Robustness analysis with LS-OPT® and LS-DYNA® for sheet metal forming simulations

Mathias.merten@dynamore.de

Abstract. This contribution shows the application of the optimization and probabilistic analysis program LS-OPT on the drawing step of a generic fender geometry simulated with LS-DYNA to judge on the robustness and reliability of the model. Input variables of a typical sheet forming simulation that are subject to uncertainties are alternated automatically within the framework of LS-OPT based on an inherent Monte Carlo approach. Using metamodel approximations as well as classifiers to evaluate statistical results is discussed. The influence of the variation of the input variables on typical sheet forming results is investigated, e.g. thickness reduction and the Formability Index. Alternated parameters were material properties like yield and tensile strength.

1. Introduction

Quantities of production processes, e.g. material properties, are often subject to scatter. This can result in an unstable production with an unacceptable high number of rejected parts. Hence those uncertainties should be considered in the design process simulation as well. Robustness analysis provides possibilities to investigate the influence of the variation of parameters on the scatter of responses.

Numerical process simulation is often used in an early stage of the product development process, where many production relevant features are not yet fixed. The knowledge of potential design flaws with respect to process stability in this stage can be helpful to track the issues during the following steps and may reduce the risk of an unstable production or help to resolve the problems in the early stage. Specialized pre- and post-processors are commercially available to set up forming simulations. The inputs generated by a preprocessor can serve as a starting point for further investigations on the process reliability.

LS-OPT, a design optimization and probabilistic analysis toolbox, is an integral part of the LS-DYNA package. Since this FE solver is mostly used for highly nonlinear applications, most algorithms in LS-OPT are based on metamodel approximations. Metamodels are approximations to the design responses calculated based on a certain number of simulations, called samples. A metamodel is created for each response, which can be any scalar result extracted from a simulation, e.g. the maximum value of the thickness reduction within the blank. Predictions evaluated on the metamodels are used to estimate statistical quantities like mean values and standard deviations, as well as probabilities of failure. As an alternative approach to estimate probabilities of failure, classifiers can be used with the optimization program, which predict the boundary between feasible and infeasible areas, and not the
response values. Based on classifiers, adaptive sampling can be used to add new samples in the interesting areas of the design space to get more accurate approximations.

Based on the drawing simulation of a generic fender geometry the metamodel- and the classifier-based approach are compared and one potential use case for the industrial and scientific forming simulation is discussed. For a more detailed overview on the used software the reader is referenced to the literature [9].

2. Numerical case study

2.1. Base simulation and results

The sheet forming tutorial example of DYNAFORM is taken to investigate the described methods available within the optimization tool. The typical fender geometry is originally intended to be made of DDSQ. The material is exchanged with DC04 as there is statistical data available in the literature, e.g. Quetting [1]. Figure 1a shows the used flow curve in comparison to the range of flow curves used in the robustness analysis. Changing the material leads to the necessary adjustment of the force factors for the analytical drawbeads to receive a good part.

Numerical parameters of the simulation were chosen with a predefined set for “quick formability”, ensuring fast results for an early stage of the product process. An under-integrated shell was used with three integration points over the thickness and blank to tool contacts were one-way-contacts together with adaptive mesh refinement. Further, the calculation of the “Formability Index” (FI) was activated. This option accesses the “NLP” (non-linear path) feature of several metallic material models available in the used FE-code. With this feature, the forming limit curve (FLC) is internally transferred into a plastic strain at failure, $\varepsilon_{ps}^{fail}$, versus strain ratio, $\varepsilon / \varepsilon_{II}$, curve. In each timestep the increment of the plastic strain of each element is divided by the plastic strain at failure for the strain ratio at the current timestep. On a history variable, namely the FI, the fractions are summed together over the course of the
simulation on an element level following equation (1). Within this approach, the FI indicates how much of the forming capability of the material is used. A value of “1.0” indicates the start of necking. In contrast, a value less than 1.0 indicates a safe process. Further theoretical background on the FI can be found in the literature [2,3,4,5]. The FLC used for postprocessing is taken from the material database of the used preprocessor. The settings for the safety margin are left default resulting in a constant shift of approx. 0.07 points of major strain.

\[ FI = \sum_{i=1}^{n} \frac{\Delta \varepsilon_{ps}^i}{\varepsilon_{ps}^{fail}} \left( \frac{\Delta \varepsilon_{i}}{\Delta \varepsilon_{II}} \right) \]  

(1)

Figure 1b) shows the percentage thickness reduction with a maximum value of 31%. The FLC-based formability plot in Figure 1c) shows a feasible part with a wrinkle tendency in the addendum area. The minimal integration point value of the FI is shown in Figure 1d) with a maximum of 0.746 also indicating a crack free part. All results are shown on unaveraged element values.

The simulation has been setup with a commercial preprocessor and based on this, the input deck has been modified to take the statistical data from [1] into account and make it accessible for the optimization tool. The modifications were limited to the used hardening rule and the concomitant parameter calculation.

