Shape Optimization of a Vehicle Crash-box using LS-OPT

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ABSTRACT

The aim of this project is to optimize the geometry of a crash-box due to impact at low velocity impact. The optimization problem is solved in LS-OPT, using Neural Networks as meta-model. The Neural Networks meta-model has been evaluated on a small test example and it shows remarkable good approximation of the responses.

The geometry was parameterized using HyperMorph. In addition to the geometry parameters, the sheet thickness and the material quality of the crash-box and the bumper-beam were also varied. The FE-model used is a passenger car from Saab Automobile. The objective is to minimize the mass of the crash-box subjected to two deformation constraints and a constraint on the maximum plastic strain in the main crash-rail, which is positioned behind the crash-box. During the optimization procedure, unfortunately, the crash-rail shown to be too weak and it need to be strengthening up using an extra component in the weak section of the crash-rail. Consequently no solution that fulfilled all constraints was found. However, LS-OPT reduced the mass of the component with 20 % and in the same time reduced the sum of all constraint violations with 50 %. Only the plastic strain constraint was violated after five iterations. The meta-modelling technique using Neural Networks showed good results with small surface approximation errors.

INTRODUCTION

When a vehicle impacts in less than 15 km/h velocity, the insurance companies require that the damage of the vehicle should be as small as possible. Then the cost to repair the vehicle will be lower and the insurance fee can be reduced.

The insurance companies requirements can e.g. be that the headlights and engine hood should be undamaged after the impact. Another constraint can be that no other structural parts of the vehicle than the most frontal ones should be damage in a frontal impact at low speed. Different countries have different impact for this evaluation, e.g. different barrier types and different velocities.

The components that are allowed to collapse in a low velocity impact are the bumper-beam and the crash-box. The total lengths of these components are generally limited by the design of the vehicle but the width and height can vary rather freely. The material properties and sheet thickness can also be modified to improve the vehicle low speed impact performance.

These components, i.e. bumper-beam and crash-box, can be changed rather independently of other structural components. Therefore it is useful to utilize mathematical optimization by altering the geometry and the material and structural properties of the bumper-beam and crash-box to improve the low speed performance.

Saab Automobile has provided the vehicle model used in this paper. To improve the low speed impact behaviour, the geometry has been optimized using LS-OPT (1). The geometries of the bumper-beam and the crash-box are parameterized using HyperMorph (3).

OPTIMIZATION METHODOLOGY

Meta-modelling techniques are necessary in design approximation when the simulations of the physical model are extremely costly. These techniques allow exploratory techniques such as optimization, variable screening, tradeoff studies etc. to be conducted using surrogate design information. Several techniques are available in LS-OPT, namely the Response Surface Methodology (RSM) based on polynomial expressions, Artificial Neural Networks and Kriging. Each has its advantages and pitfalls. The present study only focus on the optimization of

nonlinear problems in crashworthiness design using LS-DYNA (2) and Neural Networks as meta-model.
Neural methods are natural extensions and generalizations of regression methods. Like RSM, they model relationships between a set of input variables and an outcome. They can be thought of as computing devices consisting of numerical units (neurons), whose inputs and outputs are linked according to specific topologies. A neural model is defined by its free parameters - the inter-neuron connection strength (weights) and biases. These parameters are typically learned from the training data using an appropriate optimization algorithm. The training set consists of pairs of input (design) vectors and associated outputs (responses). The training set consists of pairs of input vectors and associated outputs. The training algorithm tries to steer network parameters towards minimizing a distance measure, typically the mean squared error. Figure 1 shows an example of a Neural Network. See LS-OPT user's manual (1) for the theory of the Neural Network.
In the modelling of an unknown nonlinear relationship, when there is no persuasive parametric regression model available, and the constraints are uncertain, one might believe that a good experimental design is a set of points that are uniformly scattered on the experimental domain (design space). When using Neural Networks as meta-model, the experimental design called Space Filling is used. The method maximizes the distance between design points such that the total design space will be covered. In LS-OPT, several different methods are available to generate the Space Filling design.

