

Analysis of Global Sensitivities for One-Step and Multi-step Deep-Drawing Simulations

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Agenda

- Theoretical concept
- Simulation models
- Design variables
- Objective functions
- Sobol Indices convergence
- Comparison of simulation schemes
- Conclusion

Theoretical concept

- Sobol Indices [1]: $S_{i_1 \dots i_s} = \frac{D_{i_1 \dots i_s}}{D}$
- Variances: $D_{i_1 \dots i_s} = \int f_{i_1 \dots i_s}^2 dx_{i_1} \dots dx_{i_s}$
- Objective function in conjunction with simulation model:
 $u = f(x)$
- Number of simulations for a sensitivity analysis:
 $n_{simulations} = N * (2D + 2)$

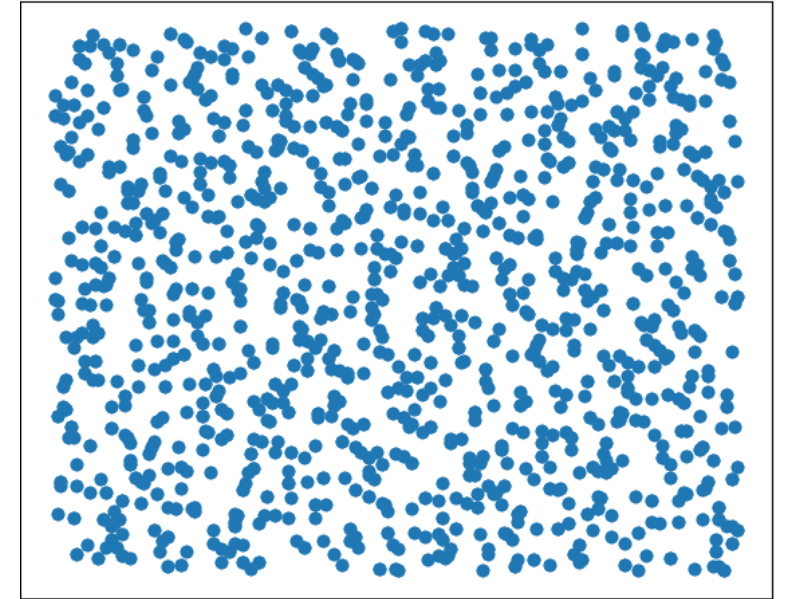


Fig. 1: The Saltelli-extended Sobol Sequence [2] of two arbitrary design variables is uniform.

[1] I.M Sobol'. "Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates". In: Mathematics and Computers in Simulation 55.1-3 (2001), pp. 271-280. doi: 10.1016/S0378-4754(00)00270-6.

[2] Andrea Saltelli et al. "Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index". In: Computer Physics Communications 181.2 (2010), pp. 259-270. doi: 10.1016/j.cpc.2009.09.018.

Simulation models

The models share:

- geometry parameters of cross die example including analytical drawbead node sets
- material model with Hockett-Sherby hardening
- manufacturing boundary conditions

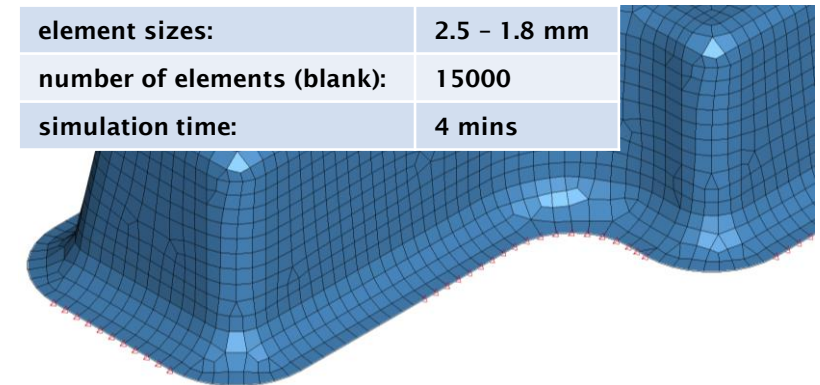


Fig. 2: Setup for the low-fidelity One-Step simulation with drawbead periphery nodes (red)

