THE IDENTIFICATION OF RATE-DEPENDENT MATERIAL PROPERTIES IN FOAMS USING LS-OPT

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Abbreviations:
RSM: Response Surface Method
DOE: Design of Experiments

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ABSTRACT

In the past years more and more complex materials, e. g. plastic and metallic foams, honey-comb materials, different types of glues, epoxy-glass materials etc., were incorporated in a wide range of products, particularly in the automotive industry. For the modeling of such materials within nonlinear dynamic problems numerous material models are available in LS-DYNA. However, the application of these material models require the knowledge of the ma-terial parameters describing the behavior of the specific material. The accuracy of the Finite-Element simulations depend authoritatively on the quality of the involved material parame-ters. In order to obtain these material parameters the calibration of the model is necessary through comparison with experimental data.

The main objective of this paper is to demonstrate the calibration of a nonlinear material model by minimizing the difference of the model response and the experimental tests. As an example, a low density styrofoam is considered which is described by a material model with strain rate effects (Fu-Chang Model (LS-DYNA, 1999)). The minimization problem is solved via the Response Surface Method (Myers, 1995) using the commercial optimization code LS-OPT.

INTRODUCTION

Simple material models, e. g. linear isotropic elastic models or perfect elastoplastic models of *v. Mises* type, allow a direct physical interpretation of the involved material parameters. For example, in a one dimensional tension test, the slope of the stress-strain curve can be interpreted as the Youngs Modulus E, presumed linear material behavior occurs. Assumptive in the test the material starts perfect yielding at a distinct point, the parameter k of the *v. Mises* yield criterion can be determined directly.

In the case of more complex material models, it is generally not possible to assign a physical meaning to each material constant. In such cases the application of a so-called inverse pa-rameter identification procedure is useful. Therefore, various experimental tests have to be performed in order to stimulate a variety of different material responses. These tests should be then simulated with the chosen material formulation by considering the boundary conditions as accurately as possible. The response of the model is a function of the set of material pa-rameters $\boldsymbol{p}$. The goal of the parameter identification procedure is to minimize the difference between the responses of the material model and the experimental observations for several boundary value problems (Figure 1) by variation of a selected set of material parameters.

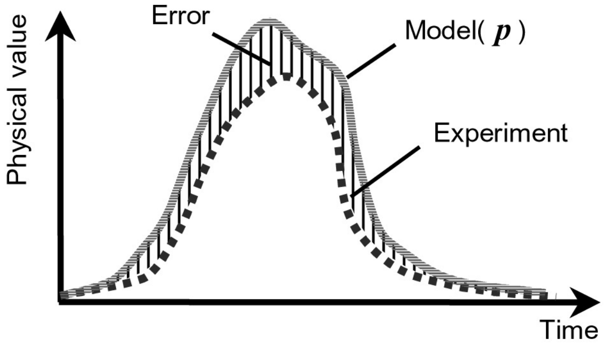

Figure 1: Difference between simulation and experiment.

APPROACH

The Response Surface Method (RSM) is applied in order solve the optimization problem of minimizing the distances of experimental points to points calculated with a specific material model. This method has become popular for optimization studies involving the simulation of nonlinear dynamical problems. The purpose of the method is primarily to avoid the necessity for analytical or numerical gradient quantities as these are either too complex to formulate, discontinuous or sensitive to round-off errors.

Optimization problem

As mentioned above the objective of the parameter identification problem is to minimize the difference between the computational and the experimental results. Therefore, an objective function based on the well-known Least-Squares-Method is introduced:

$$R(\boldsymbol{p}) = \frac{1}{2}\left\|\boldsymbol{r}_m(\boldsymbol{p})\right\|_2 = \left(\mathrm{r}_1(\boldsymbol{p})^2 + \cdots + \mathrm{r}_m(\boldsymbol{p})^2\right)^{1/2} \rightarrow \ \min \ ,$$

$$\boldsymbol{r}_m(\boldsymbol{p}) = \begin{bmatrix} y_{\exp_1} - modelresponse(x_{\exp_1}, \boldsymbol{p}) \\ \vdots \\ y_{\exp_m} - modelresponse(x_{\exp_m}, \boldsymbol{p}) \end{bmatrix}, \quad \boldsymbol{p} = (p_1, \ldots, p_n) \ .$$

Here, m specifies the number of experimental observations of any desired physical response value resulting from one or more boundary value problems. The Least-Squares functional is a function of the vector $\boldsymbol{p} \in \Re^n$ which contains n material parameters. These parameters are acting as design variables in the optimization process.

