Optimization study of a parametric vehicle bumper subsystem under multiple load cases using LMS Virtual.Lab and OPTIMUS

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Summary

This paper deals with the design and optimization of a vehicle bumper subsystem, which is a key scenario for vehicle component design. More than ever before, the automotive industry operates in a highly competitive environment. Manufacturers must deal with competitive pressure and with conflicting demands from customers and regulatory bodies regarding the vehicle functional performance and the environmental and societal impact. This, in addition to the quick-time-to-market, forces them to develop products of increasing quality in even shorter time. As a result, bumper suppliers are under pressure to increasingly limit the weight, while meeting all relevant design targets for crashworthiness and safety. To succeed in such a challenging environment, manufacturers must make upfront decisions based on multi-attribute simulations directly performed on a parametric CAD.
LMS Virtual.Lab offers an integrated platform to design engineers who are challenged with multi-attribute design of mechanical structures. For the vehicle bumper subsystem of interest, engineers can start from the CAD design, define a generic assembly model, define multi-attribute simulation models and meshes, as well as multiple analysis cases. The entire process is fully associative, enabling automated iteration of design and model changes, which is key towards an efficient optimization process with OPTIMUS. The structural bumper model is created, parameterizing its geometric and sectional properties. A Design of Experiments (DOE) strategy is adopted to efficiently identify the most important design parameters. Subsequently, an optimization is performed on small-sized Response Surface Models (RSM), in order to minimize the vehicle bumper weight, while meeting all design targets.

Keywords

Vehicle Bumper Subsystem, Design Optimization, Integrated Platform, CAD Associativity, LS-DYNA, Crashworthiness, LMS Virtual.Lab, Optimus

1 Introduction

The highly competitive environment in the automotive industry drives OEMs and suppliers towards products with reduced time-to-market, while conflicting demands from customers and regulatory bodies push technical challenges to a higher level. These complex and challenging requirements are addressed by means of virtual modelling and simulation procedures that enable optimizing the performance as early as possible in the design timeline.
During the past years passive safety is treated as an attribute with increased importance. Bumper systems play an important role in the energy management of vehicles during low-speed accidents. Optimization technology and automation process enables efficient balancing between different performance attributes. In this paper, the applicability of these tools is demonstrated shown in the domain of passive safety.

2 Integrated Methodology

A methodology is developed and presented to support early balancing between different crash attributes of the vehicle bumper system. Figure 1 presents the schematic representation of the bumper optimization process, starting from geometric design. The process consists of 3 main elements. The first element incorporates design modification and pre-processing in LMS Virtual.Lab [1]. In the second phase, the impact problem is solved with LS-DYNA. The full process of the crash scenario is then captured in the third element OPTIMUS [2], which allows the process integration and design optimization of the sequence in an automated way.

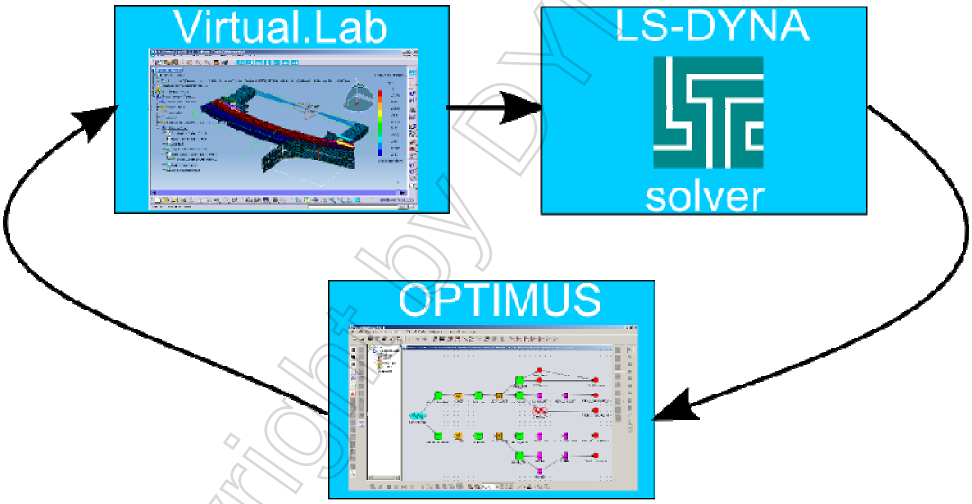
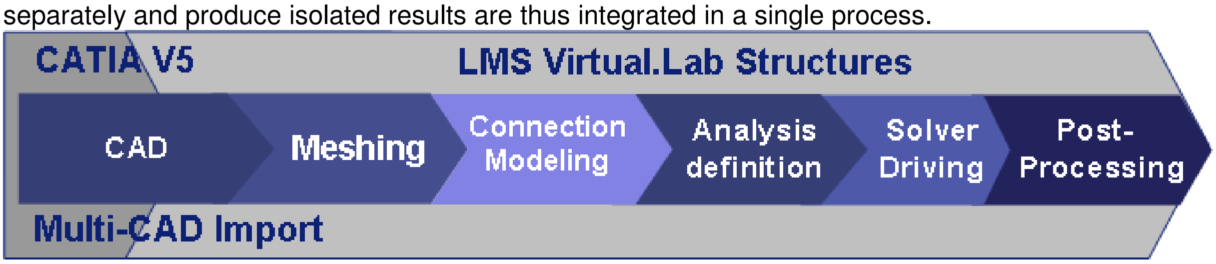


Figure 1: Schematic representation of the automated process

2.1 Integrated solution for full geometry based multi-attribute simulation

A key element in this integrated process is LMS Virtual.Lab, which addresses multi-attribute model assembly and analysis areas to perform end-to-end assessment of a design with respect to multiple performance attributes long before committing to expensive tooling and physical prototypes. Some of the key benefits in this context are listed in this section.

Integration
The LMS Virtual.Lab can be fully integrated with CATIA V5, therefore seamlessly linking CAD with CAE. It offers flexibility to run a full geometry based analysis, as well as a hybrid CAD/CAE process or a fully CAE mesh based process. The various process and simulation steps that would otherwise run separately and produce isolated results are thus integrated in a single process.



