

Lectures

Parameter identification of damage parameters of LS-DYNA GURSON material model from a tensile test

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“Parameter identification of damage parameters of LS-DYNA GURSON material model from a tensile test”

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Abstract

This paper will demonstrate a procedure how to identify mesh dependent damage parameters of LS-DYNA Gurson material model using FEM models, test data and optiSLang. A tensile test using different meshes was simulated in LS-DYNA where a stress-strain curve was created. The first step was to perform a sensitivity analysis in order to investigate important material parameters for the optimization and to determine a suitable parameter space for the identification. The second step was to identify the mesh dependent material parameters of one experiment, representing a mean value of the failure strain. The third step was to identify material parameters for three different experiments representing the min, mean and max plastic failure strain within one optiSLang identification process. The motivation of identifying sets of material values for upper and lower bounds of the failure strains was to identify a range of material parameters which could be used for robustness evaluation in crashworthiness applications [1]. Therefore the fourth step was to perform a variation analysis between upper and lower bound to show that a linear interpolation between identified min/mean and max material parameters will result in expected variation of failure strain.

Because the robustness evaluation of crashworthiness of course failure strain and yield strength have to be varied simultaneously there was the question: “Does parallel variation of yield strength and failure strain affect the resulting failure strain range?” Therefore a variation of the yield stress was introduced in addition to the variation of the plastic strain. It could later be concluded, that resulting failure strain range was largely unaffected by the yield stress variation. Therefore the identification of Gurson damage parameters could be performed without taking into account the yield strength scatter.

Keywords: Identification, Optimization, Sensitivity, Robustness

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1 Introduction

Model validation or parameter identification becomes nowadays more and more common and applicable in the engineering field where it is essential to identify unknown system parameters, in order to improve the product. The general idea behind parameter identification is identifying a set of parameters to fit the simulation responses to the experimental data. For this purpose using sensitivity study and optimization is very suitable and required [2].

The damage parameters of the LS-DYNA Gurson material model are mesh dependent and three different tensile tests with three different element lengths (2, 4 and 10 mm) were simulated using the finite element code LS-DYNA. Therefore the final parameter identification was to update Gurson parameters fitting 9 experiments in parallel.

A tensile test was simulated in LS-DYNA where a stress-strain curve was created. From the stress-strain curve the failure strain could be analytically calculated and determined. LS-PREPOST was used to extract reaction forces and displacements from the simulation results. The stress-strain curve was then calculated and created using Python. Also the failure strain was analytically calculated with the help of Python. Finally a stress-strain curve plot was created. The whole process was fully automated in optiSLang. For simplicity of the parameter identification only one result value was used, the failure strain, but it is also possible to enlarge the updating task in that way to fit the shape of the stress-strain curve.

The main task was to identify mesh dependent damage parameters in the Gurson material model [3] for min, mean and max failure strain with parameter identification procedure and then perform a variation analysis to verify resulting scatter range of the failure strain. The following steps below were performed:

- A sensitivity analysis with 100 Latin hypercube samplings to adjust parameter range and objective function and to identify the most sensitive parameters.
- An optimization in order to identify damage parameters using best design from sensitivity analysis as starting point.
- A variation analysis to verify that a linear interpolation between material values from minimal to maximal failure strain will result in a close to linear variation of failure strain.

The benefits of the sensitivity, optimization and variation analysis will be further exemplarily described and shown.

2 Simulation of tensile test

A tensile test was simulated using the finite element software, LS-DYNA. In this case three tensile specimens with element length 2, 4 and 10 mm were used. The length of the specimen, L_0 was 80 mm which was measured between two nodes (see Figure 1).

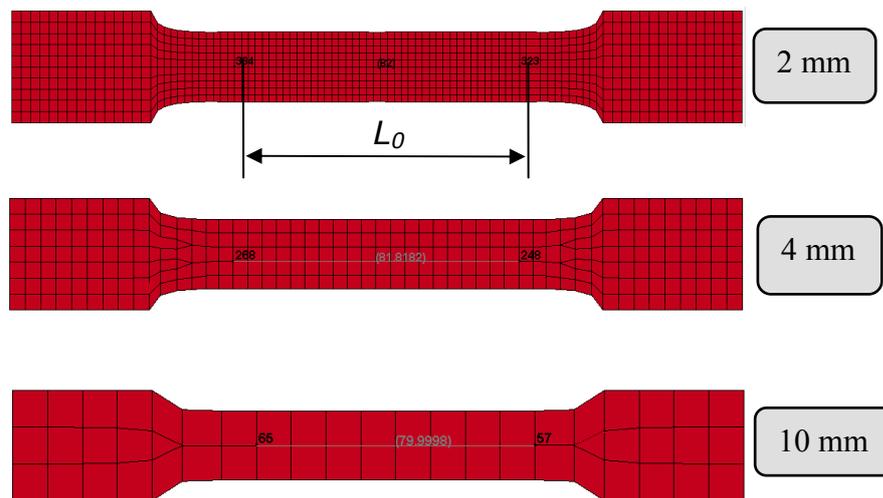


Figure 1: Three specimens with different element length.

A standard procedure of a tensile test is carried out by pulling both ends of the tensile specimen until fracture occurs. From every tensile test simulation, elongations and reaction forces at a mid-section were written out. For this purpose LS-PREPOST was used and curves for the reaction forces and the X-displacements were created (see Figure 2).

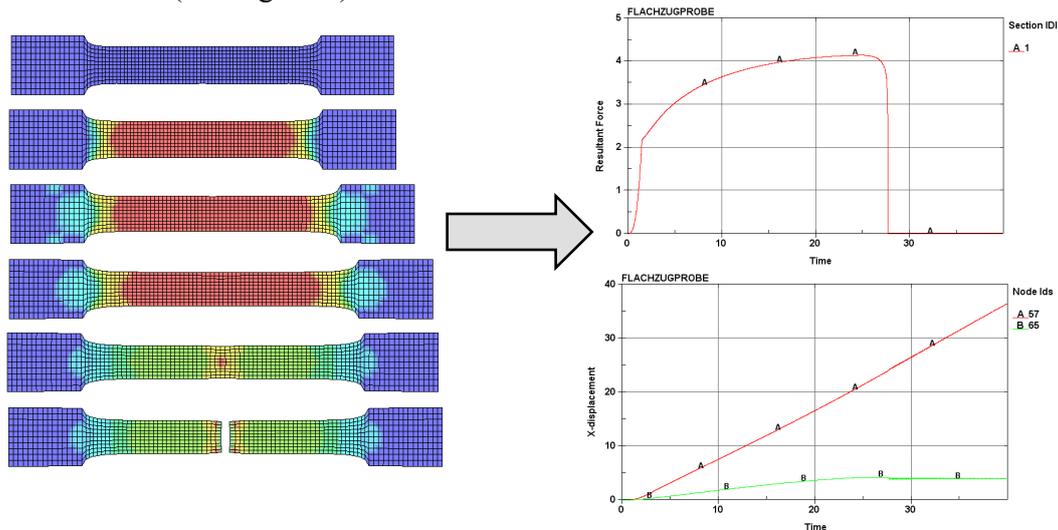


Figure 2: Tensile test; Reaction forces from mid-section (upper right) and displacements in x-direction (lower right).