In addition, sets of functions g_i and h_j may define inequality and equality constraints in order to bound the variation of the parameters:

$$\begin{aligned} g_i(\boldsymbol{p}) &\leq 0 \quad ; \quad i = 1, \ldots, k \quad , \\ h_j(\boldsymbol{p}) &= 0 \quad ; \quad j = 1, \ldots, l \quad . \end{aligned}$$

The Response Surface Method

Among several methodologies available to address optimization in a design environment, the Response Surface Methodology (RSM), has achieved prominence in recent years. The RSM is a statistical method for constructing smooth approximations to the objective function in the multi-dimensional parameter space. So called experimental design points (parameter sets $\boldsymbol{p}_e$;e=1,...;E ; E = number of experimental points) are selected within a pre-defined design space. For these points the defined model responses and the respective residuals $\boldsymbol{r}_{\mathrm{m}}(\boldsymbol{p}_e)$are calculated. In a subsequent step polynomial functions are fit to these experimental design points in order to substitute the original, possibly very noisy, response. For illustration purposes: In the two-dimensional parameter space (n = 2) the polynomial functions represent surfaces, that are adapted to selected experimental points within the three-dimensional space, see Figure 2. The fit of the polynomial functions is done by using regression analysis. Least squares approximations are commonly used for this purpose.

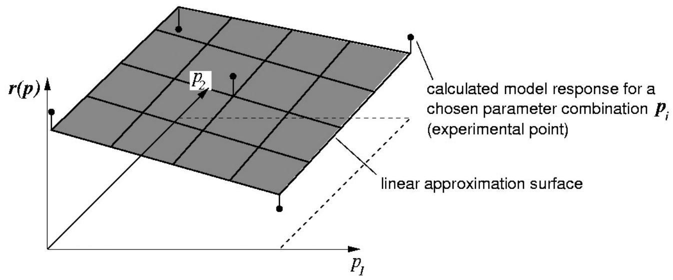

Figure 2: Approximation surface is fitted through points in the design space.

Design of Experiments (DOE) Experimental Design is the selection procedure for finding the points in the parameter design space. Many different methods are available, e. g. Koshal Design, Factorial Design, Central Composite Design, Box-Behnken Design, D-Optimal De-sign etc. An excellent review of the different design types can be found in Myers (1995).

An advantage of the D-Optimal Design is, that design regions of irregular shape and any number of experimental points can be considered. The experimental points for the D-Optimal Design are usually selected from a full factorial design by using the D-optimality criterion. The number of experimental points is of course in correlation with the order of the approximation functions. Usually oversampling of approximately 50% is recommended (Roux 1998), i.e. 50% more points are being analyzed than the minimum required.

Approximations Polynomial functions might be composed by arbitrary base functions. The selection of the base functions should lead to a best regression model. The use of full quad-ratic approximations (second-order model) is very common, but because of their cost they should be avoided for very large models. A possible solution is to use linear approximations. These are generally inaccurate beyond the immediate neighborhood of the considered design point but can be used in a successive response surface procedure.

Successive Response Surface Method For the successive response surface method a region of interest is defined as a sub-region of the entire design space. The sub-region is approximated and the optimum is determined on the approximated response surface. Then a new region of interest is defined and the center is located on the previous successive optimum. Progress is made by moving the center of the region of interest as well as reducing its size (Stander 2001). The iteration is continued until the objective function or the design variables reach stationary values.