Since the process is implemented in an associative template-driven environment, the process can also be set up to be automated & run within an optimization loop. The entire analysis process is specification-driven, and any change in a parameter will trigger all the downstream processes to be updated.

Generic assembly model

Assemblies in LMS Virtual.Lab can be defined directly on the geometry or a hardpoint wireframe model, resulting in one common generic assembly model for all the possible attributes. Starting from that generic assembly, different meshing engines can be called to create attribute specific component meshes. These attribute-specific component FE representations can then be associated as to this independent assembly. Then becomes straightforward and efficient to switch from one attribute to another, e.g. to convert an LS-DYNA model meshed with ANSA for crash to a Nastran model meshed with CATIA engines for NVH.

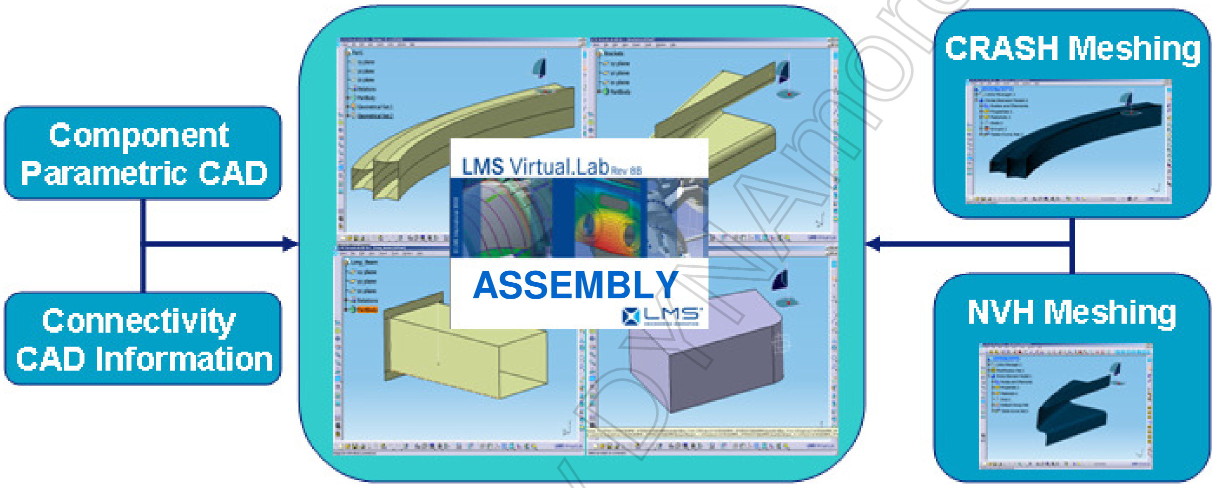


Figure 2: Generic Assembly Model

The generic assembly model becomes the new starting point for engineers to perform attribute-specific simulations. The work done to build up the assembly model does not need to be repeated for each independent attributes/simulations.

Associativity with parametric CAD

Working in an integrated environment allows to run the definition process in a fully geometry-associative way. Any parametric change in the geometry can be automatically accommodated and lead to new models for different attributes with a simple push of a button.

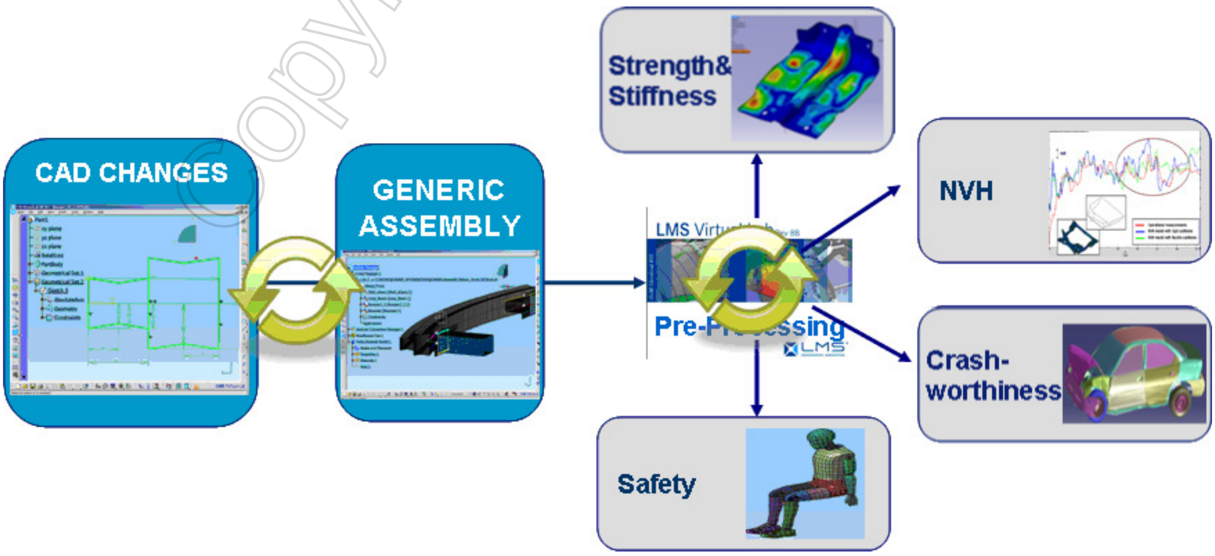


Figure 3: Update mechanism – from CAD changes to new models

The associativity enables performing fast design iterations. Through the “update” mechanism, the mesh can be updated to match CAD modifications. Subsequently, the multi-attribute analysis cases and finally the post-processed results are automatically updated. In the example in Figure 4, this capability allow to quickly study the influence of the section width of a box beam on the buckling behavior of the beam.