Using these results, stresses and strains were analytically calculated. The equations for the analytical calculations are showed below:

$$\sigma = \frac{F}{A_0} = \frac{res_forc.out}{height \cdot thickness} \quad (1)$$

where F is the reaction force and A_0 is the initial area

$$\varepsilon = \frac{u}{L_0} = \frac{dispx_nXX1.out - dispx_nXX2.out}{L_0} \quad (2)$$

where u is the X-displacement and L_0 is the initial length. From these analytical calculations, a stress-strain curve was obtained and the plot is showed below (see Figure 3).

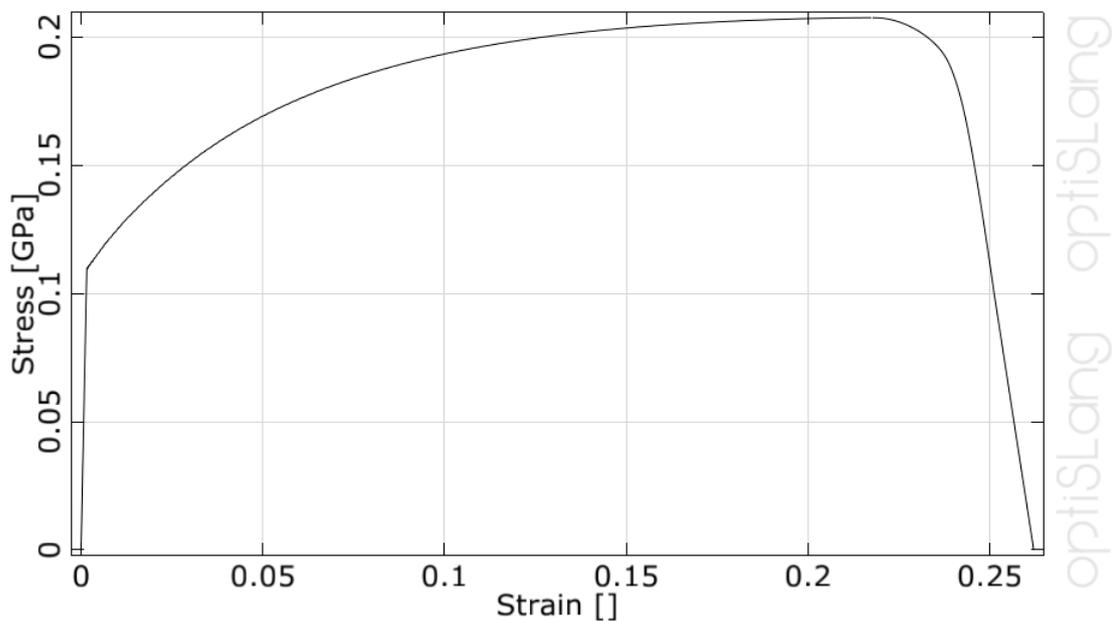


Figure 3: Stress-strain curve

From existing stress-strain data the failure strain could be determined. Using a linear equation and two approximated stress levels the failure strain was analytically calculated. The whole procedure is illustrated below. The first step was to calculate the gradient, a choosing two stress levels (Y_2 and Y_1):

$$a = \frac{y_2 - y_1}{x_2 - x_1} = \frac{0.15 - 0.10}{0.2505 - 0.2490} = 41.7 \quad (3)$$

The gradient in this case was 41.7. The second step was to calculate the failure strain, x_0 according to the equation below:

$$x_0 = \frac{(y_0 - y_1) \cdot (x_2 - x_1)}{y_2 - y_1} + x_1 \Rightarrow y_0 = 0 \Rightarrow \quad (4)$$

$$x_0 = \frac{(0 - 0.1029) \cdot (0.2490 - 0.2502)}{0.1508 - 0.1029} + 0.2502 = 0.252977$$

where the failure strain was 0.252977. All approximations and results from the calculations are showed in the stress-strain curve in Figure 4.

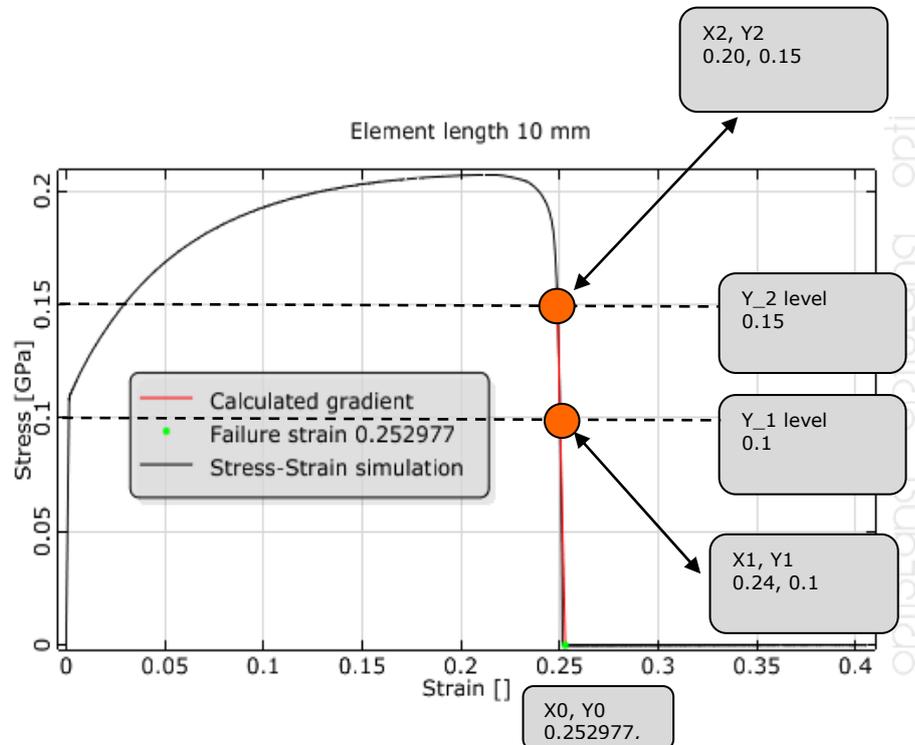


Figure 4: Approximations in stress-strain curve

3 LS-DYNA Gurson Material model

The following task was to identify damage parameters in a material model called MAT_GURSON which belongs to the material library of LS-DYNA. A more detailed description of the Gurson material model can be found in the LS-DYNA Keyword User's manual [4].

The following damage parameters in the Gurson model had to be identified (see Figure 5):

- FC which is the critical void volume fraction f_c where voids begin to aggregate.
- EN which is the mean nucleation ϵ_N .
- FF which is the failure void volume fraction f_F .