Main Advantages of the Method:

- GLOBAL OPTIMIZATION The Response Surface Methodology has a ten-dency to capture globally optimal regions. Local minima caused by noisy re-sponse are avoided.
- PARALLEL COMPUTATION Successive Response Surface Schemes allow the simultaneous computation of all selected experimental points within the cur-rent region of interest.
- FLEXIBLE DESIGN EXPLORATION Design Exploration can be changed within the optimization process.
- TRADE-OFF STUDIES Since the response surface is determined, easy exami-nation of varying constraint bounds is possible.

Software: LS-OPT

The above mentioned methods have been incorporated in the program LS-OPT, a general optimization program which is closely interfaced with LS-DYNA (LSTC/2 1999). Access to most quantities available in the LS-DYNA database has been provided and maximum, mini-mum, averaged and filtered quantities can be automatically extracted (LSTC/1 1999).

EXAMPLE: PARAMETER IDENTIFACATION OF LOW DENSITY FOAM

Goal

In general, the goal of material parameter identification is to find appropriate parameter values of a constitutive model in order to map the realistic (experimental) material behavior as accurately as possible. In the current example a low density foam of a motorcycle helmet is considered.

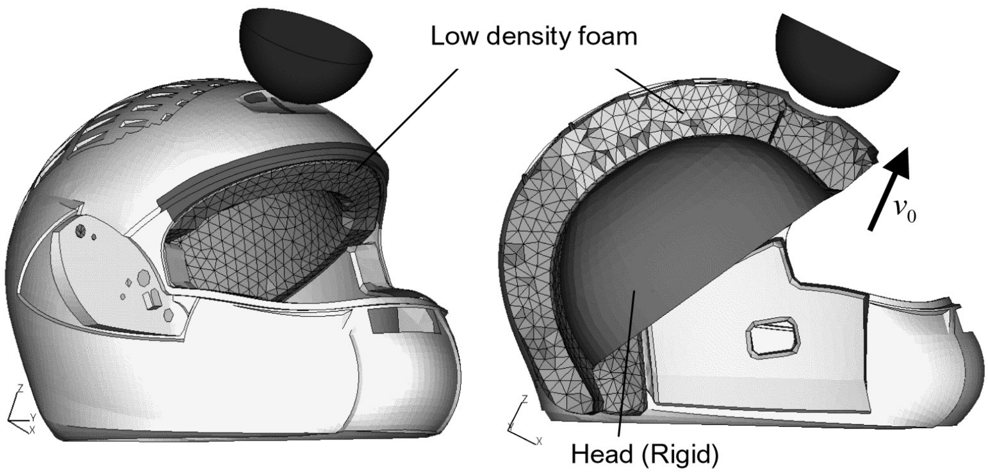

Figure 3: Impact of a helmet on a rigid hemisphere.

The focus of the study is on the impact of the helmet on a rigid hemisphere with an prede-fined initial velocity. Experiments have been carried out for this case. Simulations of the problem have been performed with an intuitive choice of material parameters for the low density foam inside the helmet (Figure 3). The low density foam is modeled by a rate-dependent material law. Here the question arises: how to obtain better material parameters for the considered material model in order to improve the results of the simulation with regard to the experimental response.

Component Drop Tests

The idea is to perform simple experiments by dropping rigid spheres with an initial velocity on a foam block, compare Figure 4. Two different spheres with radii of 50 and 130mm are used. In total, there are 5 different tests:

- Sphere with radius 50mm; falling height 2.0 m; mass1
- Sphere with radius 130mm; falling heights 1.0/1.5/2.0/2.5 m; mass2

In the experiments the acceleration of the spheres versus time are measured.

In addition to the dynamical drop tests, quasi-static uniaxial tension tests are used.

Simulation of the component tests

The above mentioned drop tests are simulated with the FE-code LS-DYNA. The sphere and the base plate are assumed to be rigid. The foam block is modeled by a material law called MAT_FU_CHANG in LS-DYNA. This is a rate sensitive reversible model, where the mate-rial properties might be defined by stress-strain load curves, see Figure 6. This means, load curves of dynamic compression tests with different strain rates might be used directly as in-put. The load curves can be provided either by true strain rates or by engineering strain rates. For the one dimensional case the engineering strain rates are given by

$$\dot{\varepsilon} = \frac{v}{l_0} \quad .$$

As a consequence, by using engineering strain rates in the input load curves, the results of uniaxial experimental tests performed at constant velocity v could be used directly. The problem is, that for these tests, particularly for high strain rates and for large deformations, very large forces occur. The experimental set-up of such tests is rather difficult. Thus, rather simple drop tests with spheres on foam blocks (Figure 4) are performed and by inverse opti-mization for several strain rates the load curves are determined.