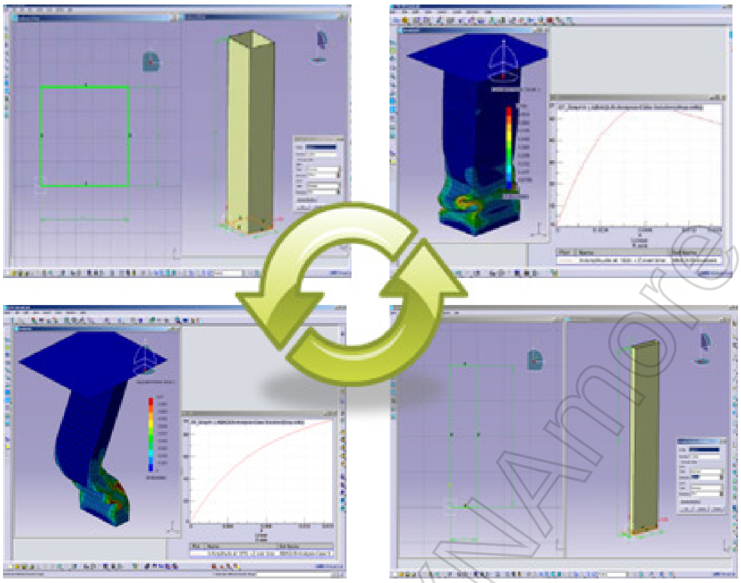


Figure 4: Example of fast iteration – Buckling behaviour

This capability enables the running of CAD optimization. Models generation for design space exploration and optimization process becomes straightforward, avoiding tedious preparation and manual mesh editing.

In summary, the integrated solution for CAD-based simulations offers the benefit of decreasing analysis time by quick model updates, by offering an integrated platform for assembly and multi-attribute analysis in mechanical engineering.

2.2 Process integration and automation for optimization purpose

In order to automate the entire design procedure from parameter changes to analysis results processing, the above process has been formalized and integrated. For the present case, the OPTIMUS [2] software package has been used to apply the selected analysis methodology and to integrate the different analysis tools for parameter pre-processing, mesh regeneration, crash analysis as well as output extraction and post-processing. The process integration workflow has enabled the automatic execution of the different analysis phases in order to automatically iterate during the optimization process and find the optimal design. This way, the generation of new combinations of input parameters can be fully automated. This integrated process captures the various tasks that are usually performed manually and automates them to reduce user intervention to the minimum.

Figure 5 shows the workflow of the multi-attribute optimization process, which has been captured in OPTIMUS, a dedicated platform solution for process integration and design optimization. It has dedicated interfaces to commercial software programs such as LMS Virtual.Lab, CATIA, LS-DYNA, ABAQUS, MATLAB… In the current case, OPTIMUS interfaces with LMS Virtual.Lab for crash analysis pre-processing and with LS-DYNA for crash analysis.

In this workflow, OPTIMUS generates new values of the design parameters, which are then fed into LMS Virtual.Lab. Since the entire process is fully integrated in LMS Virtual.Lab and associative with the parametric CAD, a new LS-DYNA model can be generated without any user intervention. In the subsequent process step, the LS-DYNA input file is passed to the crash analysis run. When the crash results are computed, outputs are read and then returned in the optimization algorithms to find the most suitable design within the admissible design space.

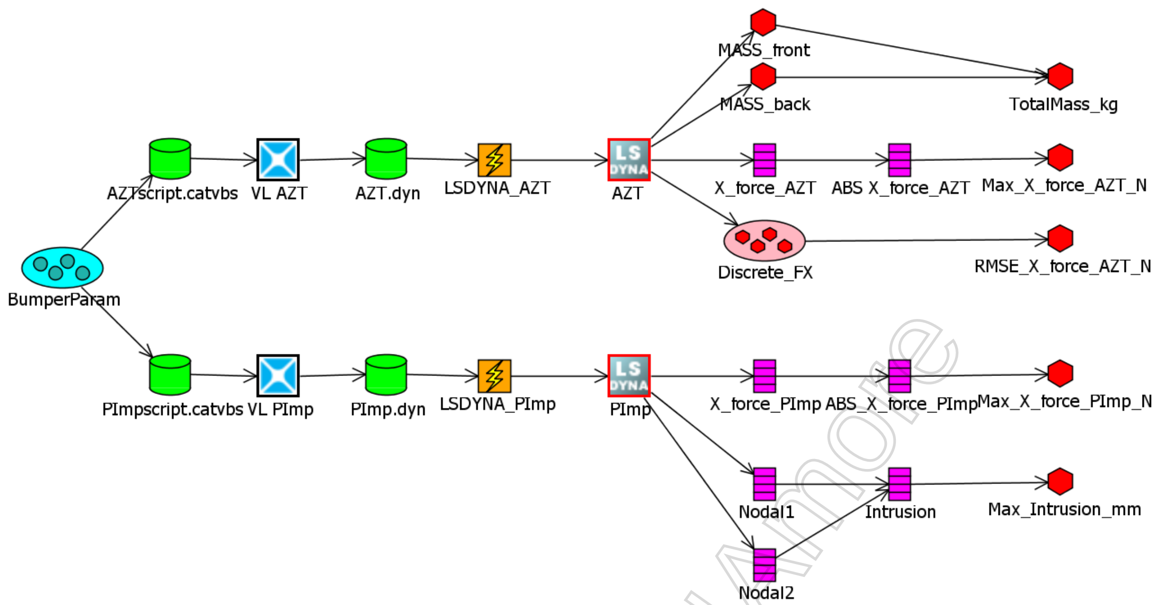


Figure 5: Process integration workflow in Optimus

2.3 Design exploration and optimization tools

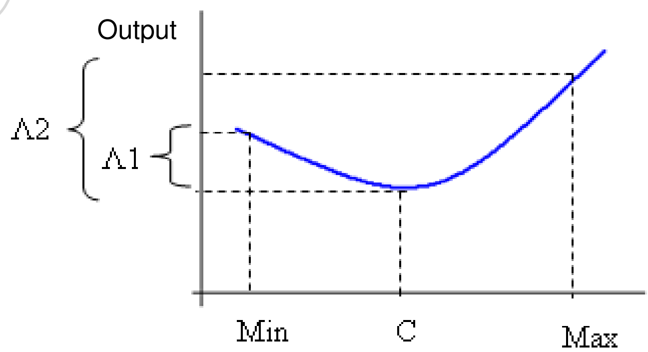
Design of Experiments (DOE)

Design of Experiments is a general approach to investigate complex relations between input parameters and output response quantities. DOE is a technique [4] that in a statistics context allows the analysis of correlations or shows the statistical significance of an effect, but it is also used for screening purposes or to build meta-models. The experiments are set up in such a way that a maximum amount of information is obtained in a minimum amount of computation time. OPTIMUS provides wide a range of DOE methods for different kinds of applications, such as factorial designs, Box-Behnken, Latin Hypercube, Taguchi or Monte Carlo sampling [3].