*MAT_GURSON								
\$	MID	Ro	E	PR	SIGY	N	Q1	Q2
\$	1	0.285E-05	70.0000	0.3300	0.11002	0.0000	1.5000	1.0000
\$	FC	FO	EN	SN	FN	ETAN	ATYP	FFO
\$	0.0035	0.0020	0.4000	0.1000	0.0100	0.0000	3.0000	0.1600
\$	eps1	eps2	eps3	eps4	eps5	eps6	eps7	eps8
\$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
\$	sig1	sig2	sig3	sig4	sig5	sig6	sig7	sig8
\$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
\$	lc1	lc2	lc3	lc4	ff1	ff2	ff3	ff4
\$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
\$	lc55	lc1f	numint					
\$	1		1					

Figure 5: Material card of Gurson material model.

4 Process automation

The automation of the process is very essential and necessary in order to perform sensitivity, optimization and robustness analysis using optiSLang. The whole process automation is illustrated in Figure 6 below. LS-DYNA was used for the simulation of the tensile test. LS-PREPOST was used for automatic result extraction of all the necessary results into ASCII text files. Python was used to process ASCII text files data in order to calculate the stress-strain curve and the failure strain. Finally SLang was used to plot the stress-strain curve. The whole process was automated using a batch run script, which was integrated into optiSLang.

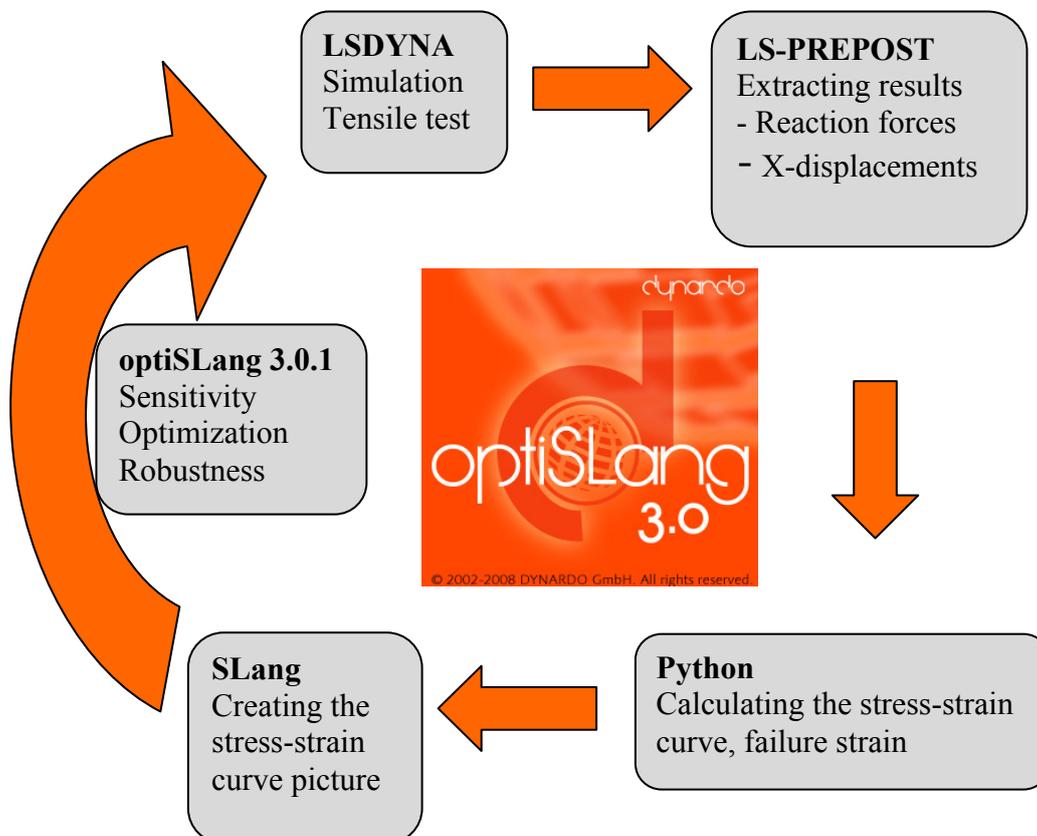


Figure 6: Workflow of process automation.

5 Sensitivity analysis

Before performing an optimization a sensitivity analysis is highly recommended where the design space is scanned by varying material parameters within upper and lower bounds. In this case Latin Hypercube sampling was used to cover the design space and the variation of the responses could be estimated. Further on a correlation analysis was performed in order to investigate which material parameter had the most influence on the responses. It has to be noted that parameters which show no significant correlation are recommended to be removed from the identification process.

The design variables were:

- *FC* - the critical void volume fraction.
- *FF* - the failure void volume fraction.
- *EN* - the mean nucleation.

The response was:

- *FAIL_STRAIN* – the failure strain

5.1 Check parameter variation interval

A very important step before starting an optimization is to check the variation space of input parameters and responses. In this case the input parameters were varied with $\pm 50\%$ bounds around the reference value (see Table 1 below).

Inputs	Reference value	Variation range
FC_2MM	0.0035	$\pm 50\%$
FC_4MM	0.0035	$\pm 50\%$
FC_10MM	0.0035	$\pm 50\%$
FF_2MM	0.12	$\pm 50\%$
FF_4MM	0.07	$\pm 50\%$
FF_10MM	0.03	$\pm 50\%$
EN	0.4	$\pm 50\%$

Ta-

ble

1: Variation of the design variables.

Figure 7 shows the variation of the resulting failure strain for element length 2 mm. The variation space of the failure strain is from 0.1397 to 0.2772 according to the histogram on the left. Later in the identification task a min, mean and max failure strain, respectively 0.20, 0.25 and 0.30 were identified. For example in the case where the max value of 0.30 was identified, an adjustment of the design space of the input parameters was necessary. The lower and upper bounds of *FC_2MM*, *FF_2MM* and *EN* were increased in order to reach the max failure

strain. The stress-strain curve to the right shows the scatter of the resulting failure strain.

