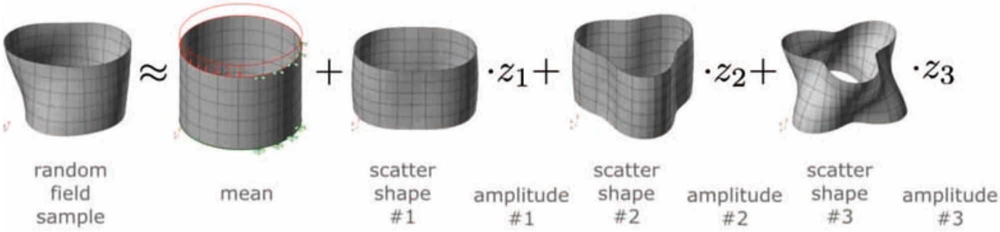

Fig. 3 Decomposition of a random field sample (here: a geometric perturbation) into deterministic shapes and a small set of random amplitudes. Source: [4]

3. 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) [3]. 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.

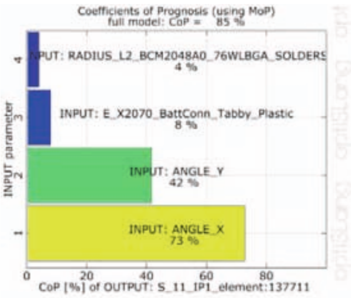

Fig. 4 Sensitivity analysis using 30 random input parameters: Identified 4 important input scatter parameters.

Within the context of random fields, one must decide between two different approaches:

- **Local sensitivity analysis**
  Herein, one first locates the finite element node or finite element of interest (e.g. with largest failure probability). The samples at this location are extracted in *SoS* as scalar random parameters and exported to *optiSLang*. Therein, the MOP can be analysed.
  An important issue of 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).

- **Global sensitivity analysis**
  Herein, the random field is decomposed into scatter shapes and amplitudes in *SoS*. The amplitudes will then be analysed by the MOP in *optiSLang*. The individual CoP values can then be related to the locations on the FEM mesh using the scatter shapes in *SoS*. See the example for further details.

4. Summary: Typical flow of a robustness study in CAE design process

Define properties of the input scattering variables: distribution types and distribution parameters, correlation between individual parameters and (in case) spatial correlation structure of random fields. Then create a sampling (design of experiments) and solve each design by your CAE solver. In a robustness study, two issues are of interest:

- Evaluate robustness measures and identify the locations of potential failure
- Perform a cause analysis, i.e. identify those input parameters whose scatter influences the robustness at most. The properties of these parameters can then be changed to improve the robustness.

5. Demonstration example: Simulation of a deep drawing manufacturing process

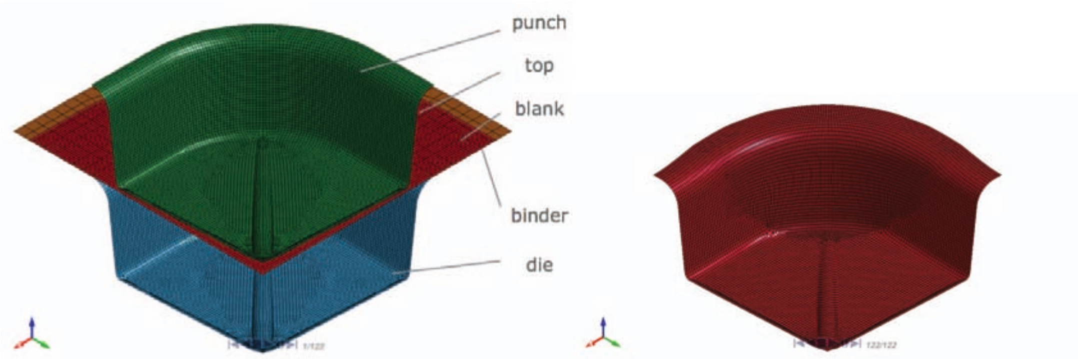

Fig. 5 Setup (left) and resulting sheet after rebound (right) of a deep drawing process simulation