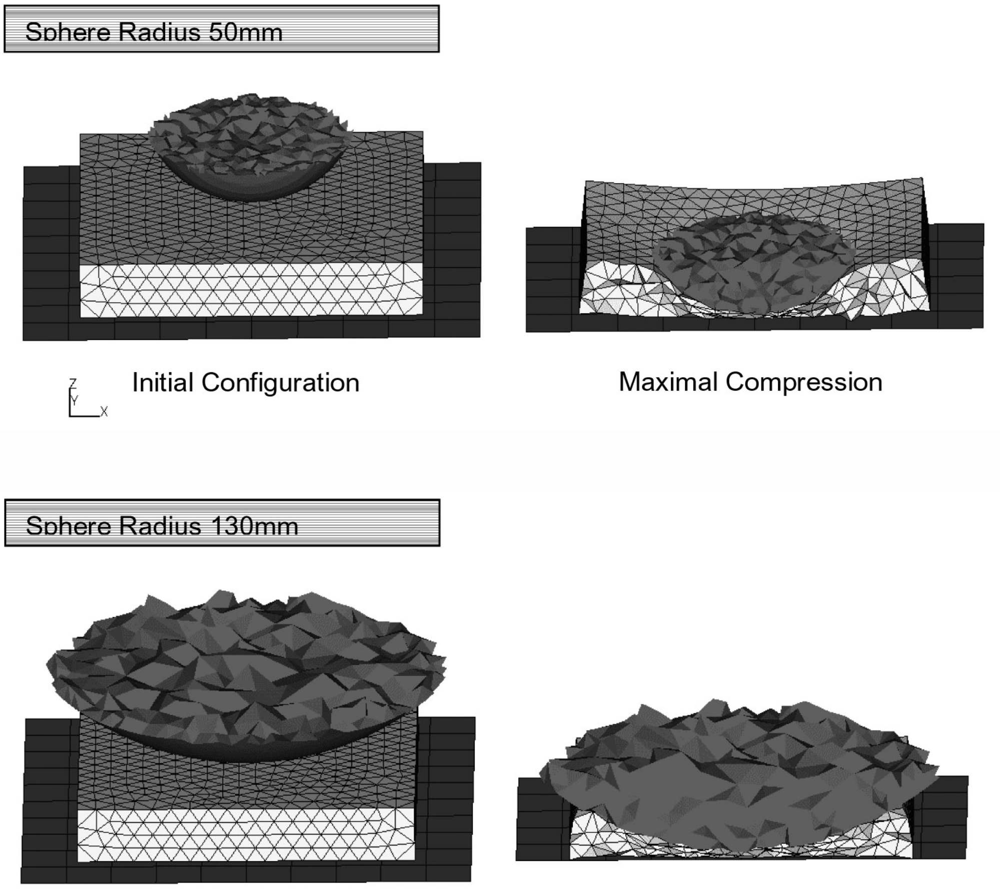

Figure 4: Simulation of the experimental drop tests.

The Optimization Problem

Objective Function The aim of the optimization procedure is to adapt the model response to the results of the component tests by varying material parameters of the FU_CHANG material model. Thereby, it is focused on the maximum acceleration value of the spheres. The optimization problem is formulated in order to minimize the differences between the maxima of the model and the experimental responses $\Delta\max_1 \ldots \Delta\max_5$ (compare Figure 5):

$$R(\boldsymbol{p}) = \left(\Delta\max_1(\boldsymbol{p})^2 + \cdots + \Delta\max_5(\boldsymbol{p})^2\right)^{1/2} \rightarrow \min .$$

Here, $\Delta\max_1 \ldots \Delta\max_5$ refer to the above mentioned tests with different falling heights and different radii and weights of the spheres.