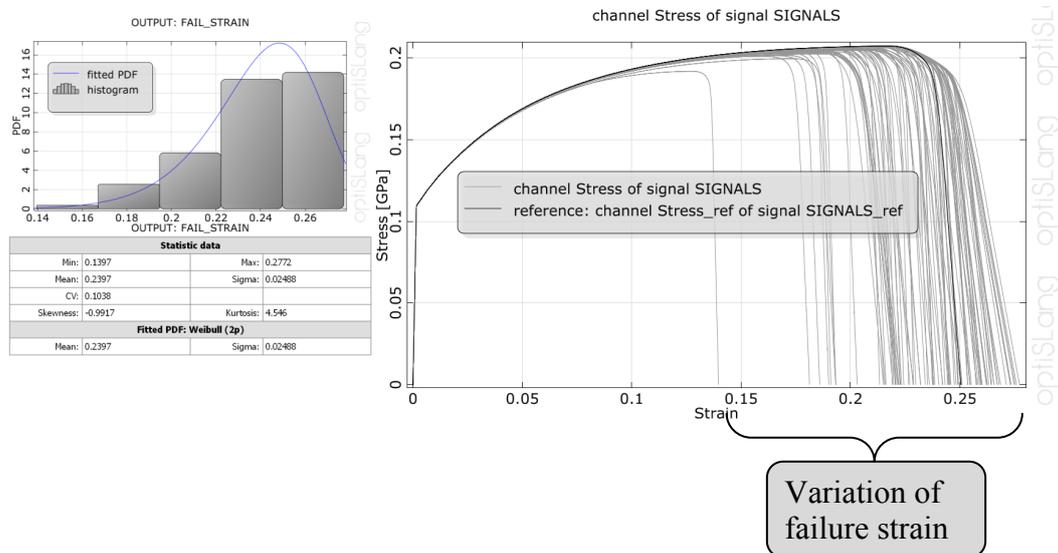


Figure 7: Histogram and stress-strain curve for element length 2 mm.

In the case with element length 4 mm, the variation of failure strain was 0.1301... 0.3059 so no adjustment of the design space was required (see Figure 8). The stress-strain curve shows the scatter of the failure strain.

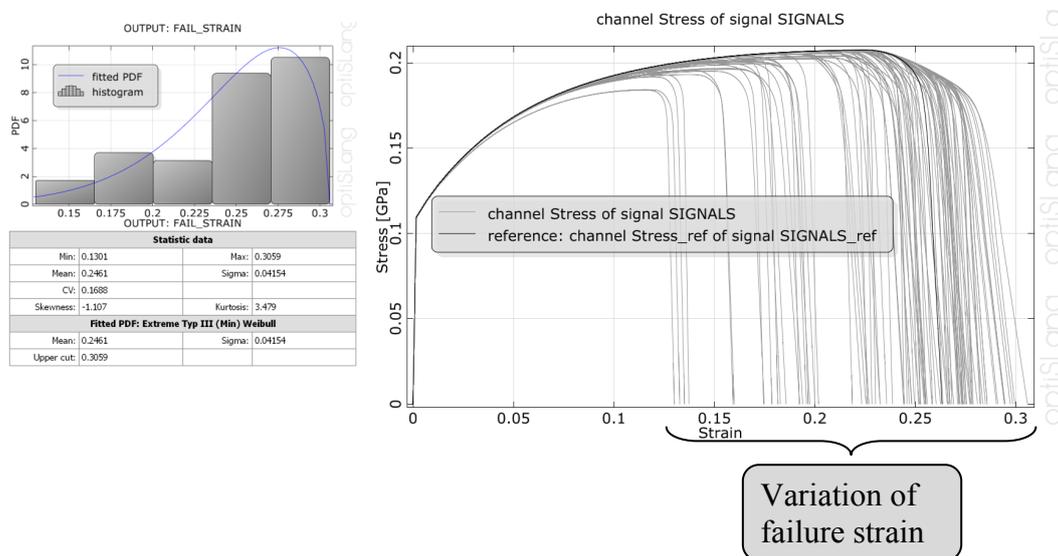


Figure 8: Histogram and stress-strain curve for element length 4 mm.

In the case with element length 10 mm the existing design space of FC_10MM and FF_10MM, resulted in the failure strain variation of 0.05865... 0.3209. An adjustment of the design space was not necessary in order to reach the failure

strains of 0.20 (min) and 0.30 (max). The histogram and stress-strain curve show the variation of the failure strain (see Figure 9).

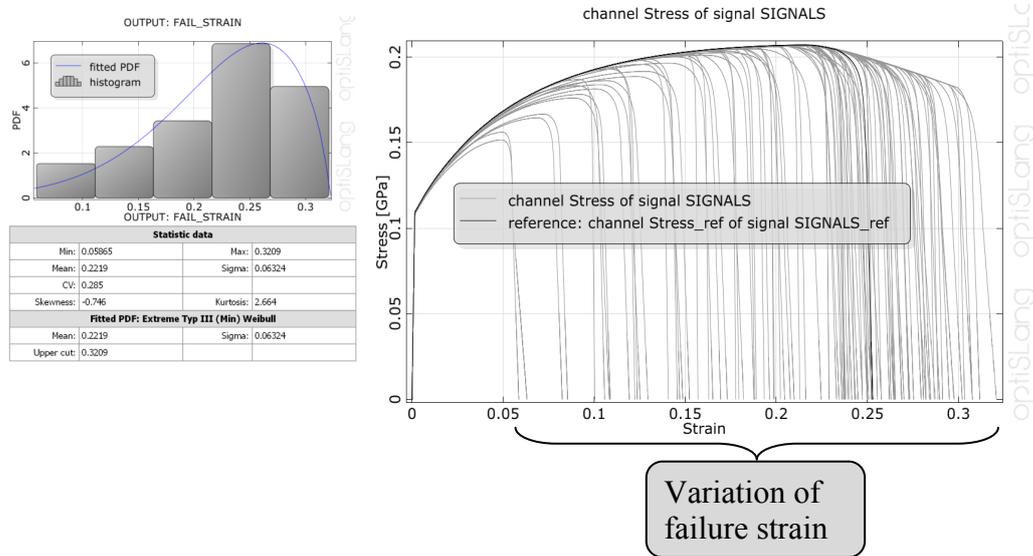


Figure 9: Histogram and stress-strain curve for element length 10 mm.

5.2 Check importance

One of the main reasons of a sensitivity study is to investigate how important and how much influence the input parameters have on the responses, using a correlation analysis. A very useful statistical measurement of importance/influence in optiSLang is the so called Coefficient of Importance, which explains the influence of an input parameter on a chosen output parameter. Based on the correlation analysis very important information regarding the optimization can be received. First it is checked that the CoI for the full model is high, otherwise a large amount of response variation cannot be linked to input variation and the response values may be too noisy for parameter identification. In our case the failure strain for all three element sizes show very high CoI. At a second step the importance of input variables is checked. Design variables which show no significant influence to the response, can be removed and reduced from the design space. The optimization problem can be simplified consisting of only the most important design variables.

The results from the sensitivity analysis can be seen in Figure 10 below. The Coefficient of Importance plots show that for element length 2 and 4 mm, design variable E has the most significant influence on the failure strain. In the case with element length 10 mm the most important design variable is FC followed by EN. Design variable FF shows no influence.

A further benefit of the sensitivity analysis is that a suitable starting (best design from sensitivity scan) design can be applied to the optimization.