In the bumper optimization process, the DOE strategy is used with double purpose: on the one hand it allows the extraction of global sensitivities or so called degree of influence (DOI) [6], on the other hand, the DOE experiments serve as a basis for response surface models (RSM).

Degree of Influence (DOI)

In order to identify the most significant parameters in an optimization process, a large scale sensitivity analysis is performed. Opposed to the generally applied local sensitivity measures based on finite differences, this approach provides large-scale sensitivity information that is calculated based on DOE. Given that for each parameter ***i***, a specific output ***o*** is available at 3 different levels (minimum, centre, maximum), the variation of the output ***o*** with respect to parameter ***i*** is approximated: the large-scale sensitivity is given by $VAR_i^o = \left(|\Delta 1| + |\Delta 2|\right)$ (see Figure 6).



The DOI for each parameter-output pair is expressed with the following formula:

$$DOI_i^o = \frac{VAR_i^o}{\sum_i VAR_i^o}$$

The DOI information is used to select a subset of parameters that have strong influence on the outputs. Parameters with a minor influence can be omitted form further analysis. This way, the computational burden on the optimization is relaxed.

Response Surface Modelling (RSM)

DOE is often used to build a RSM [5]: a meta-model of a certain order is estimated from the experimental data, to build an approximate functional relationship between the input parameters and the true response. In this context, OPTIMUS offers a whole range of meta-models, from the simple polynomial approximations to more advanced Radial Basis Functions or Kriging models [3].

2.4 Multi-objective Optimization

In many cases, design engineers are faced with multiple objectives, possibly conflicting with each other, so that some trade-off between the optimality criteria is needed. Multi-objective optimization allows the solution of such problems. For this purpose two categories of algorithms exist in OPTIMUS [3]:

- methods that construct the so-called Pareto front
- methods that converge towards one compromise solution between the different objectives

In the optimization context, the Pareto front is defined as the border between the region of feasible points and the region of infeasible points. The goal of the different methods that generate the Pareto front is to find a number of points on the Pareto surface, by giving different weights to the different objectives [3].

In order to limit the total computational effort required for a full optimization process, a hybrid optimization approach has been used, taking advantage of DOE and RSM techniques. The approach used can thus be summarized in the following steps:

- Design space exploration with DOE
- Response surface modelling of the functional performance
- Multi-objective optimization, based on the response surface model
- Validation of the obtained results

The main advantage of this approach is that the calculation of the DOE generally requires a fixed computational effort that depends essentially on the number of parameters. A global or local optimization process has no fixed computational effort that can be estimated, since this depends on the satisfaction of a convergence criterion for the specified algorithm and on the dimensionality of the problem for gradient based algorithms. For the present paper, given the computational time required for one single execution of the complete analysis, the DOE approach limits the total computational effort that needs be spent. The optimization relies on the creation of response models to considerably speed up the process. To guarantee the validity of the optimum found with the efficient RSM analyses, the results of the optimization process obtained with the RSM have to be verified with a single final full simulation. This allows assessing the error between the analytical response model and the simulation analysis in the optimal point.

3 Application: mass optimization of a bumper system

To illustrate the methodology described in Section 2 of this paper, an optimization study is performed on an industrial parametric CAD bumper system. This application case has been defined by LMS and PUNCH as a representative bumper design scenario of semi-industrial complexity, which will be used in this paper to demonstrate the structural simulation optimization methodologies.

3.1 Bumper system

The bumper geometry has been taken from an industrial design practice with a mesh density that is both acceptable for the predictions of interest and also feasible in terms of computational effort.

The geometry consists of a constant cross section made of 2 chambers where all corners and fillets are removed, in order to avoid small elements during the meshing process (see Figure 7).

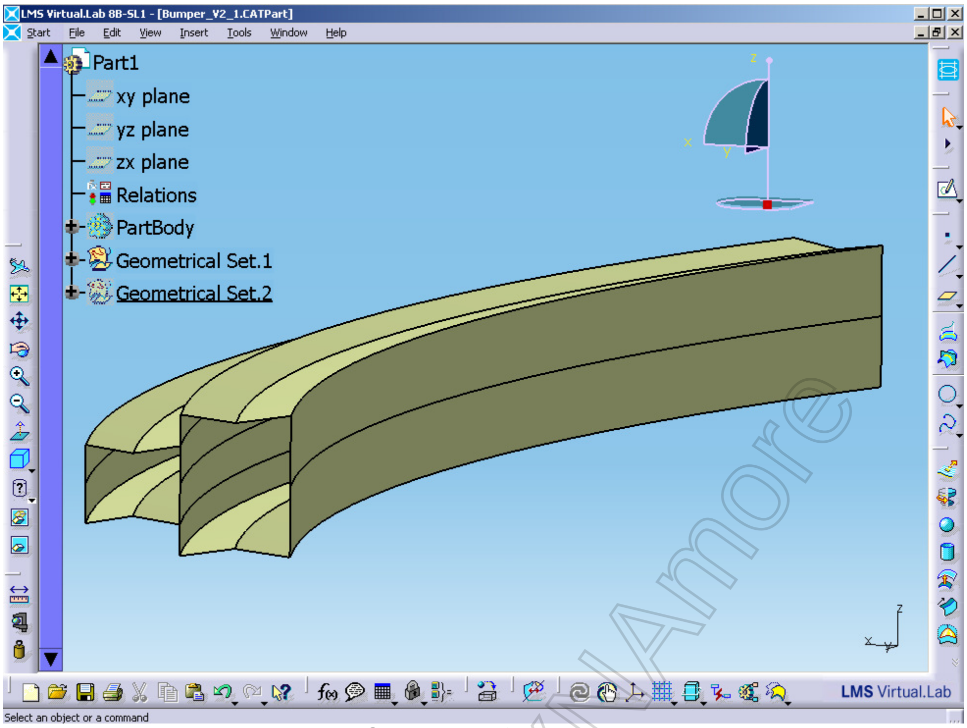


Figure 7: Geometry of the bumper beam

Subsequently, an assembly is made to connect with the bumper, the longitudinal beams through brackets. Seamweld connections are used to connect the bumper to the brackets, and rigid connections are used to connect the brackets to the longitudinal beams (see Figure 8).