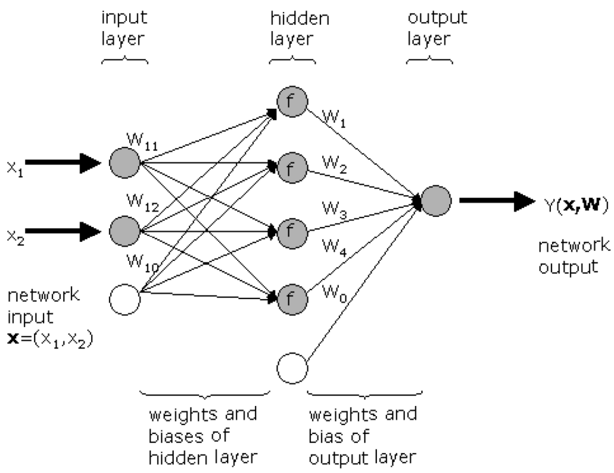


Figure 1 Example of a Neural Network

TEST EXAMPLE

In this section the Neural Networks meta-modelling technique is evaluated on a small FE-model, which consists of a crash-box, a bumper-beam and a supporting structure behind the crash-box, see Figure 2. A rigidwall impacts into the bumper-beam, which has symmetry boundary conditions on the left side. The supporting structure is clamped at the end.

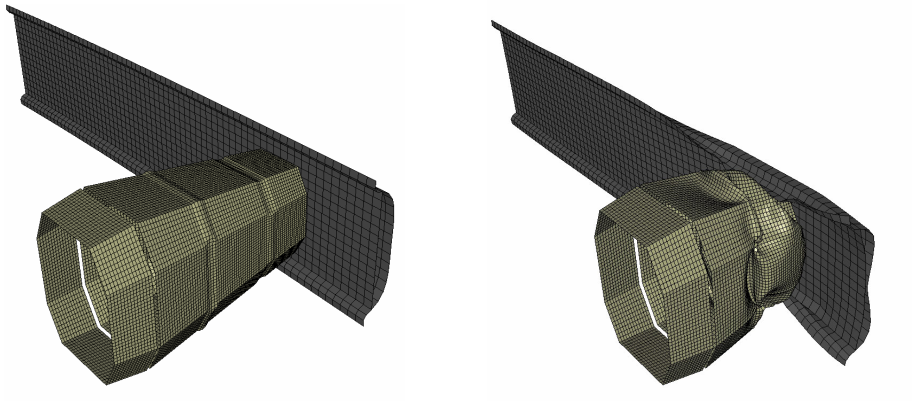


Figure 2 Small FE-model

The quality of the Neural Network meta-model in LS-OPT is evaluated by determining how well the interpolated responses are fitted. Similar variables and responses as we will use in the large optimization problem are used here. The sheet thickness of the crash-box and the height of the end of the crash-box are used as design variables, see Figure 3. The maximum displacement of the rigidwall is used as a response and denoted intrusion. The second response is the maximum plastic strain in the supporting structure behind the crash-box after the impact.