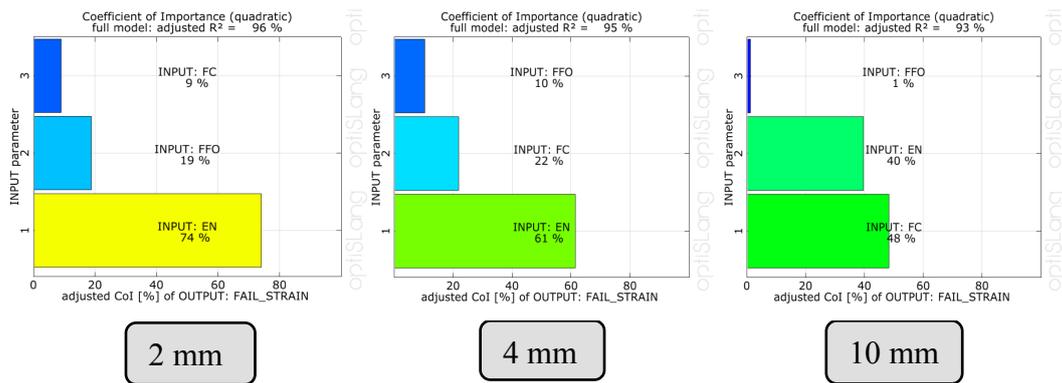


Figure 10: Coefficient of Importance, most important inputs.

6 Optimization

6.1 Parameter identification of mean failure strain

For the parameter identification an optimization was performed. The parameter identification problem consisted of 7 design parameters (FC_2MM, FC_4MM, FC_10MM, FF_2MM, FF_4MM, FF_10MM and EN). The choice of optimization algorithm ended up on optiSLang's *Adaptive response method* [5] because the number of design variables, were fewer than 15.

In the content of optimization it is necessary to formulate an objective function. In this case the objective function was:

$$obj_func = abs|FAIL_STRAIN - TARGET_STRAIN \rightarrow 0| \quad (5)$$

where $FAIL_STRAIN$ is the resulting failure strain from every simulation and where $TARGET_STRAIN$ is the requested failure strain. The difference between these strains should be minimized.

For every design three calculations (three simulations for element length 2, 4 and 10 mm) were carried out. The first task was to identify Gurson parameters for the so called mean value of the failure strain, 0.25. The results from the optimization are shown in Figure 11. The identified Gurson parameters can be seen in the picture to the upper left (see Best design #130). The response data shows the optimized failure strains for corresponding element length (see RESPONSE DATA). The stress-strain curve for element length 2 mm can be seen to the right in Figure 11. The optimization procedure described above made it possible to identify Gurson material parameters for three different element lengths and one failure strain (mean value) just by using default values of optiSLang.

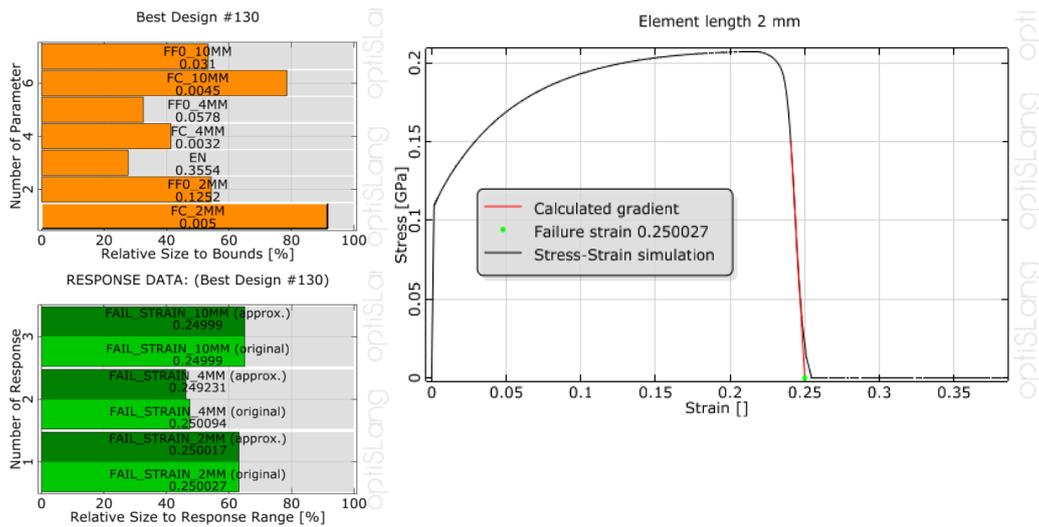


Figure 11: Best design for failure strain 25 % (mean value).

6.2 Parameter identification of min, mean and max failure strain

The next task was to identify Gurson parameters for the min and the max failure strain in same way described in section 6.1. A variation of $\pm 20\%$ of the mean value was introduced, resulting in a min value of 0.20 and a max value of 0.30. The optimization results for failure strain 0.20 are shown below in Figure 12.

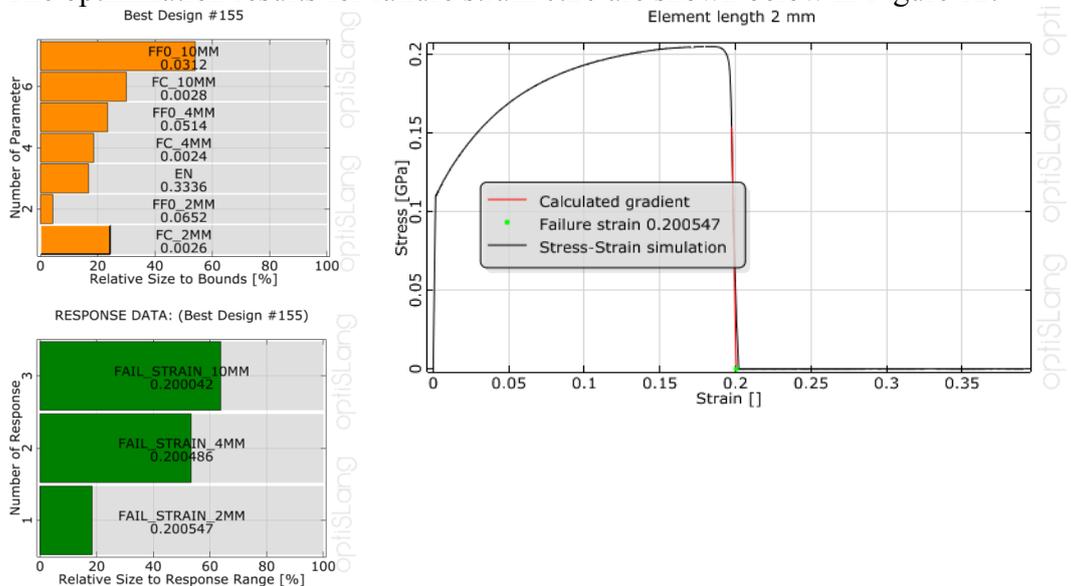


Figure 12: Best design for failure strain 20 % (min value).

The optimization results for failure strain 0.30 are shown in Figure 13.