2.2. Statistical parameter variation for yield and tensile strength
Statistical and material data for DC04 is taken from [1]. Based on 825 tensile tests from the incoming quality control, Quetting suggested a Gosh-type hardening following equation (2) within a 3-parameter Barlat model (*MAT_036) with fixed parameter \( \varepsilon_0 = 0.0325023 \) and \( n = 0.137766 \), respectively. Based on [1] a constant \( A_g \) of 0.24 is used. With \( \varepsilon_0, n \) and \( A_g \), Gosh’s parameters \( k \) and \( p \) can be calculated based on equations (3) and (4). These equations were used in the FE solver input as parametrized expressions to calculate \( k \) and \( p \) based on yield and tensile strength, which were again defined parametrized enabling the optimization tool to access them easily. Their statistical properties are listed in table 1 and used directly as input for the robustness analysis. Figure 1a shows the range of calculated flow curves depending on the variation of yield and tensile strength.

\[ \sigma_y(\varepsilon_p) = k(\varepsilon_0 + \varepsilon_p)^n - p \]  

(2)

\[ k = \frac{R_m(A_g + 1) - R_{p02}}{[\varepsilon_0 + \ln(A_g + 1)]^n - \varepsilon_0^n} \]  

(3)

\[ p = k \varepsilon_0^n - R_{p02} \]  

(4)

| Table 1. Statistical data for DC04 from [1]. |
|-------------------------------------------|
| \( R_{p02} \) [MPa] | \( R_m \) [MPa] |
|-----------------|-----------------|
| Minimum         | 130             |
| Maximum         | 225             |
| Mean Value      | 166             |
| Standard Deviation | 13.5        |
| Distribution    | Normal          |
|                 | Normal          |
2.3. Robustness and Reliability Analysis

A sequential metamodel-based Monte Carlo Analysis with five simulations per iteration and a maximal number of ten iterations is performed. Hence 50 simulations were executed in total. The process is visualized in Figure 2a). Radial Basis Functions are used to approximate the responses including simulation results from previous iterations. Thus, the accuracy of the metamodel is improved in each iteration. Statistical values such as mean and standard deviation are calculated using metamodel approximations to judge on the robustness of the model, therefore the quality of the metamodel affects the quality of those results. Classifiers [7] are used to calculate the probability of failure as well as for an adaptive sampling to get more accurate approximations of the classifier boundary [8] and hence more accurate estimations of the probability of failure for the constraints. The classifier boundary prediction also includes simulation results of previous iterations, which improves the accuracy. To judge on the convergence of the sequential analysis, the evolution of e.g. the probability of failure can be considered, Figure 2b). Since the values of the probability of failure vary only slightly from iteration 7, the user could have decided to stop the process earlier to save computational effort. Constraints are defined on the FI and the thickness reduction as FI < 1 and thickness reduction < 35.

![Figure 2](image-url)

**Figure 2.** a) Workflow used for robustness analysis within the optimisation tool; b) Convergence of the probability of failure. A sequential metamodel-based Monte Carlo Analysis is performed.

3. Results

3.1. Metamodel- and classifier-based results

The results of the evaluation of 10000 points on the metamodels are used to calculate statistical quantities to judge on the robustness of the model. Figure 3 displays the histogram for both FI and thickness reduction. Additionally, the mean values and standard deviations are shown, and the background is colored by feasibility. Since histograms are approximations to the response distributions, they can be used to estimate the scatter of the responses caused by the scatter of the variables. To get information which variables contribute most to the scatter of the responses, the linear correlation, stochastic contribution, and in our simple case with only two variables also the surface plot can be considered, Figure 4.
Figure 3. Histogram of FI (a) and thickness reduction (b). Mean value as well as standard deviations are displayed, the background is colored by feasibility.

Figure 4. Results for thickness reduction: a) Metamodel and simulation points with residuals; b) Linear correlation; c) Stochastic contribution of the variables to the variance.

To evaluate the probability of violating a constraint, both metamodel and classifier approximations may be used, Table 2. The values are quite similar, but the metamodel approximation misclassifies some of the points, Figure 5.
Figure 5. Metamodel- (a) and classifier-based (b) failure boundary. The points misclassified by the metamodel-based failure boundary are highlighted by a circle.

Table 2. Probability of Failure

|               | FI   | thickness reduction |
|---------------|------|---------------------|
| Metamodel     | 1.76%| 16.4%               |
| Classifier    | 1.53%| 16.5%               |

3.2. Visualisation of statistical data
In addition to the statistical results calculated for scalar values respective information can be generated for the whole model and used as fringe component on the finite element mesh. Figure 6 shows the maximum, the standard deviation and the mean value of the FI and the thickness reduction, based on metamodel predictions. This visualization allows the identification of potential design flaws caused by variant parameters as it indicates where the variance of the results will be the largest.