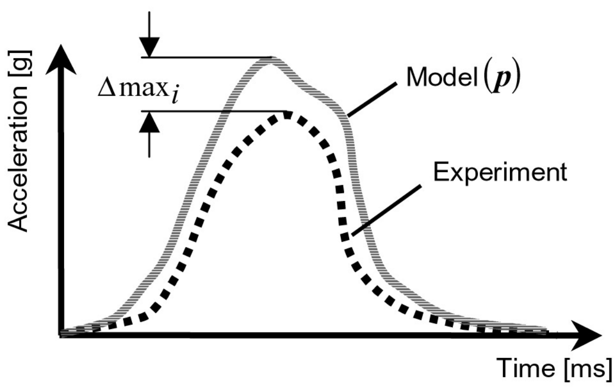

Figure 5: The target value to be minimized within the optimization.

Design Variables The material behavior of the foam is described by load curves for differ-ent strain rates in the compression as well as in the tension range. The averaged values of the quasi-static uniaxial compression tests are used as base load curve in the compression regime (dashed curve in Figure 6). In order to cover the strain rate effects in a wide range, three ad-ditional load curves are introduced. These load curves are generated by multiplying the ordi-nate values (stress values) with scale factors. For the optimization process these scale factor are defined as design variables. The static load curve is also provided with a scale factor in order to allow minor changes to the quasi-static values.

There are no experimental results available in the tension range. Hence, a bilinear curve is assumed, fixed by two points at values of 5% and 100% tensile strain. The corresponding stress values are defined by two additional design variables (see Figure 6).

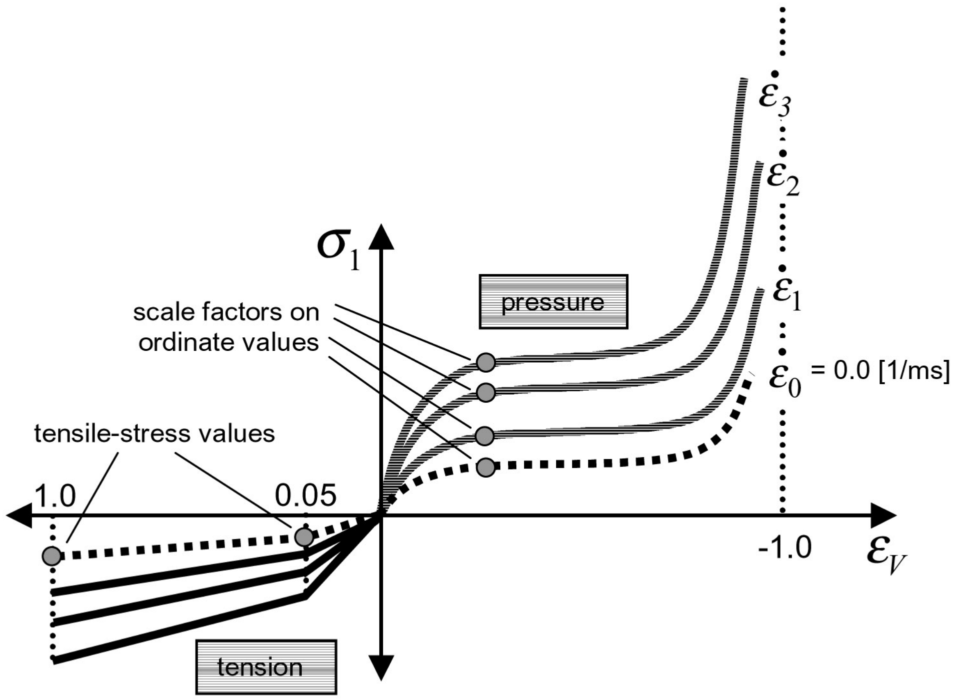

Figure 6: Definition of the design variables: 4 ordinate scale factors + 2 tensile stress values.

Constraints It is intended to provide load curves for the Fu-Chang material model with a monotonic increase of the stress values for increasing strain rates. The intersection of the load curves has to be avoided. Consequently, a monotonic increase of the ordinate scale factors is necessary. The monotonicity is enforced by the constraints:

$$\text{scfac0} < \text{scfac1} < \text{scfak2} < \text{scfak3},$$

where scfac0...scfac3 are the ordinate scale factors referred to the load curves in Figure 6.