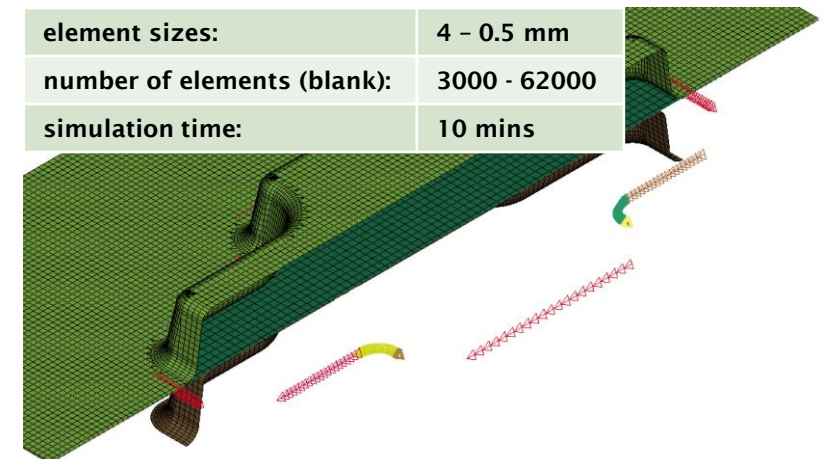


Fig. 3: Setup for the high-fidelity multi-step deep-drawing simulation

Design variables

- assignment of an input variance per design variable
- definition of two sets of design variables

Tab. 1: The ranges for each design variable are assigned for typical drawing setups. One design variable set contains all nine design variables. The second set contains four design variables.

geometry		material		boundaries	
sheet thickness	0.8 - 1.8 mm	Lankford coefficient	0.8 - 2.5	coefficient of friction	0.08 - 0.12
slant depth	12.0 - 35.0 mm	yield strength	140.0 - 180.0 MPa	blankholder force	130 - 190 kN
die radius	6.0 - 9.0 mm	Considère strain	0.15 - 0.25	drawbead cover ratio	0.1 - 1.0

Objective functions

- plastic strain: $f_{ps} = \frac{\epsilon_{pl,max_n}}{n}$
- area-normalized weighted distances [3]:
 $f_{wd} = \text{dist_flc} + w * \text{dist_wlc}$