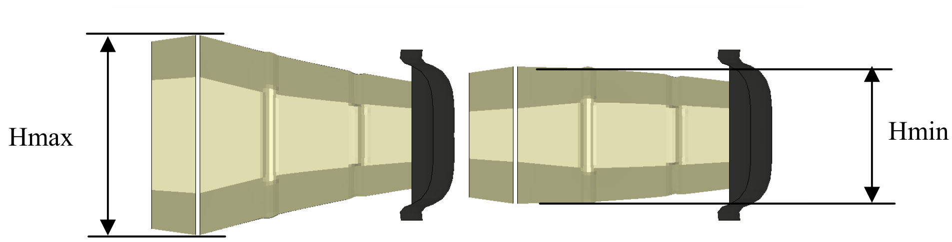


Figure 3 The change in height of the small FE model

To be able to plot how well the meta-model interpolates the responses, we run two separate optimization problems. One for each design variable, i.e. the sheet thickness and the height. LS-OPT ran for three iterations using four FE simulations for each iteration, i.e. a total of 12 FE simulations. Next a tradeoff curve is determined for each response and each design variable. This curve shows how well the meta-model has interpolated the response. Figure 4 shows how the intrusion and plastic strain depend on the sheet thickness, which is varied between 0.8 mm and 2.5 mm. The squared dots in the figures denote the simulated values and the line denotes the interpolated values. The figure shows that the interpolation is good and can capture both linear and nonlinear effects within the same interpolation function. The plastic strain is almost zero from 0.8 mm up to a sheet thickness of 2 mm and after that the plastic strain is raised to 0.85 at a sheet thickness of 2.5 mm. The Neural Networks covers all these effects well. Next the height of the end of the crash-box is varied and the trade-off curves are shown in Figure 5. Here the intrusion shows a nonlinear behaviour, which the Neural Networks covers exactly. The plastic strain is not as nonlinear as the intrusion, however the interpolation is also good for this response.

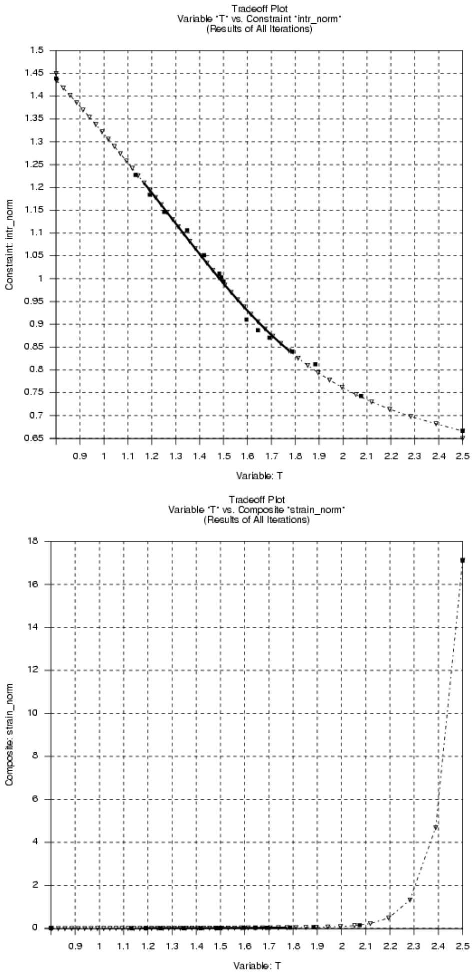


Figure 4 Trade-off curve when varying the sheet thickness, the intrusion to the left and the plastic strain to the right. The square markers are all simulated values.