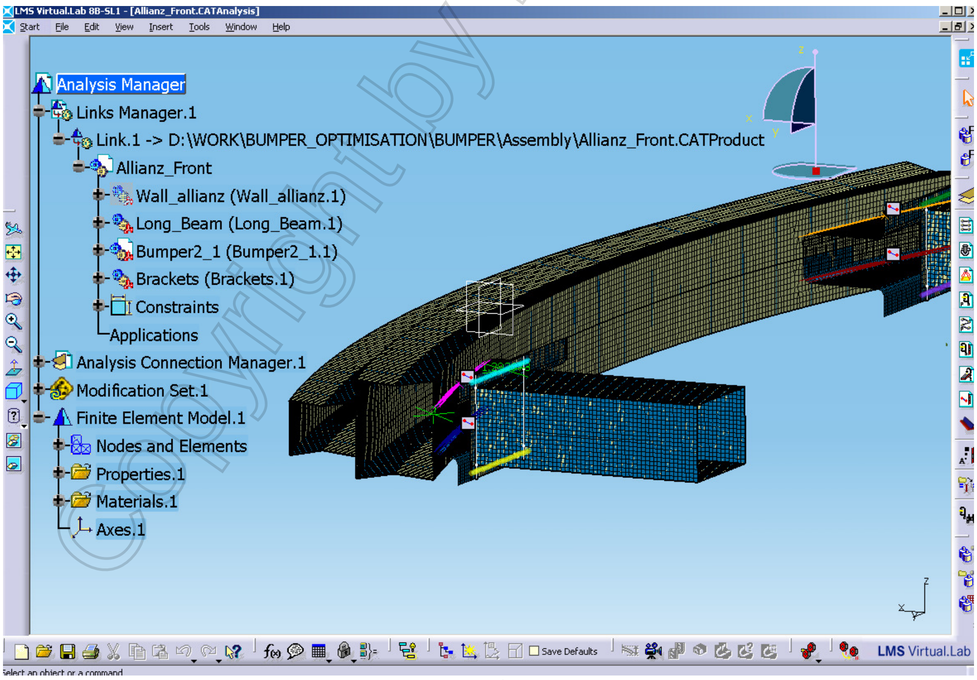


Figure 8: Assembly of the bumper system

3.2 Load cases: reparability low speed impact

2 load cases are considered for the evaluation of the crashworthiness performance of the vehicle bumper system: the Allianz crash repair test and the impact to pole test.

3.2.1 Allianz (AZT) test

The Allianz test is the most important low speed load case in the vehicle bumper design. This test aims at evaluating the reparability cost, and is used by insurance companies to determine the insurance fee of a vehicle. The more damage the vehicle will endure in this impact case, the higher the insurance fee will be. The AZT test protocol prescribes a 40% offset impact at 16km/h against a rigid barrier with an impact angle of 10 degrees (see Figure 9).

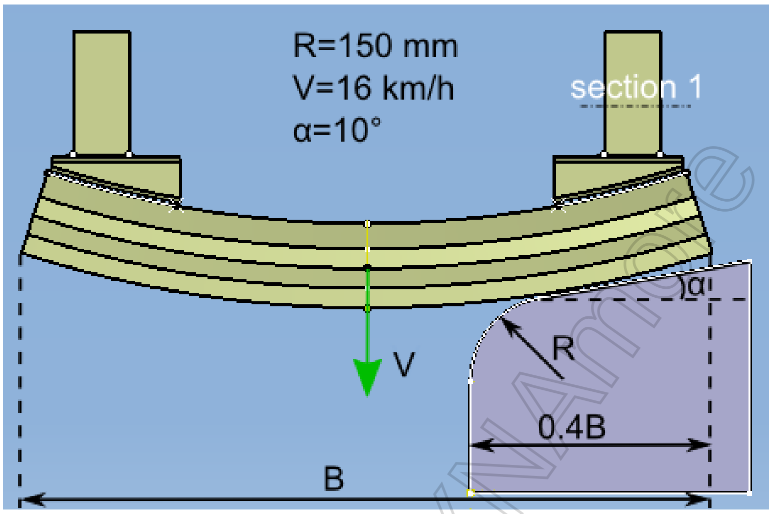


Figure 9 : Allianz front crash repair test

To minimize the reparability cost, the deformation should be limited within the bumper system and minimal load should be transferred to the longitudinal members. In particular, permanent deformation must be avoided.

3.2.2 Frontal pole-impact test

This test is used to study the intrusion during a frontal impact with a rigid pole. Similarly to the AZT test, it allows evaluating the repairability cost of the bumper system in a different typical crash scenario. The larger the intrusion, the higher the risk of damaging costly parts, such as the engine cooling system. This test consists of a 15km/h central impact against a rigid pole (see Figure 10).

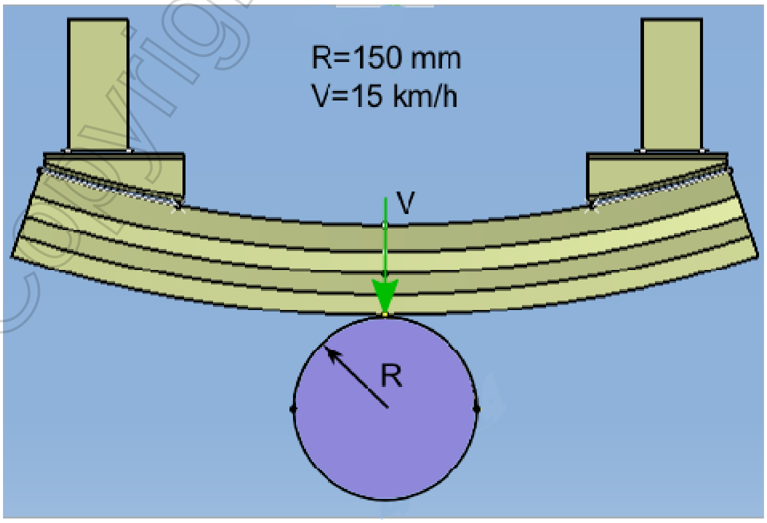


Figure 10: Impact to pole test

4 Optimization

The goal of the optimization process is to obtain an optimized bumper profile in terms of mass and Allianz test crash performance, while satisfying a set of design constraints. Multi-objective optimization ensures an optimal trade-off between the two selected objectives. At each iteration of the DOE experiments, 2 parallel analyses are performed, one analysis for each load case.

