Multi-Disciplinary Design Optimization for Occupant Safety: Leveraging Your LS-DYNA® Simulations

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Abstract

Automotive companies have become increasingly educated in safety related performance, setting the bar higher for automotive crashworthiness. Process Automation and Design Optimization (PIDO) tools help LS-DYNA users to reach these safer designs in a shorter period. In this paper, various application cases are used to demonstrate how PIDO tools can leverage your existing simulation codes. In the first application case, a multi-disciplinary crash optimization case, executed at an automotive company, is discussed in detail. How can you optimize systems while taking into account multiple different government safety regulations? How can you reduce the throughput time of your CPU intensive LS-DYNA simulations? How can you manage and visualize the obtained data? During the second application case, an industrial example of an A-pillar trim design optimization for occupant head safety is presented. During the optimization the variability present in actual testing conditions is also taken into account. The analysis aims mainly at minimizing head injury by using a Reliability-based approach that takes into account a probabilistic constraint formulation

Introduction

The use of Computer-Aided Engineering (CAE) programs is already standard practice in the automotive industry for many years. Functional performances like energy, mass and displacements are predicted and consecutively fine-tuned on the basis of numerical predictions, so that the expensive physical prototyping phase can be shortened considerably. But the virtual design process is based on trial-and-error. A simulation package that could automate different simulation processes and steer the design to its optimal performance would increase the efficiency during the design process.

In this article, the capabilities of a dedicated Simulation Process Integration and Design Optimization package are illustrated with multiple case studies.
The paper is organized as follows. The first section provides a description of simulation process management. It is followed by a description of different design improvement methods. The third section contains a case study focusing on a multi-disciplinary optimization. The paper is concluded with Reliability Based Design Optimization Study.

Simulation Process Management

LS-DYNA allows an engineer to perform crash simulations. However, executing these analyses has some drawbacks. First of all, for each analysis the engineer needs to execute the following steps:

1. First, updating the input decks with the new design parameters.
2. Then, executing the job, most probably on a cluster.
3. Finally, extracting the results from the various output decks once the analysis is completed.

These steps require user interaction from the engineer, except if he uses a Process Automation tool. A Process Automation tool, like OPTIMUS (reference 3), allows you to build a draft of your flowchart, defining the components of your simulation process. These components are the design parameters, the simulation input decks, the different analyses that needs to be completed, the output decks with results extraction rules and the outputs scalars and vectors of interest. A big advantage is the visualization of the flowchart, which makes it immediately clear which components are part of the simulation process. An example of a flowchart is shown in Figure 1. This figure shows the integration of static, NVH and 5 crash simulation codes together with the post-processing tools. This simulation process is executed on a cluster of hundreds of CPUs, reducing the throughput time considerably.