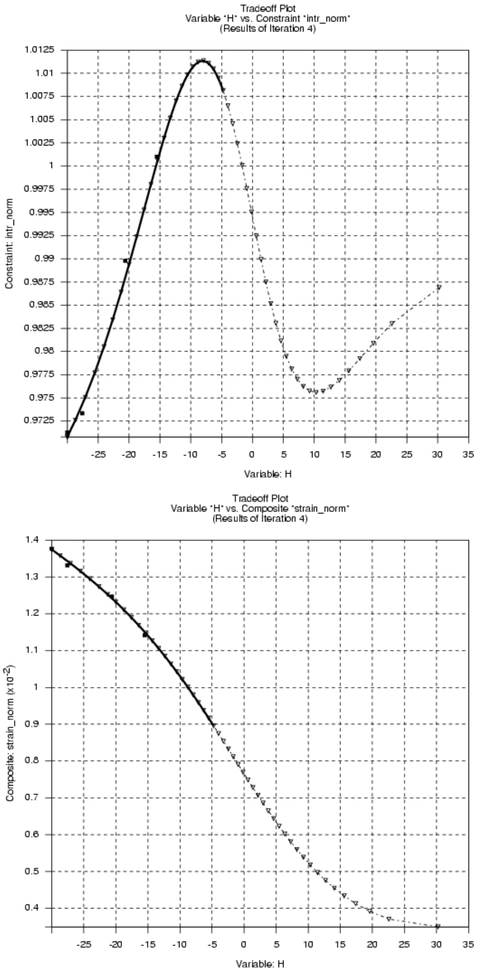


Figure 5 Trade-off curve when varying the height of the box, the intrusion to the left and the plastic strain to the right. The square markers are all simulated values.

All interpolations for all responses relative to all variables show excellent results and this can be used as meta-model for the large FE model used in the next section.

OPTIMIZATION OF THE GEOMETRY OF A CRASH-BOX USING LS-OPT WITH NEURAL NETWORKS

In this section the results from the optimization of the geometry of a crash-box using LS-OPT with Neural Networks. The FE model provided Saab Automobile, consists of 250.000 elements. It is subjected to 16 km/h impact into a rigidwall. This loading case is called Danner and it is simulated for a response time of 100 ms. The computing time was 18 hours on two Linux 3.2 GHz computers using the MPP-version of LS-DYNA version 970. The FE vehicle model used is shown in Figure 6. Figure 7 shows the deformed vehicle model at the final time state. Figure 7 also shows the geometry of the rigidwall.
For the low speed impact loading cases the insurance companies require that e.g. the headlights and engine hood must be undeformed after the rigidwall impact. Other requirements are that no other components than the most frontal ones, e.g. bumper-beam and crash-box, should be damage. This means that the

crash-rail behind the crash-box must be undeformed after the impact. Three different constraints for the optimization problem can be formulated.
Two of these constraints are exemplified in Figure 7. The first constraint is that the back of the bumper-beam should not deform the radiator. This is denoted the “intrusion y0”. The second constraint denoted “intrusion” is that the rigidwall should not deform the headlights and engine hood. Figure 7 illustrates these two constraints. The third constraint is that the maximum plastic stain in the crash-rail must be limited such that it does not need to be repaired after a low speed impact. A moderate plastic strain is allowed in the crash-rail but it should not be too large. This constraint is denoted “plastic strain”. If the crash-box collapses in a correct manner, the forces and moments applied on the crash-rail are small. All forces and moments calculated in a section directly behind the crash-box are summed to a scalar value, which is constrained in the optimization. Finally the mass is not allowed to increase from its original design. The objective is to minimize the mass of the components that are varied.