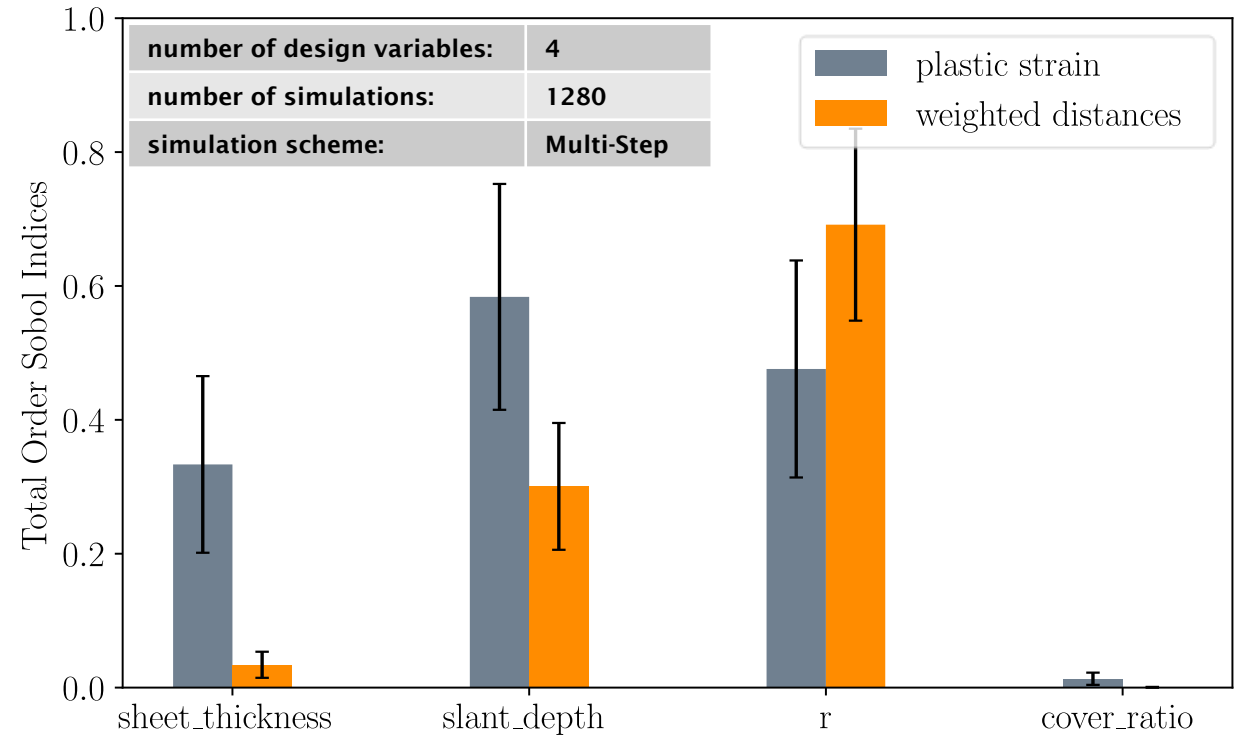


Fig. 4: The plastic strain objective shows wider confidence intervals compared to the weighted distances approach.

[3] Guangyong Sun et al. "Multi-fidelity optimization for sheet metal forming process". In: Structural and Multidisciplinary Optimization 44.1 (2011), pp. 111-124. doi: 10.1007/s00158-010-0596-5.

Sobol Indices convergence

- computationally intensive for small confidence intervals
- for deep-drawing simulations, at least 1000 simulations should be conducted

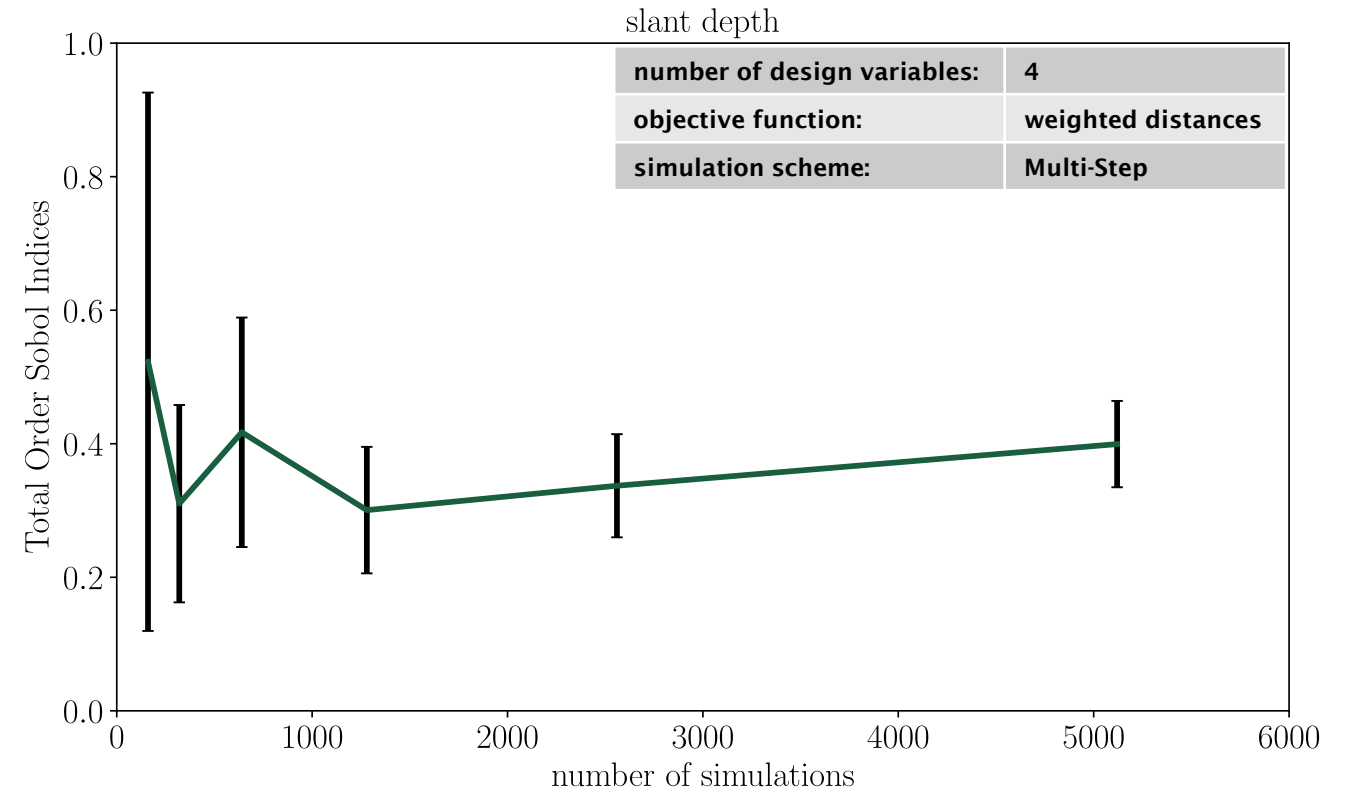


Fig. 5: The confidence interval (confidence level of 95%) decreases with number of simulations. It converges to the limitations by the objective function.