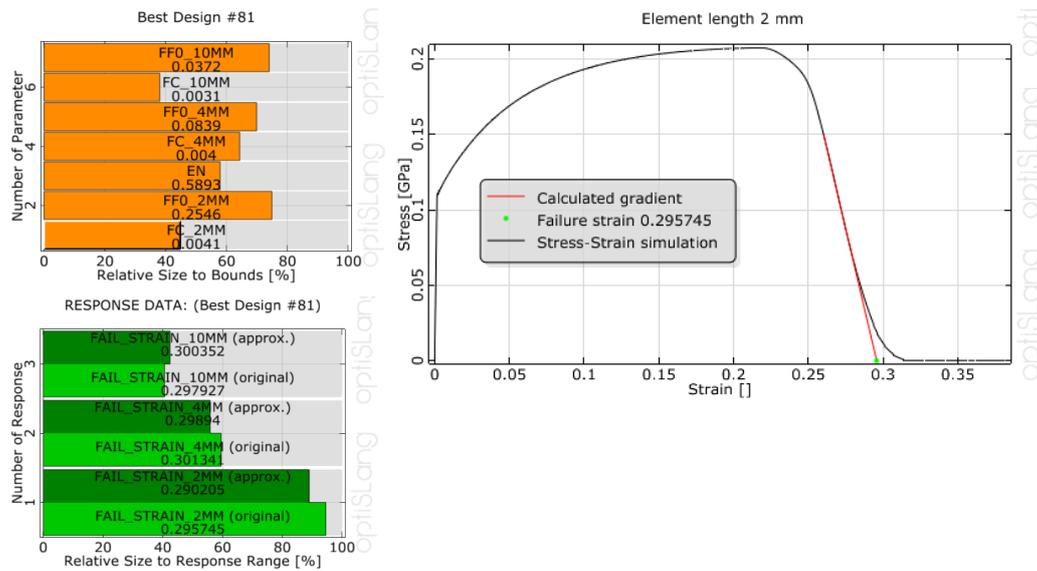


Figure 13: Best design for failure strain 30 % (max value).

All results are assembled in Table 2 below. The table contains the identified Gurson parameters for min, mean and max value of failure strain.

Optimization results							
Failure strain	FC 2MM	FF0 2MM	EN	FC 4MM	FF0 4MM	FC 10MM	FF0 10MM
20 %	0.0026	0.0652	0.3336	0.0024	0.0514	0.0028	0.0312
25 %	0.005	0.1252	0.3554	0.0032	0.0578	0.0045	0.031
30 %	0.0041	0.2546	0.5893	0.004	0.0839	0.0031	0.0372

Table 2: Results from the parameter identification.

The mesh dependent values, FC and FF from the table above are plotted in relation to the element length, L_o below (see Figure 14). The plot shows that the mean curve of the FF values (red curve) is inside the bound of the min and max curve. Only the identified $FF0_{10MM}$ value for failure strain 0.25 (mean curve) was modified in order to be inside the min and max curve. Because of the very low importance of that parameter to the response variation (See section 5.2 Check importance) that parameter cannot be identified and adjustment will have no influence to the resulting failure strain.

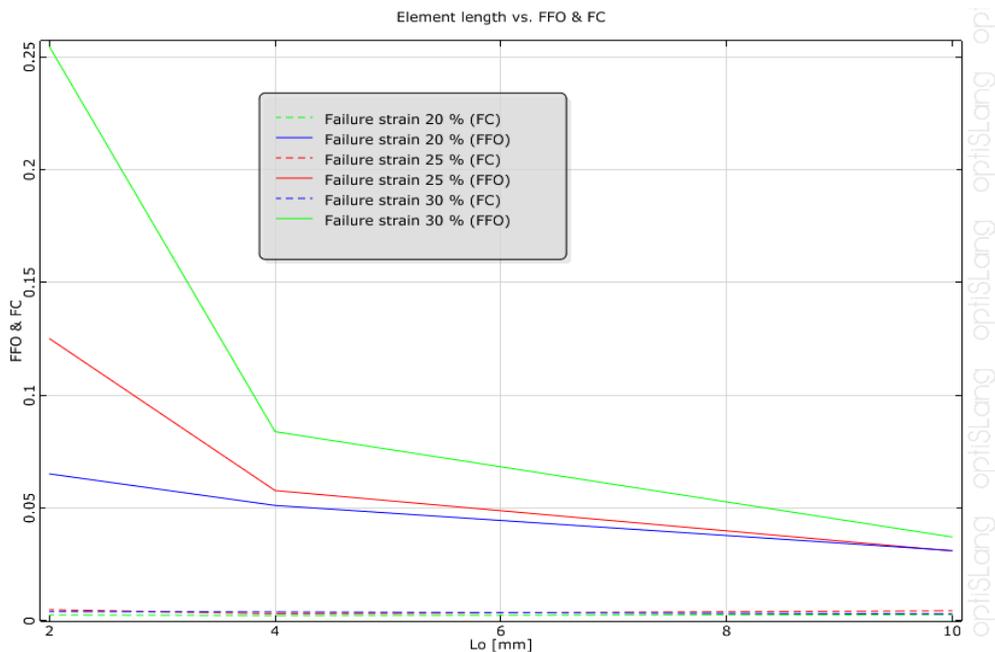


Figure 14: FF and FC values vs. element length, L_0 .

7 Variation analysis

The main purpose of the variation analysis was to generate Gurson parameters for arbitrary failure strain values between 0.20 and 0.30 using linear interpolation. Using conditional dependent variables in optiSLang made the linear interpolation between the Gurson parameters and the failure strains possible. For the variation analysis two robustness evaluations were performed in order to check and verify the resulting failure strain ranges. The identified lower and upper bounds from the optimizations were used for the FF, FC and EN values for every element length. The first variation evaluation only included 1 stochastic variable with a uniform distribution:

- Failure strain varying from 0.20 to 0.30

The second variation evaluation included 2 stochastic variables with a uniform distribution as well:

- Failure strain varying from 0.20 to 0.30
- Variation of the yield curve multiplier from 0.85... 1.15 ($\pm 15\%$)

Also a correlation coefficient, $r = -0.40$, between the failure strain and the yield strength was introduced in optiSLang. This correlation was in the range which was seen by experiments. Then the major question here was: *Did the introduction*

of scattering yield stress have any significant influence on the scatter of the resulting failure strain?