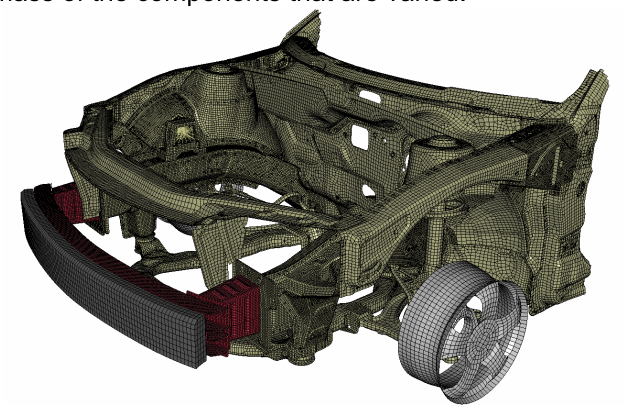


Figure 6 The vehicle model

There are three geometrical parameters, two sheet thicknesses and two material properties. The geometrical parameters are parameterized in HyperMesh using the morphing interface and all three parameters can be changed independently of each other. The first geometrical variable is the height of the front of the crash-box and the bumper-beam, which can vary between -20 and 60 mm from its initial position, see Figure 9.
The second variable is the width of the crash-box, which can vary from –25 to 45 mm from its initial position, see Figure 10. The last geometrical parameter is illustrated in Figure 11. Inside the bumper-beam it is an empty space of which the height (height space) can be varied from –15 to 20 mm. Finally the sheet thickness, the material-hardening curve of the bumper-beam and the crash-box are varied. This gives a total of seven design variables. All responses are normalized against each constraint value, such that all the constraints should have the same dimension. If LS-OPT does not find any design that fulfils all constraints, the program will find the design point that violates the constraints the least. If the response values have large differences in values, only the response with largest value might be reduced even if the violation in percentage is lower compared to the other responses.

The optimization problem is formulated as:

$$
\begin{aligned}
&\min \text{ mass} \\
&\text{s.t. } \text{mass} < 1.0 \\
&\quad \text{intrusion} < 1.0 \\
&\quad \text{intrusion y0} < 1.0 \\
&\quad \text{plastic strain } < 1.0 \\
&\quad \text{force and moment} < 1.0
\end{aligned}
\qquad
\begin{aligned}
&0.8 < t_{cb} < 2.5\ \text{mm} \\
&0.8 < t_{bb} < 2.5\ \text{mm} \\
&0.54 < mat_{cb} < 1.6 \\
&0.62 < mat_{bb} < 3.1 \\
&-20 < \text{height} < 60\ \text{mm} \\
&-25 < \text{widht} < 45\ \text{mm} \\
&-15 < \text{height}_{space} < 20\ \text{mm}
\end{aligned}
$$

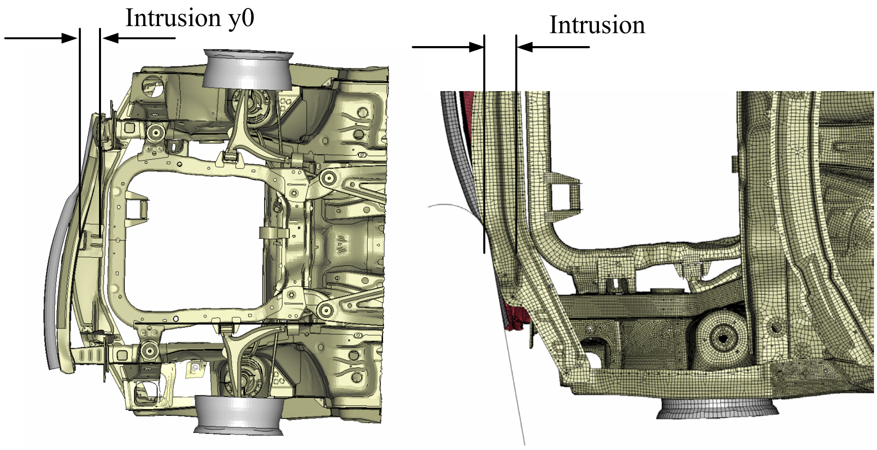


Figure 7 Bottom and top views of the maximum deformation

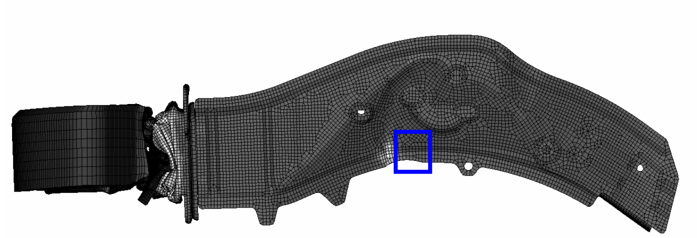


Figure 8 Fringe plot of the plastic strain. The maximum value in the crash beam is used as a response. The maximum value is found inside the box in the picture

LS-OPT ran for five iterations using 12 FE simulations per iteration. The quality of the meta-model Neural Networks was very good. Figure 12 and Figure 13 shows the computed vs. the simulated values of the responses. If the prediction is perfect, all the dots should be on the straight line in the figures. The global prediction for all responses shown in the Figure 12 and Figure 13 are good. Table 1 shows the optimum result from each iteration and Figure 14 the optimization history of the mass. Figure 15 show the optimization history of all constraints and Figure 16 shows the optimization history for the sum of all constraint violations.