In our example the left side of the wheel arch area shows a standard deviation of the thickness reduction of approximately 2.5% and of approximately 0.1 for the FI. It can be concluded that the work hardening in this area will also be subject to scatter. The part is still feasible based on the simulation models, but larger hardening may lead to a deviation in the spring back behavior.

The evaluation of the maximum values of thinning reduction and FI allows the identification of the critical areas and may lead to decisions in the design process. In our case, the top side of the fender, close to the a-pillar shows a local maximum of the FI. Together with the resulting probability of failure from Table 2 cracks can be expected in the real production in both areas.

3.3. Discussion of the results
The probabilities of failure estimated in the metamodel- and the classifier-based approach show similar values for both responses chosen as criteria to judge on the formability of the part, since the adaptive sampling based on the classifiers also improves the quality of the metamodel in the interesting areas.

More advantages of classifiers, e.g. for discontinuous response, are discussed in [7]. The boundaries in
Figure 5 are also quite similar, but the metamodel misclassifies some points close to the boundary. The overall tendency of both methods leads to similar statements and may lead to design changes, as roughly 1 of 6 parts does not satisfy all defined quality criteria in this example.

The visualization shows the critical regions of the part where changes may be necessary to improve the reliability of the model. With the combined views of statistical data in Figure 6 one may conclude, that the top corner close to the A-pillar is the most critical area of the part, but with respect to variation the left area of the wheel-arch is more critical, as this area shows a higher standard deviation. This could also indicate a higher scatter in the spring back results.

It should be pointed out, that the data for scatter of material for this scenario was chosen due to its free accessibility. There is no limitation to this approach, so even further material scatter, e.g. for the n- and r-values or the necking strain could be considered, if data describing those uncertainties is available. It may be interesting to see if the consideration of other statistical data for DC04 will result in similar conclusions than the results based on Figure 6.

![Figure 6.](image)

**Figure 6.** Top row shows FI, bottom row thickness reduction. From left to right maximum, standard deviation and mean value

### 4. Conclusions and outlook

An overview on different methods available to estimate the robustness and reliability based on numerical simulation has been given. The generic example of a fender geometry with scatter of material data from the literature showed a potential use case for the detection of the critical areas of the part for the forming process. As the framework of the applied optimization tool is very general, it is up to the user to define the parameters subject to scatter and also the responses and constraints. Further scalar responses as well as output curves may be defined, and further parameters may be used as variables. In this example the scatter of material data was considered, and the process parameters were kept constant, which are also subject to uncertainties.

In industrial sheet metal forming the gathering of reliable data for the statistical variance of the process parameter is non-trivial and subject of research, e.g. for adaptive process or tool design. To train e.g. AI-based tool controls, simulations created during robustness analysis may be useful as many
samples can be generated using the available algorithms and submitted automatically, and additional predicted values could be generated using metamodel evaluations.

As the estimation of the metamodel is based on numerical simulations, the simulations model itself needs to be able to predict the effects. As nearly every simulation parameter in a forming simulation can be accessed via a parametrized framework, the influence of many parameters may be investigated if desired by the user. It is up to the user to define a reasonable statistical distribution of the parameter, e.g. based on real world measurement like tensile tests for the material data shown in our example. Further investigations may include the spring back of the part, as all compensation procedures known by the authors do not include the scatter of data and their influence on the spring back.

References

[1] Quetting F 2018 Entwicklung eines innovativen Planungssystems zur Voraussage und Kontrolle der Prozessrobustheit bei der Fertigung von Karosseriebauteile (Doctoral Thesis) Zürich
[2] Zhang L and Zhu X 2012 Advance in sheet metal forming - failure criteria, friction, scrap trimming and adaptive meshing Proc. of 12th Int. LS-DYNA Users Conf.
[3] Tharrett M and Stoughton T 2003 Stretch-bend forming limits of 1008 AK steel SAE Technical Paper 2003-01-1157
[4] Stoughton T B and Zhu X 2003 Review of theoretical models of the strain-based FLD and their relevance to the stress-based FLD Int. J. of Plasticity 20 1463-1486
[5] Zeng D, Zhu X, Chappuis L B and Xia C Z 2008 A path independent forming limited criterion for sheet metal forming simulations SAE Proc.
[6] Zhu X 2010 A more accurate approach to evaluate material formability Proc. of 9th LS-DYNA Forum
[7] Basudhar A, Witowski K and Gandikota I 2018 Classification-based optimization and probabilistic analysis using LS-OPT Proc. of 15th Int. LS-DYNA Users Conf.
[8] Basudhar A, Witowski K and Gandikota I 2020 “Sequential optimization & probabilistic analysis using adaptively refined constraints in LS-OPT Proc. of 16th Int. LS-DYNA Users Conf.
[9] Stander N, Basudhar A, Roux W, Liebold K, Eggelston T, Goel T and Craig K 2020 LS-OPT Users Manual Version 7.0