As mentioned before the intention with the variation analysis was to check if these Gurson values were valid for linear interpolation between the failure strain range of 0.20... 0.30. A small example below will illustrate how to interpolate the FC_2MM values choosing an arbitrary failure strain in the range 0.20... 0.30 (see Figure 15). During the variation analysis one arbitrary stochastic failure strain will be generated, for example FAIL_STRAIN = 0.2095 (see Figure 15). Using this failure strain the FC_2MM value can be linearly interpolated with the help of following equation below:

$$FC_2MM = abs\left(\left[\frac{(FAIL_STRAIN - 0.20) \cdot (0.005 - 0.0026)}{0.25 - 0.20}\right] + 0.0026\right) = 0.003056 \quad (6)$$

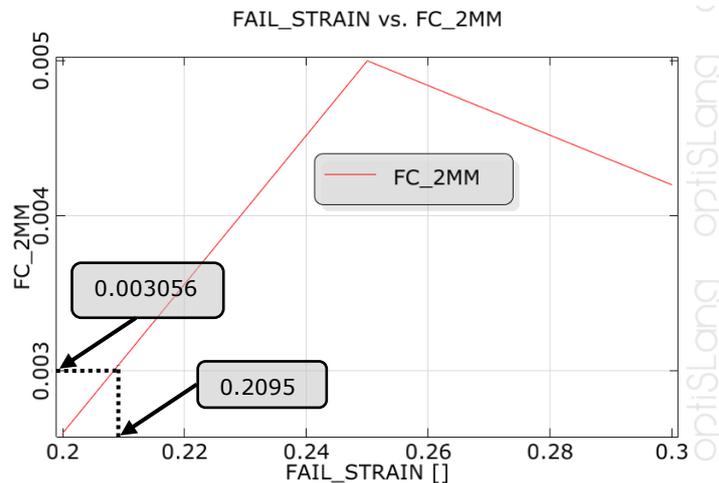


Figure 15: FAIL_STRAIN vs. FC_2MM values.

The FC_2MM value was 0.003056 in this case. The next step would be to perform a new tensile test simulation using the linear interpolated value of FC_2MM and check if the resulting failure strain (FAIL_STRAIN_2MM) was the same as the stochastic failure strain (FAIL_STRAIN). The results are shown in section 7.1 and 7.2. In the same way values for FF0_2MM, EN, FC_4MM, FF0_4MM, FC_10MM and FF0_10MM were interpolated using conditional dependent variables in optiSLang. All three tensile test simulations were repeated with the new linear interpolated Gurson values.

7.1 Results – variation analysis 1

The anthill plots in Figure 16 show that the scattering failure strain was inside the valid range of the resulting failure strain (0.20... 0.30). There is almost a linear dependency between the scattering and the resulting failure strain which can be seen by the correlation coefficient, r closed to 1.0. In all cases the correlation coefficient is over 0.98 and it considers being a linear relationship.

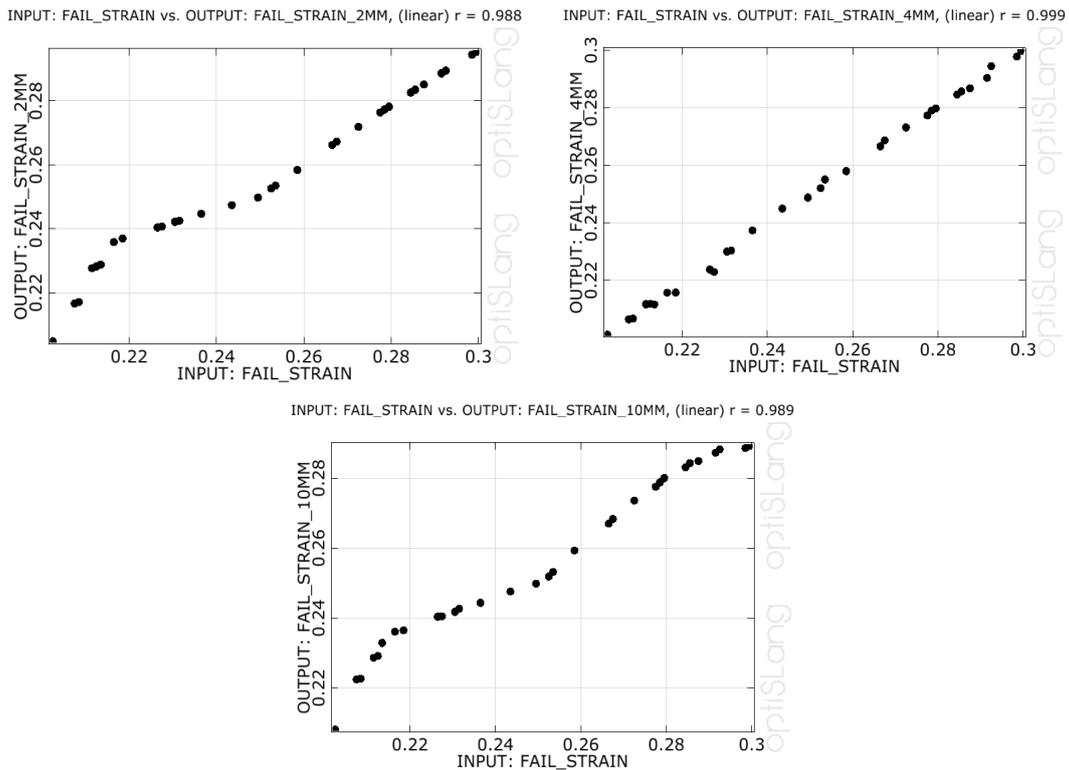


Figure 16: Anthill plots, 2D-visualization of the pair wise relation between input and output.

7.2 Results – variation analysis 2

Despite the introduction of the scattering yield stress the resulting failure strain was inside the valid range of 0.20... 0.30 and seemed to have no significant influence (see Figure 17). The anthill plots still show the linear relationship between the stochastic and the resulting failure strain. Due to the high correlation coefficient, r here also exist a linear relationship.

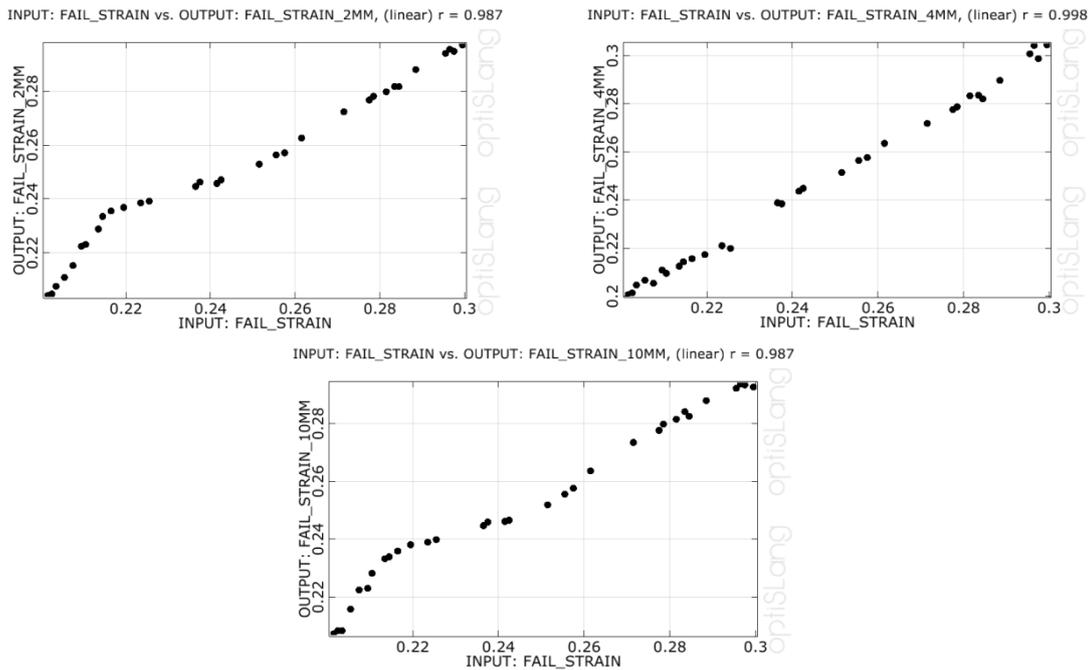


Figure 17: Anthill plots, 2D-visualization of the pair wise relation between input and output.