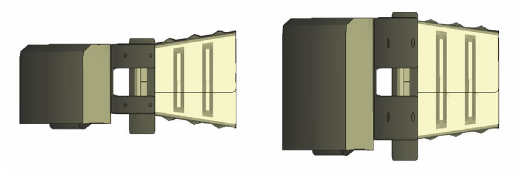


Figure 9 Example of how the beam height can vary

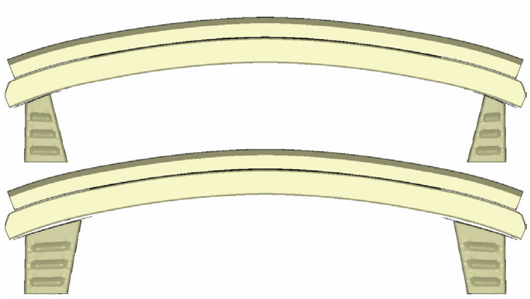


Figure 10 Example of how the height space width can vary

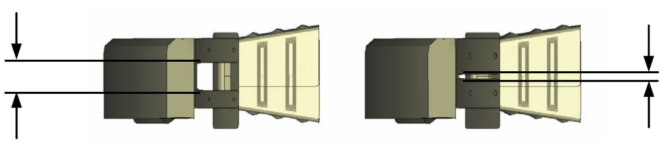
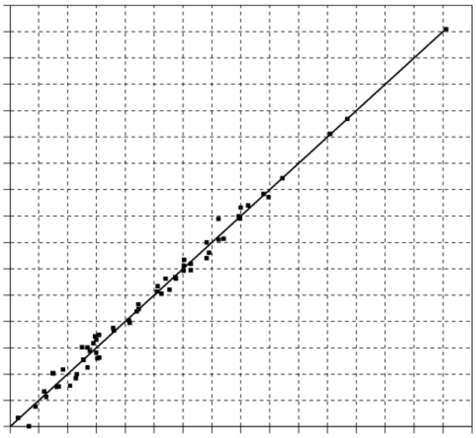


Figure 11 Example of how the height space can vary



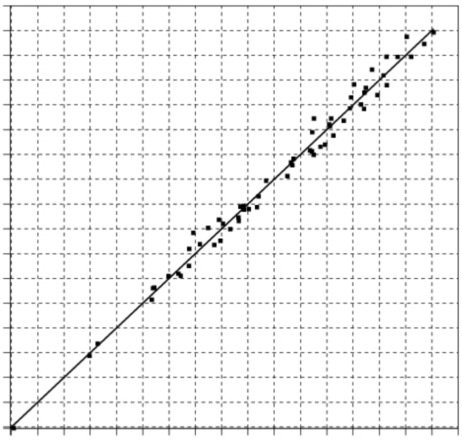
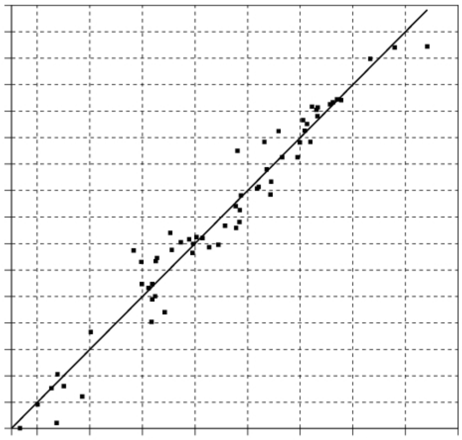


Figure 12 The computed vs. the evaluated values for the intrusion to the left and intrusion y0 to the right

The initial design of the vehicle did not fulfil all the constraints; the plastic strain was 80 % above the acceptance value and the force and moment response was 17 % larger than the constraint limit. During the optimization procedure, unfortunately the crash-rail shown to be too weak and it needs to be strengthening up using an extra component in the weak section of the crash-rail. This will be left for future work. Using the present crash-rail, no solution that fulfilled all constraints was found.