Input parameters

In order to optimize the bumper system, 9 parameters are considered. Parameters L_1, H_1, H_2, G_1, G_2, D_1 and D_2 are geometrical parameters that define the profile of the bumper, while t_1 and t_2 represent shell thickness values. The cross-sectional length of the bumper is considered to be fixed to L=150mm. The parameter ranges and the nominal values are presented in table 1.

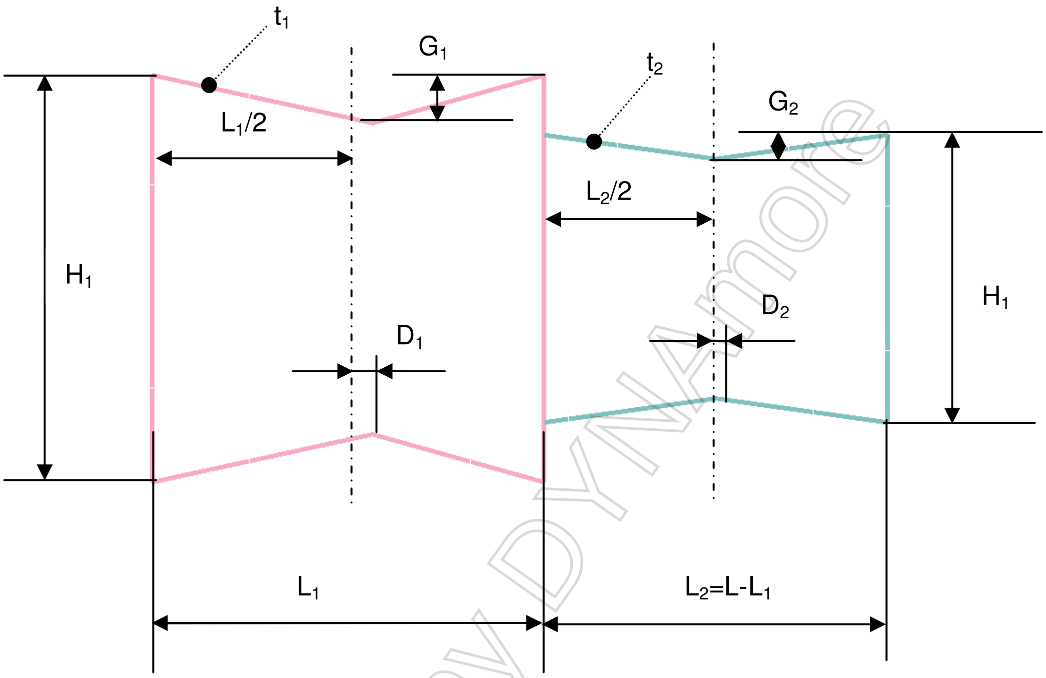


Figure 11: bumper parameters

Parameter	L_1	H_1	H_2	G_1	G_2	D_1	D_2	t_1	t_2
Min [mm]	60	70	55	5	0	-15	-15	2	2
Max [mm]	100	100	65	15	10	15	15	4	4
Nominal[mm]	85	85	60	10	5	0	0	3	3.3
Range [mm]	40	30	10	10	10	30	30	2	2

Table 1: design parameter

Objectives and constraints

Nowadays, with the increasing awareness of the environmental footprint of the vehicle, mass reduction of the different vehicle subcomponents is mandatory. Reducing the mass of the bumper is therefore the primary objective.

To optimize energy absorption potential of the bumper for the Allianz test, the deviation with respect to an ideal 85kN constant curve is considered. The target curve is the ideal force level to absorb the total kinetic energy of a 1200kg car that crashes into the rigid barrier in conformity with the Allianz test, with an initial velocity of 16km/h. The target force level is equivalent to 11,9kJ (total initial kinetic energy), based on a deformation length of 140mm (total collapse of the bumper section). The average deviation of the actual force-deflection curve from this ideal curve is expressed with the root mean squared error (RMSE) formula that is based on 10 sample points:

$$RMSE\_F_X = \sqrt{\frac{\sum_{i=1}^{10}\left(F_X^i - 85kN\right)^2}{10}}$$

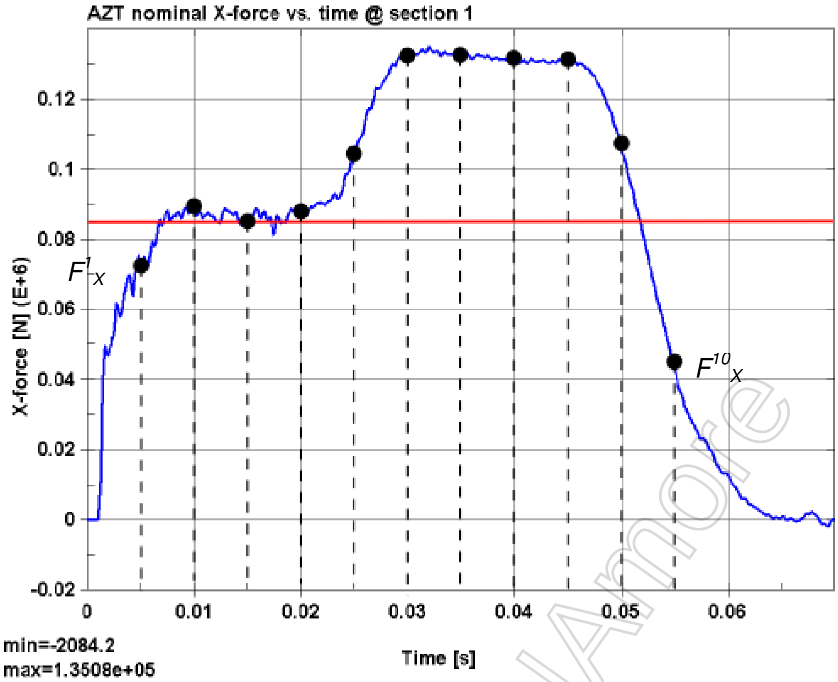


Figure 12: X force at section 1 vs. time

Figure 12 shows the AZT load case sectional force X at section 1 for the nominal bumper variant. The red line represents the ideal force curve, while the black dots represent the sampled data for the RMSE calculation.