The demonstration example presents a simulation of a deep drawing process, see figure 5. Therein, an aluminium sheet (“blank”) is deformed using vertical motion of the “punch”. The CAE solver is LS-DYNA. The FEM model of the blank consists of ~10.000 3 and 4 noded shell elements. Due to symmetries only a quarter of the structure is modelled. The material model is a bilinear plastic law. Element erosion was configured for plastic strains larger than 45%. Uncertain material parameters include mass density, elastic modulus, poisson ratio, yield stress, plastic failure and others. An uncertain geometric parameter is the shell thickness. Only scalar random parameters are varied as inputs. The design of experiments is carried out by *optiSLang*. The responses (plastic strain and shell thickness reduction) are analysed in *SoS* as random fields being distributed among the FEM mesh of the final shape of the blank.
The next sections demonstrate the usage of *SoS* in typical steps of a robustness analysis.

5.1 Hot spot detection in Statistics on Structures

Fig. 6 Schematic flow of using *SoS* and *optiSLang* in hot spot detection of a robustness analysis.

The actual robustness evaluation involves three steps:

- Identification of potential failure locations (“hot spots”), e.g. regions with large variation (in *SoS*)

- Evaluation of the robustness at these hot spots (in *SoS*)
- Export of samples at hot spots as random parameters to *optiSLang* for detailed robustness analysis and local sensitivity analysis.

The post processing of *SoS* plots statistical properties directly on the FEM mesh. It further can highlight regions that violate 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.

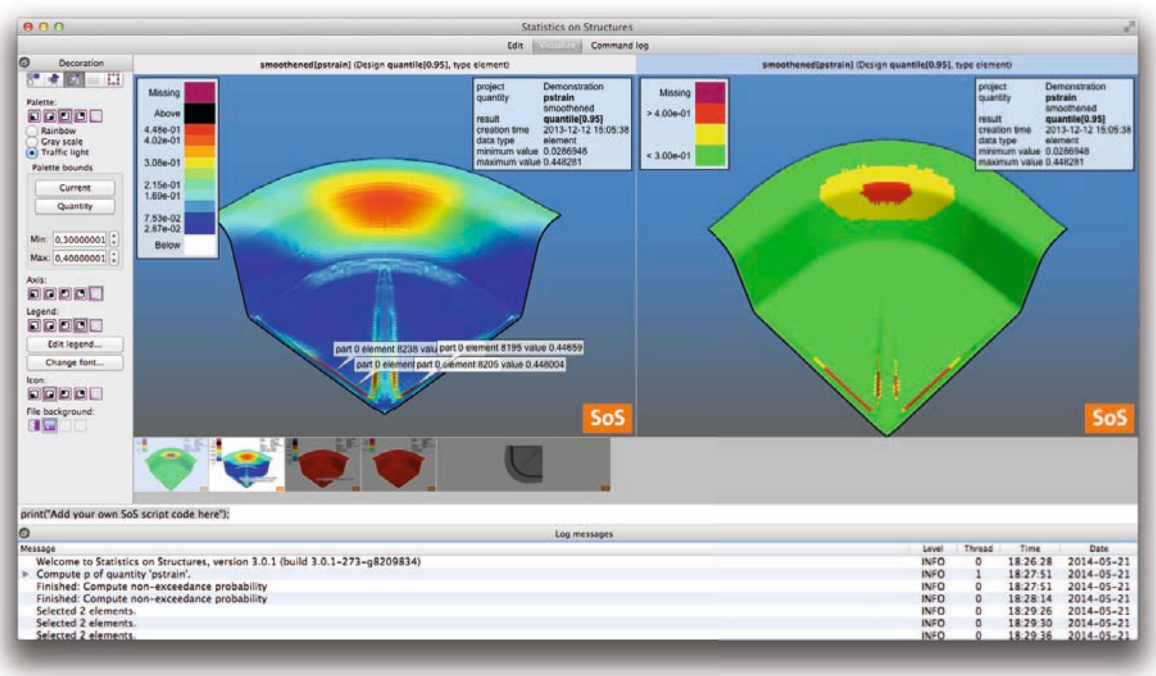

Fig. 7 Robustness evaluation based on quantile values: Left: Plot of all values of plastic strain that are exceeded with a probability of 5%, selected elements are the maxima. Right: Traffic light plot of the same quantile values (green: plastic strain <0.3, yellow: 0.3<pstrain<0.4, red: >0.4)