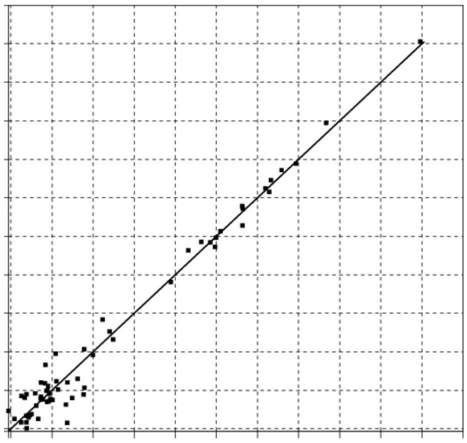


Figure 13 The computed vs. the evaluated values for the force and moment to the left and plastic strain to the right

However, in the optimum solution the mass was reduced with 20 % and the sum of all constraint violations was reduced by almost 50 %. Only the plastic strain violates the constraint limit.
The design variables that change the most from their starting points are the thickness of the bumper-beam that was reduced to 1 mm, the material curve for the bumper-beam was scaled with 80 %, the height of the crash-box was increased with 12 mm and the width was increased with 20 mm. The other design variables oscillate around each starting points but end rather close to their original values. The geometry of the box tends to be straighter, see Figure 17, compared the initial design.

Table 1 Optimization results for all responses in each iteration

Iter	Mass	Force and moment	Intrusion	Intrusion y0	Plastic strain	Sum of all constraint violations
0	1.00	1.17	0.97	1.08	1.80	1.05
1	1.02	1.38	1.15	1.46	5.30	5.29
2	0.80	1.17	1.18	1.51	2.80	2.66
3	0.84	0.94	1.06	1.18	1.54	0.72
4	0.83	1.06	1.01	1.24	1.51	0.82
5	0.80	1.04	0.95	1.00	1.50	0.54