7.3 Comparison - variation analysis 1 and 2

Two stress-strain curves from robustness 1 and 2 with element length 2 mm are shown in Figure 18 and Figure 19. The scatter range of the resulting failure strain from robustness 1 and 2 are almost the same according to the curves below. The stress-strain curve from Robustness 2 shows that the scattering yield stress had no significantly influence on the resulting failure strains and verified that the scatter was inside the range of 0.20... 0.30.

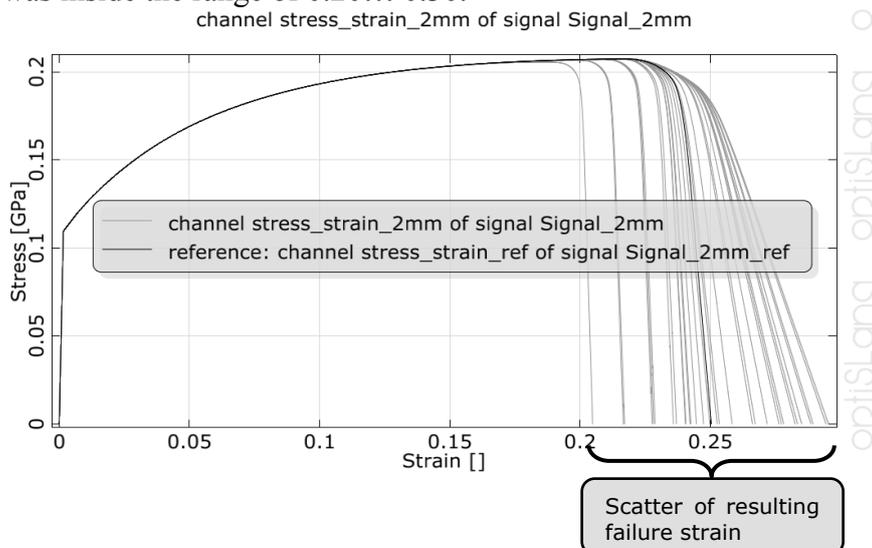


Figure 18: Stress-strain curve for element length 2 mm.

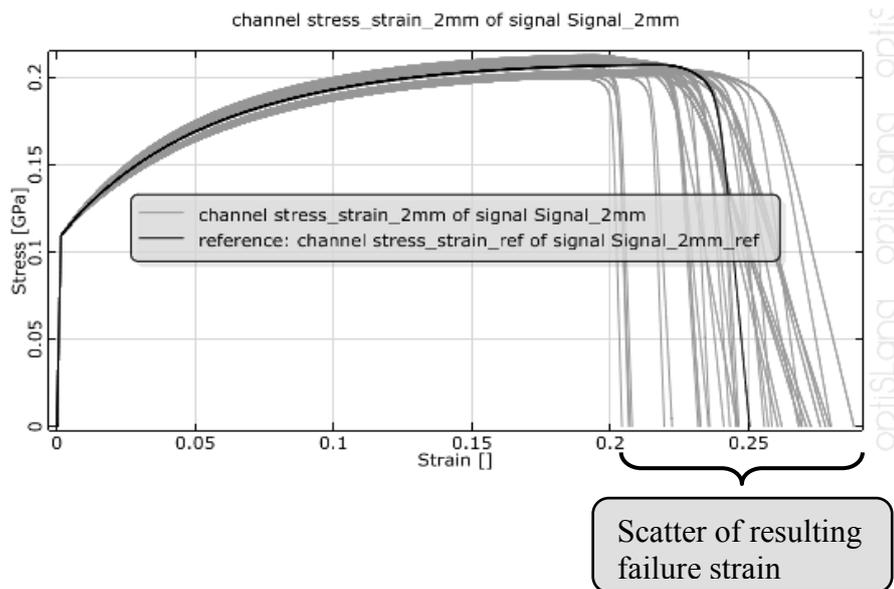


Figure 19: Stress-strain curve for element length 2 mm.

8 Conclusion

optiSLang provided an automatic process of identifying mean and min/max values for the damage parameters (EN, FF, FC) of the LS-DYNA Gurson material model. The whole process is automated in optiSLang included a sensitivity, optimization and variation analysis to check resulting intervals of failure strain variation. The sensitivity analysis was used to check the design space and to investigate the important design parameters. A further benefit of the sensitivity analysis is that a suitable starting (best design from sensitivity scan) design can be applied to the optimization. For the parameter identification optiSLang default settings of the adaptive Response Surface Method or the evolutionary Algorithms were used. As a verification procedure, two variation analyses were performed in order to verify the resulting failure strain ranges. During the verification procedure the identified material values from the optimization, the FF and FC values were linearly interpolated between values at minimum, mean and maximum failure strain for different mesh sizes. The first variation analysis included only one stochastic variable, the failure strain. The second variation analysis consisted of two stochastic variables, the failure strain and the scale factor of the yield curve. The stochastic variation of the yield curve did not significantly influence the resulting failure strain range. Both of the variation analyses verified that the resulting scattering failure strain was inside the range of the expected failure strain.

With establishing fully automatic process of identifying Gurson material parameters for min, mean and max experimental values and verifying that these values

can be used in Robustness evaluations of crashworthiness applications. Finally we have set up a very cost efficient procedure to translate experimental values into Gurson Material parameters for deterministic and stochastic analysis.

References

- [1] Will, J.; Frank, T.: Rechnerische Robustheitsbewertung von Strukturlastfällen bei der Daimler AG; Proceedings Weimarer Optimierung- und Stochastiktag 5.0, 2008, Weimar, Germany (www.dynardo.de)
- [2] J. Will: Der Abgleich von Messung und Simulation als Optimierungsaufgabe, Proceeding NAFEMS Seminar Virtual Testing – Simulationsverfahren als integrierter Baustein einer effizienten Produktentwicklung“ April 2006, Wiesbaden, Germany
- [3] LS-DYNA keyword User’s manual – Volume 1, *MAT_GURSON pages 447-451
- [4] optiSLang – the optimizing Structural Language version 3.0.1, DYNARDO GmbH, Weimar, 2009, www.dynardo.de
- [5] optiSLang documentation – the optimizing Structural Language, *Section 5 Multidisciplinary non-linear optimization, 5.6 Adaptive Response Surface Methodology* pages 126-130.