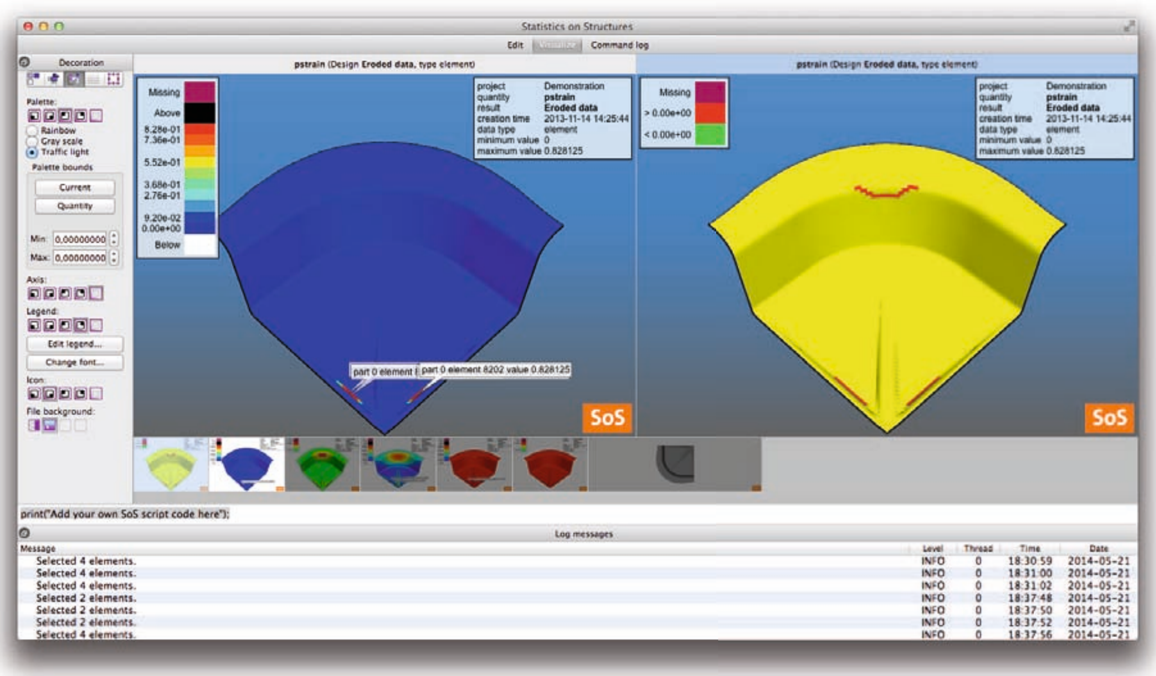

Fig. 8 Element erosion frequency (Crack statistics): Left: Plot of the probability of element erosion and selection of maxima. Right: Traffic light plot of the same quantity (yellow: never eroded, red: at least once eroded)