In the tension range it has to be guaranteed that the absolute stress value at 100% is higher than at 5% tensile strain, because softening should be avoided. This leads to the following constraint:

$$\left|\sigma_{0.05}\right| < \left|\sigma_{1.0}\right|.$$

Settings for the RSM The most successful and efficient approximation functions for the pre-sent problem are linear polynomials. For the linear approximation 11 iterations by the succes-sive response method are sufficient to achieve a converged result. For each iteration 11 ex-perimental points are selected by the D-Optimal criterion. This means, in total

11 experimental points X 11 iterations X 5 simulations (5 component tests) = 605 runs

have to be calculated. In addition to the optimization run using linear approximation, elliptic and quadratic settings are tested for this problem. Elliptical approximations are based on full quadratic polynomials, but diagonal terms only. In Table 1 the main values with respect to a converged optimization result are summarized. The finally achieved optimum points are ap-proximately the same for the different approximations.

Approximation	DOE	Basis Design	Exp. Points	Iterations	Total Runs
Linear	D-Optimal	3^6	11	11	605
Elliptic	D-Optimal	5^6	20	9	900
Quadratic	D-Optimal	5^6	43	7	1505

Table 1: Comparison of different approximations.

Results

In Figure 7 the evolution of the objective function R($\boldsymbol{p}$) for the linear approach is plotted. After 11 iterations the change of the design variables is less than a pre-set tolerance value. The squares display the results of R($\boldsymbol{p}$) by computing the acceleration responses of the above described component tests (computed values). On the other hand the solid line represents the objective R($\boldsymbol{p}$) by the evaluation of the approximated response surface (predicted values). The predicted values are very close to the computed values. This indicates a rather good approxi-mation of the response surface and that the initial region of interest could probably have been chosen larger, thereby forcing convergence in a significantly lower number of iterations.

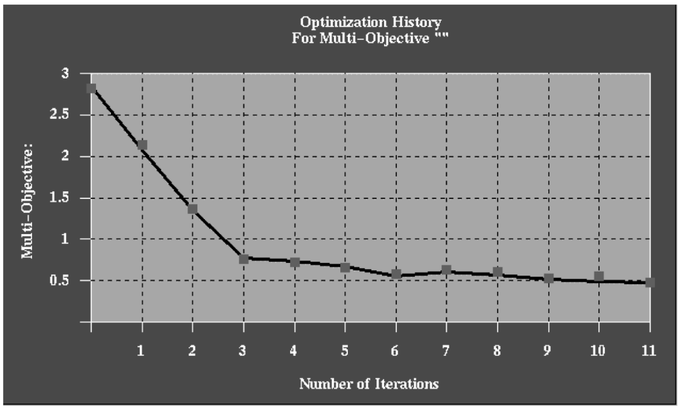

Figure 7: History of the objective function.

The comparison between the results of the simulated component tests using the initial and the optimized parameters is shown in Figure 8.