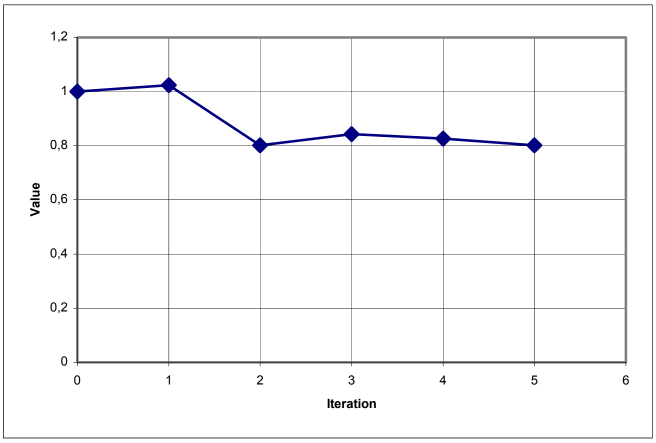


Figure 14 The optimization history of the mass

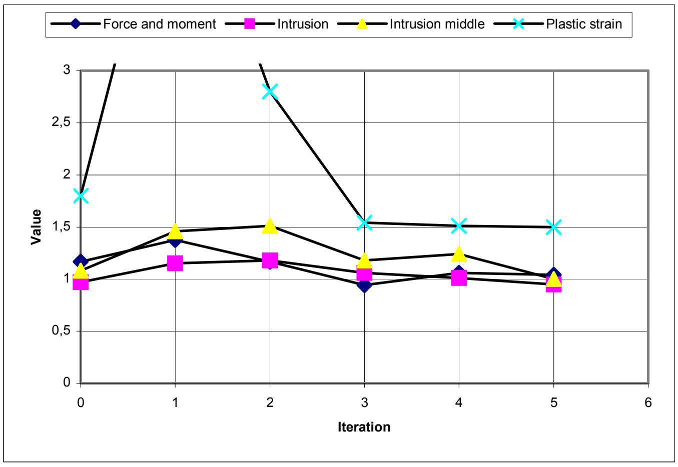


Figure 15 Optimization of all constraints. The upper limit is equal to one for all constraints

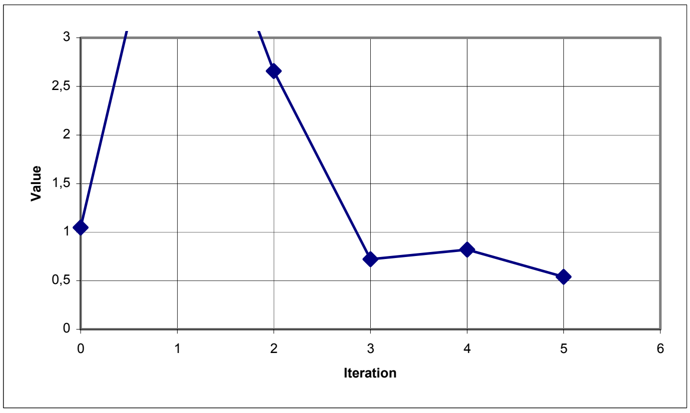


Figure 16 The optimization history of the sum of all constraint violations

The geometry of the crash-box was changed such that the height of the crash-box is a bit larger in the back compared to the front. The width increases from the back to the front. However, the geometry of the crash-box is dependent of the geometry of the crash-rail and the constraints will try to load the crash-beam such that it does not buckle.

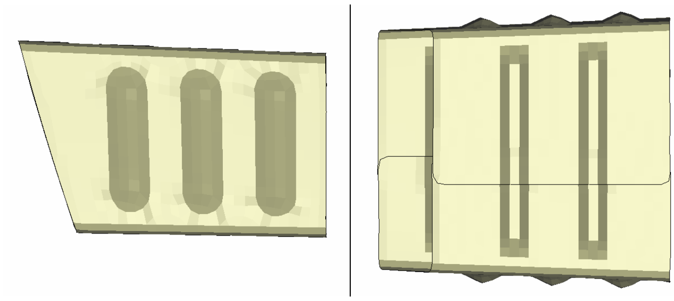


Figure 17 The geometry of the crash-box in the optimal design point. Top and left views

Summary and Conclusions

The optimization problem is solved in LS-OPT, using Neural Networks as a meta-model. The Neural Networks has been evaluated on a test example and it has shown to interpolate the responses remarkable well.
In LS-OPT version 2.2 a new interface is implemented to HyperMorph, which is a module in HyperMesh to parameterize the geometry. Using this interface, LS-OPT can automatically change the geometry. The height and width of the crash-box were parameterized and they can be varied independently of each other. The last geometry parameter is the height of an inner space of the bumper-beam. In addition to the geometry parameters, the sheet thickness and the material quality of the crash-box and the bumper-beam were also varied.
The FE model is a Saab Automobile passenger car. The objective is to minimize the mass of the crash-box subjected to two deformation constraints and the maximum plastic strain constraint in the crash-rail behind the crash-box was limited.
During the optimization procedure, unfortunately, the crash-rail shown to be too weak and it needs to be strengthening up using an extra component in the weak section of the crash-beam. Therefore no solution that fulfilled all constraints was found.
However, LS-OPT reduced the mass of the component with 20 % and at the same time reduced the sum of all constraint violations with 50 %. Only the plastic strain was violated after five iterations. The meta-modelling technique using Neural Networks showed good results with small surface approximation errors.

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