Comparison of simulation schemes

- no given agreement between the Sobol Indices of the simulation schemes
- no definitive pattern in the sensitivity of higher order sensitivities between both simulation schemes

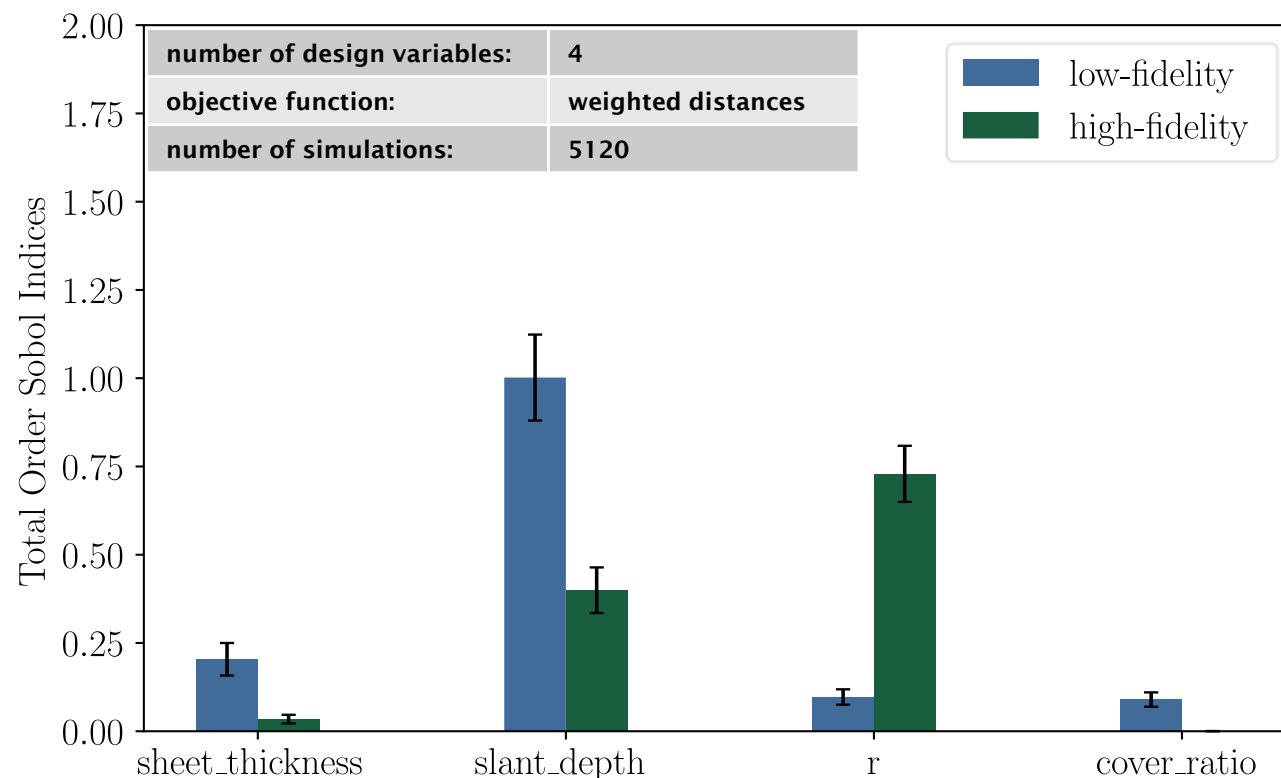


Fig. 6: The compared Sobol Indices show different values per design variable for the two simulation schemes.

Conclusion

- remaining difference in global sensitivities between the simulation schemes
- choosing a representative objective function and conducting >1000 (>500 neglecting Second Order Indices) simulations is key for „accurate“ results
- limiting the amount of design variables yields earlier convergence and therefore better interpretability
- optimizing your simulation setup only based on One-Step simulations will lead to „non-optimal“ results

Thank you for your attention!