Objectives	Abbreviation	Nominal value
Total bumper mass	Mass	5.54kg
AZT test: Root mean squared error of X force section 1 (AZT), with respect to 85kN	RMSE_F_x	33kN

Table 2: summary of the objectives

The optimization is subject to two constraints: the X force level at section 1 during the AZT test is limited to 120kN, and the intrusion for the pole impact scenario is limited to 100 mm.

Constraints	Abbreviation	Nominal value	Limit value
AZT test: highest X force section 1	Max_F_x	135kN	120kN
Pole impact test: largest bumper intrusion	Max_Int	52mm	100mm

Table 3: summary of the constraints

First screening results: DOI

In order to identify the most significant parameters with respect to the objectives and constraints, a first output screening based on the DOE is performed. The objective of this step is to reduce the number of parameters from 9 to 5. This parameter reduction results in a reduced number of experiments used as basis for the RSM. For a 3-level full factorial (3FF) design, the full set of 9 parameters would result in 19683 experiments. 3FF design based on the reduced set of parameters results in a feasible number of 243 experiments. The DOE adopted for the large scale sensitivities (DOIs), consists of a set of experiments that includes the central point and the extreme points, requiring a total number of 19 evaluations.

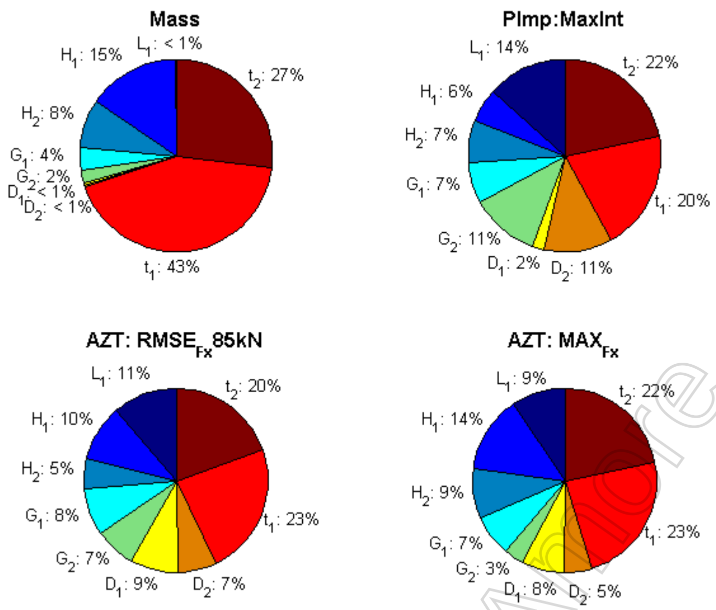


Figure 13: DOI of the 9 parameters with respect to objectives and constraints

Based on the DOI results (see Figure 13), a set containing 5 parameters is selected: L_1, H_1, H_2, t_1, t_2

DOE and RSM selection

The 5 considered parameters are used for a DOE based on 3FF design, to ensure uniform sampling of the design space. The experimental results of the objectives and constraints are then used to build a meta-model for each objective and constraint. The Radial Basis Functions-based (RBF) interpolating response models [7] are adopted for this purpose, and subsequently used in the multi-objective optimization routine.

Bumper Design Optimization

The multi-objective optimization problem is solved with the Normal-Boundary Intersection (NBI) method which searches the Pareto front that represents the set of optimal trade-off solutions [8]. The Pareto front for the bumper optimization problem is shown in Figure 13, with the 2 objectives along the 2 axes. Table 4 summarizes 5 selected Pareto-optimal solutions that are obtained with 1367 iterations based on the RSM using the NBI method.

	L_1 [mm]	H_1 [mm]	H_2 [mm]	t_1 [mm]	t_2 [mm]	Mass [kg]	Weight Mass	RMSE_ F_x [kN]	Weight RMSE	Max_F_x [kN]	Max_Int [mm]
Opt 1	60	75.6	56.7	2.29	2.89	4.38	1	19.3	0	119	94
Opt 2	60.5	75.1	55.9	2.34	2.88	4.41	0.75	17.7	0.25	119	92
Opt 3	61.5	74.4	55.2	2.44	2.89	4.49	0.5	16.3	0.5	120	88
Opt 4	63.8	74.5	55	2.62	2.94	4.68	0.25	15.1	0.75	117	80
Opt 5	73.3	82.7	55.8	2.92	2.94	5.12	0	14.5	1	107	61

Table 4: 5 different trade-off optimums

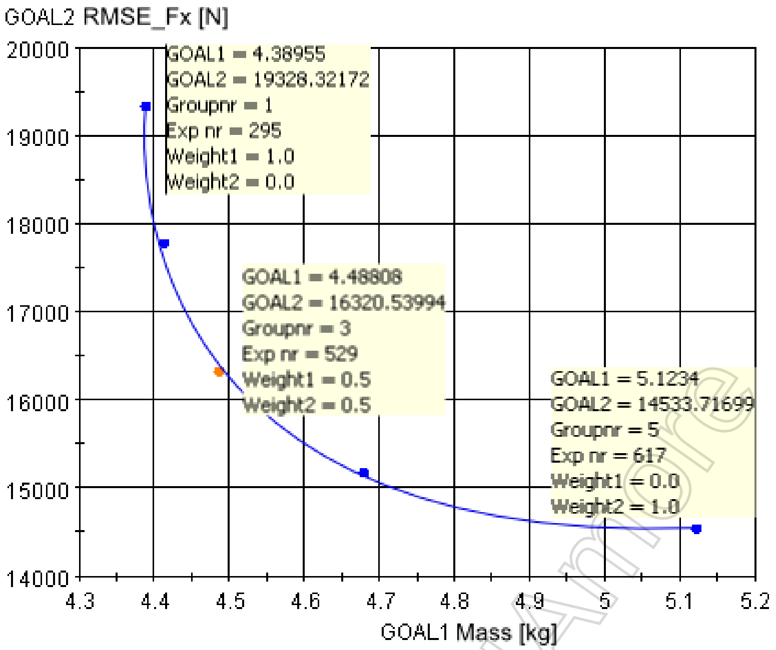


Figure 14: the Pareto front representing a range of optimal solutions

As a final step, the optimum with weight of 0.5 for both objectives has been selected and validated (see Table 5). The validation of the optimum shows some difference (13%) as compared to the RMSE objective, which indicates room for improvement of the RSM for this specific output.