5.2 Cause analysis in optiSLang and SoS

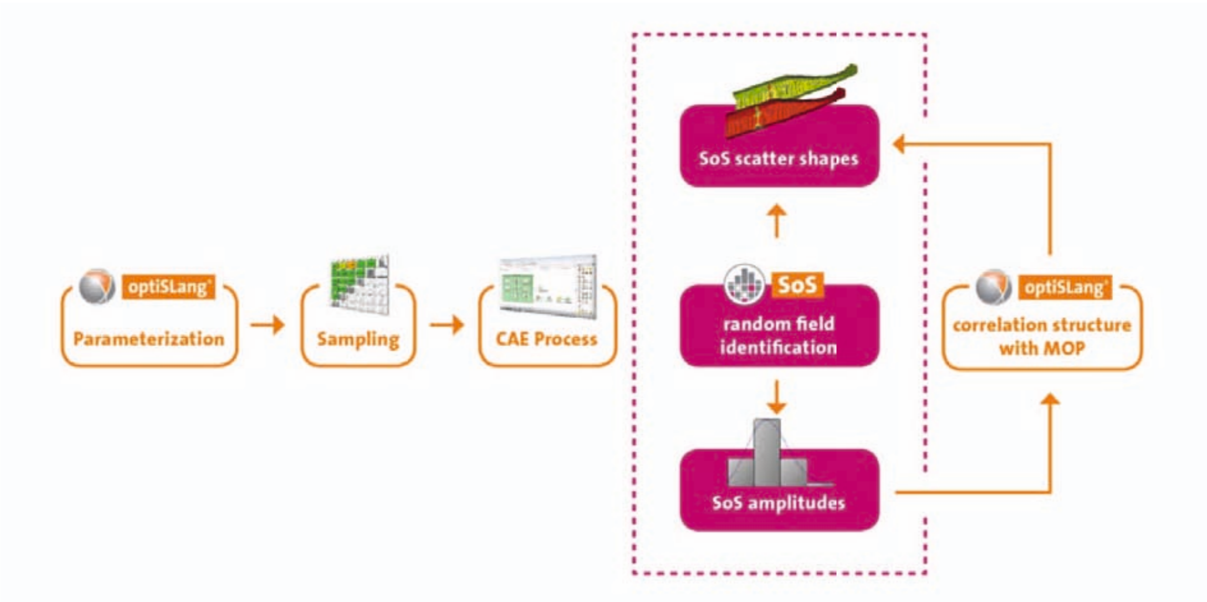

Fig. 9 Schematic flow of a global sensitivity analysis.

A 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*. The schematic flow is illustrated in figure 9, while some results are shown in figure 10.

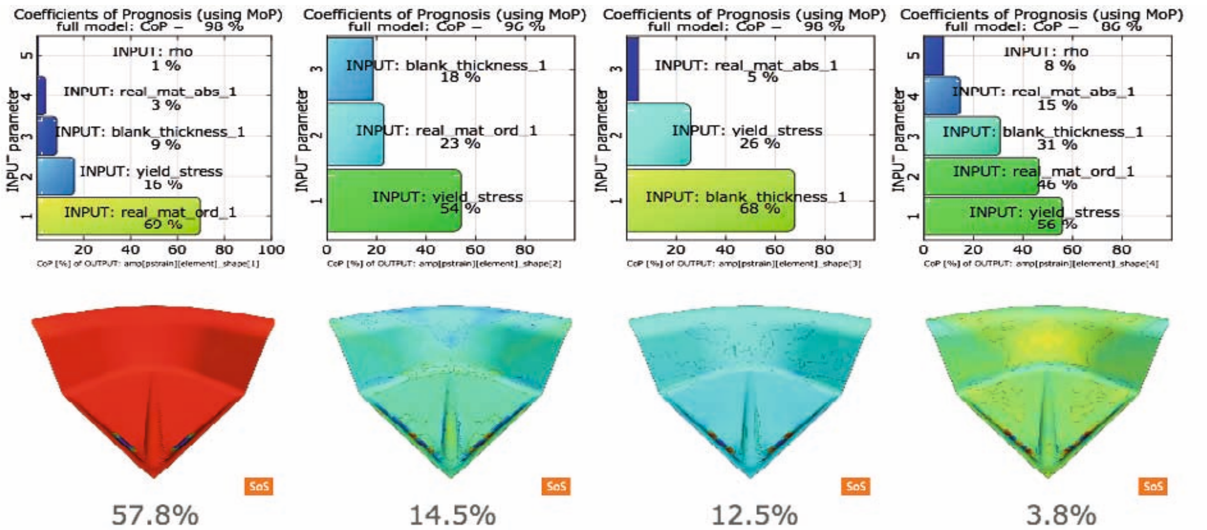

Fig. 10 Global sensitivity analysis of plastic strain field. on top: CoP values for the first 4 amplitudes, below: the associated scatter shapes that associate the individual CoP values to the nodes of interest. Bottom: Amount of total variability in the model being explained by the respective amplitude.

5.3 Simulation of random fields with Statistics on Structures and optiSLang

By combining *SoS* and *optiSLang* one can simulate random field samples. Consider a second forming step after the deep drawing of the currently considered example. The spatial distribution of the plastic strains and the thickness in the blank typically affects the performance and robustness of the subsequent production steps. There are several ways to take the randomness of these quantities into account:

- Create a simulation model that includes all production steps in one row. In this case one needs to simulate only the random input parameters of the whole model (e.g. of the first production step). The approach is, however, not always the best solution in practice. Since the total model becomes more complex, one may need much more samples being evaluated in the design of experiments. Further, statistically insignificant perturbations and solver noise are multiplied and may lead to non-interpretable data for the whole model. Aside from that, often different departments are responsible for the numerical modelling of the individual production steps such that a complete simulation flow is not possible.
- Analyse the statistics of the random fields that are responses of the first production steps. Then set up a second simulation model of the second production step. Generate random samples for all uncertain input parameters including the fields that were the responses from the first model. The flow of this analysis is sketched in figure 11.
  The basic idea is to perform a random field decomposition of the responses of the first step (e.g. plastic strains, sheet thickness, coordinate deviations, residual stresses). The field decomposition serves as a parameterization with respect to the random field amplitudes. The statistical properties of the amplitudes can be identified in *optiSLang* while the spatial correlation structure is stored by *SoS*. When generating new random samples, one uses *optiSLang* to generate random samples for the amplitudes. For each design, one can use *SoS* to create a random field sample from the sample of amplitudes and the previously stored random field decomposition. The random field sample is then exported to the CAE solver as input parameter.
  Using this strategy, one achieves a separation of both simulation steps, a reduction of required simulation time and a reduction of noise in the responses of the last simulation step.

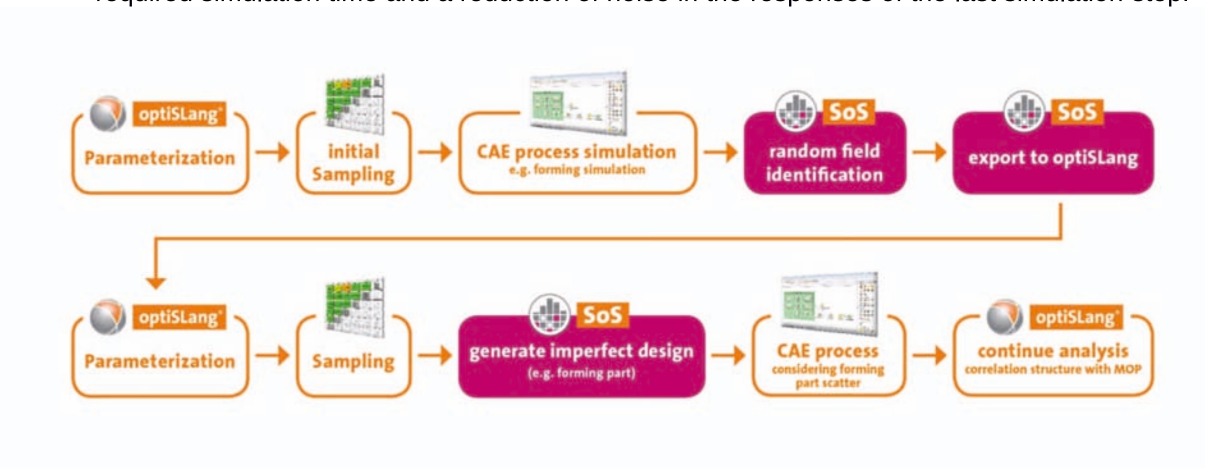

Fig. 11 Schematic flow for simulation of random fields in two consecutive simulation models.

6. Statistics on Structures version 3.0

Statistics on Structures 3.0 is a new software product that was rewritten from scratch providing an extensible software platform and implementing improved algorithms compared with previous software versions.
Most improvements are related to the algorithm for performing the random field decomposition. The old algorithms needed to allocate huge temporary matrices which eventually limited the size of finite element meshes to 16000 nodes and elements. In order to treat larger FEM meshes, a mesh coarsening was employed internally that reduced the size and resolution of the original FEM mesh. Within *SoS* 3.0 algorithms were employed that avoid the allocation of huge matrices. Hence no mesh coarsening is required any longer. As a result, the time of analysis was reduced from several hours to a few seconds. Further, the graphical user interface was reinvented allowing flexible work flows, see figure 12. Advanced features of *SoS* can be accessed through an embedded script language.
The following statistical quantities can be evaluated:

- Statistics
  - Descriptive statistics (mean, stddev, cov, linear correlation, etc.)
  - Variable range (min, max, range)
  - Robustness measures (quantiles, QCS, exceedance probability, etc.)
- Random fields
  - Decomposition (amplitudes, scatter shapes) from sampling data

- o Noise elimination
- o Generate random field samples from amplitudes
- Eroded data (frequency of erosion)
- Detection of geometric deviations between non-matching meshes

The GUI allows a flexible work flow. SoS stores all imported designs and results in a single database file. There are no pre-defined work flows. The sequence of actions is defined by the user. For example, one can import and analyse a design of experiments. If one finds out that one has to extend the DoE by further 100 samples, one can add them and update the analysis. One can identify and deactivate statistical outliers. Unused designs and parameters can be erased form the database at any time.