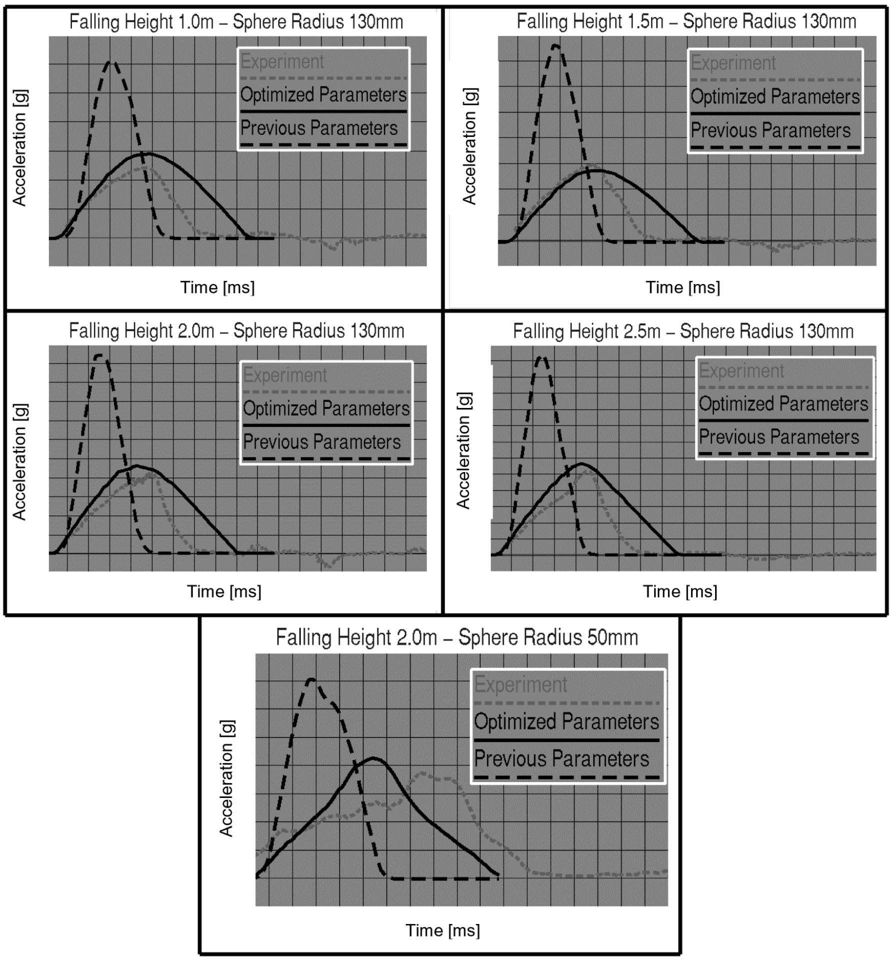

Figure 8: Results of the component tests.

Using the optimized parameters for the simulation of the helmet problem, a significant im-prove of the results with respect to the experimental observation is achieved, see Figure 9.

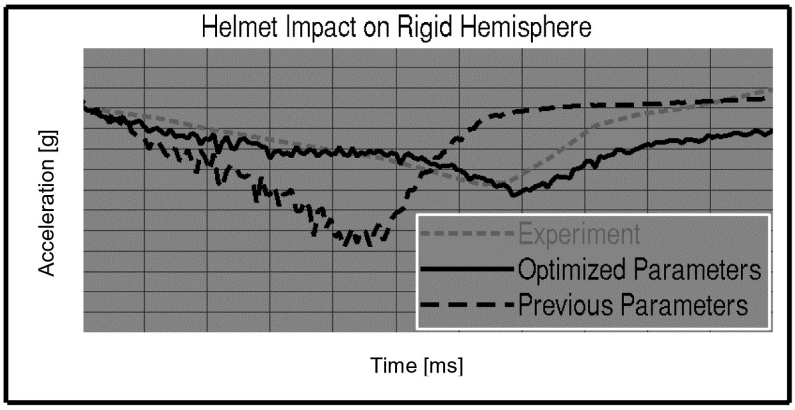

Figure 9: Simulation and experimental data of the helmet drop test.

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CONCLUSIONS

LS-OPT was used successfully to determine input parameters for a low density foam. The five load cases of simple drop tests were chosen such that the load is considerably close to the load in an actual drop test of a complete motorcycle helmet. To simulate the reversible be-havior of the foam, the LS-DYNA material model FU_CHANG was selected. The irreversible properties of the foam were not considered. The maximum decelerations of the impactors were used to define the objective function. A D-optimal criterion using linear polynomials as approximation for the response surface was applied.

The optimized material parameters were used in the simulation of a motorcycle helmet test and showed a vastly improved behavior when compared to the initial set of parameters and a very good agreement with the experimental results.

It is judged that the linear approximations are good enough for this type of material identifi-cation. Future studies could highlight whether the number of iterations can be reduced signifi-cantly by increasing the size of the initial region of interest and by using a coarser tolerance. In addition, it could be explored if the inclusion of additional discrete points or an integral criterion in the objective function has a significant effect on the results.

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