	L_1 [mm]	H_1 [mm]	H_2 [mm]	t_1 [mm]	t_2 [mm]	Mass [kg]	RMSE_ F_x [kN]	Max_F_x [kN]	Max_Int [mm]
Start	80	85	60	3	3.3	5.54	33.7	135	52.5
RSM	61.57	74.43	55.27	2.446	2.895	4.49	16.3	120	88.5
Simulation	~	~	~	~	~	4.5	18.8	118.5	90.5
Relative error						0.2 %	13 %	1.2 %	2.2 %

Table 5: the selected optimum

The start and optimized geometries of the bumper are showed in Figure 15.

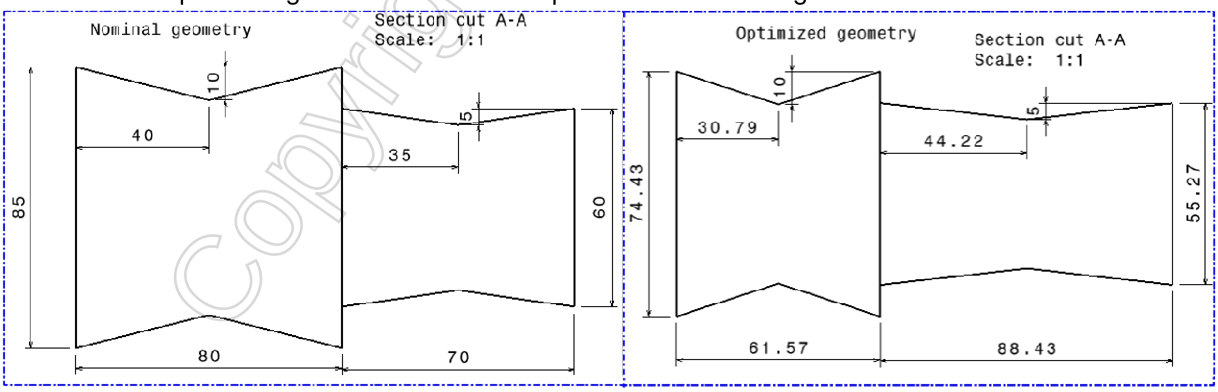


Figure 15: the initial and the optimized bumper geometries

Figure 16 compares the normal sectional force profile for both the initial and the optimized design. The optimized bumper has an improved performance: the mass is reduced with 18.7% and the RMSE of the normal sectional force as compared to the ideal force profile is reduced with 44%, while the imposed constraints are satisfied.

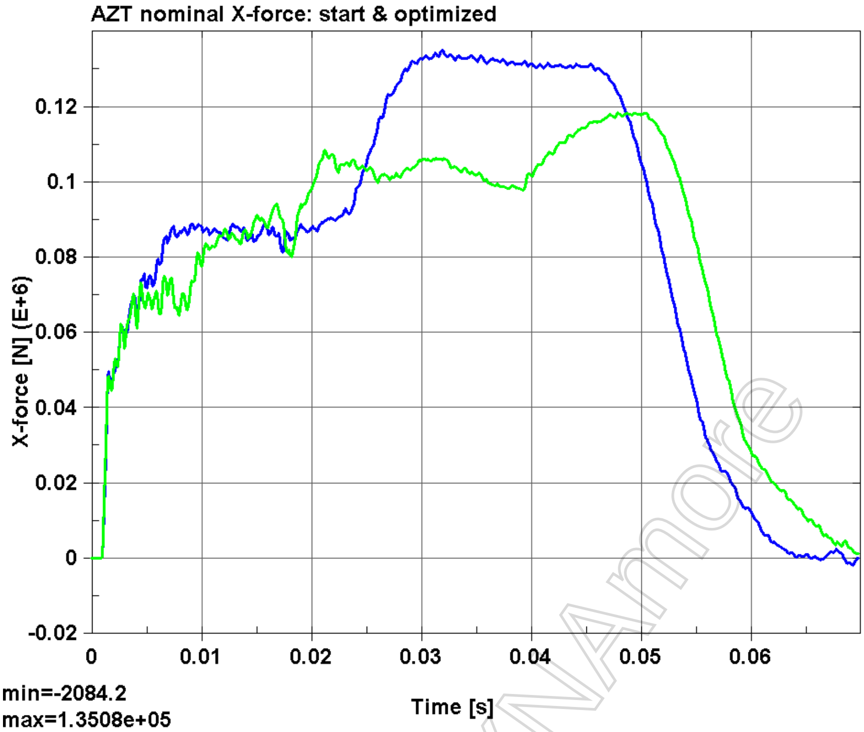


Figure 16: the original design (blue) and the optimized design (green)

5 Conclusions and discussion

This paper presents a generic methodology for automated crash performance optimization, which is illustrated on a real-case scenario. LMS Virtual.Lab offers an integrated solution for CAD-based simulations with the benefits of decreasing analysis time by means of quick model updates, by offering an integrated platform for multi-attribute system modelling for design engineers. The crash design process from parametric model modification & preprocessing in LMS Virtual.Lab and the solution of the crash problems with LS-DYNA is captured with the use of OPTIMUS. The OPTIMUS software package is a dedicated platform for process automation that enables multi-disciplinary design optimization. The automated methodology is illustrated on a vehicle bumper system that is subject to multiple load cases. It is shown that the multi-objective optimization process based on DOE and RSM significantly improves the crash performance of the bumper while reducing mass and satisfying different crash criterias.

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