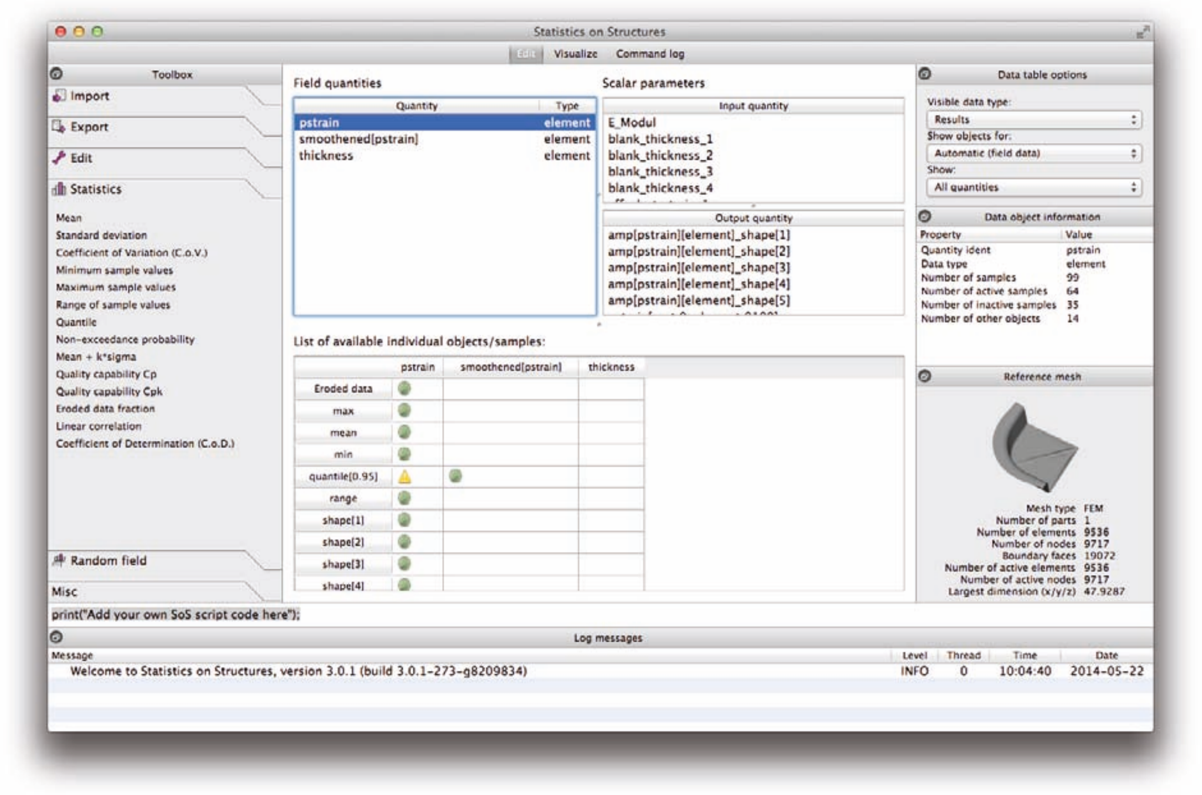

Fig.12 Graphical user interface of *Statistics on Structures* 3.0

Version 3.0 supports 3- and 4-noded shell elements only. FEM meshes (and data) can be imported from LS-DYNA, Nastran and STL. Random field samples for various quantities can be exported to LS-DYNA and Nastran. Scalar parameters (used for detailed analysis at hot spots or for simulation of amplitudes) can be exchanged with optiSLang (binary format) or other applications like e.g. MS Excel (by CSV format).

Current software development for the upcoming release focuses on new finite element types (linear and quadratic shell and volume elements), random field models (allows the simulation of random field samples based on a few a priori assumptions only) and automatic data import from incompatible and deformed meshes (if mesh refinement/coarsening is employed in the DoE).

More information on *SoS* version 3.0 can be found in [6].

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