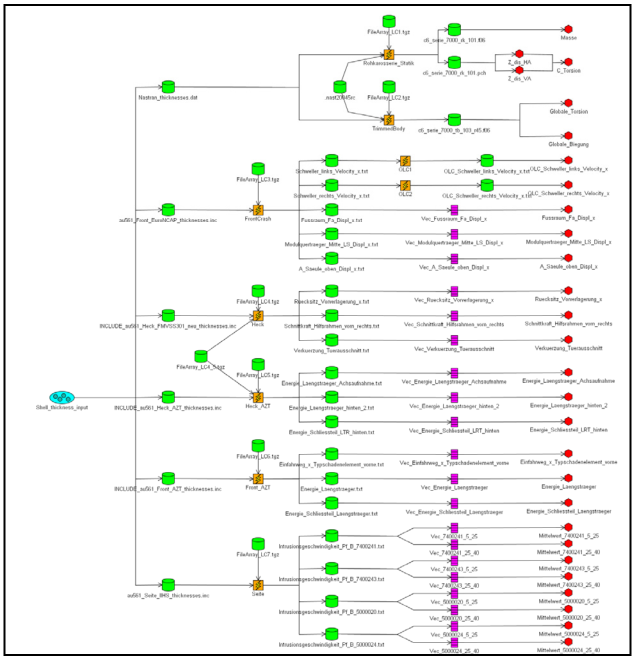
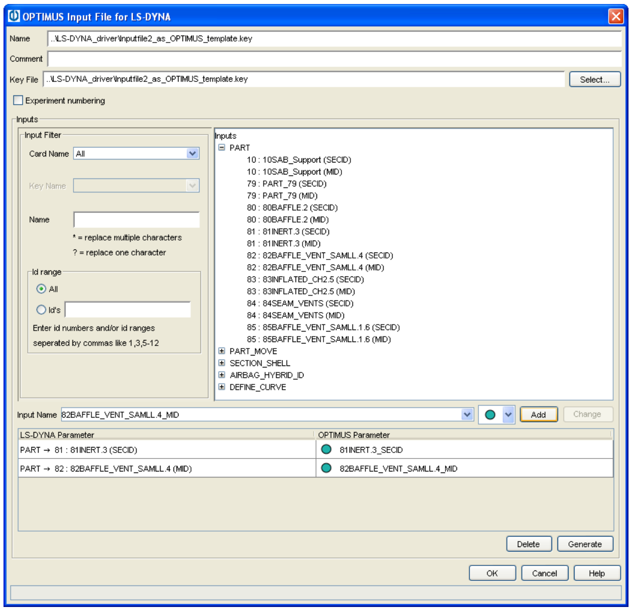


Figure 1: A Corporate Crash Simulation Process Example

Secondly, standard process automation tools integrate simulation codes by manual defining the parameters inside the input deck and the extraction rules in the output deck. However, this can become a tedious job for LS-DYNA simulations with many output vectors that need to be extracted. Therefore, the direct graphical user interface to LS-DYNA that is included in OPTIMUS facilitates the integration process because it enables the definition of the input parameters and output vectors or scalars interactively. Once the selection of the required parameters and outputs is completed, the flowchart is automatically created in the OPTIMUS environment. An example of the LS-DYNA interface is shown in Figure 2.



OPTIMUS Input File for LS-DYNA

Name: ..\LS-DYNA_driver\Inputfile2_as_OPTIMUS_template.key
Comment:
Key File: ..\LS-DYNA_driver\Inputfile2_as_OPTIMUS_template.key

☐ Experiment numbering

Inputs

Input Filter
Card Name: All
Key Name:
Name:
* = replace multiple characters
? = replace one character

Id range
● All
○ Id's
Enter id numbers and/or id ranges
seperated by commas like 1,3,5-12

Inputs
- PART
  - 10 : 10SAB_Support (SECID)
  - 10 : 10SAB_Support (MID)
  - 79 : PART_79 (SECID)
  - 79 : PART_79 (MID)
  - 80 : 80BAFFLE.2 (SECID)
  - 80 : 80BAFFLE.2 (MID)
  - 81 : 81INERT.3 (SECID)
  - 81 : 81INERT.3 (MID)
  - 82 : 82BAFFLE_VENT_SAMLL.4 (SECID)
  - 82 : 82BAFFLE_VENT_SAMLL.4 (MID)
  - 83 : 83INFLATED_CH2.5 (SECID)
  - 83 : 83INFLATED_CH2.5 (MID)
  - 84 : 84SEAM_VENTS (SECID)
  - 84 : 84SEAM_VENTS (MID)
  - 85 : 85BAFFLE_VENT_SAMLL.1.6 (SECID)
  - 85 : 85BAFFLE_VENT_SAMLL.1.6 (MID)
- PART_MOVE
- SECTION_SHELL
- AIRBAG_HYBRID_ID
- DEFINE_CURVE

Input Name: 82BAFFLE_VENT_SAMLL.4_MID

LS-DYNA Parameter	OPTIMUS Parameter
PART → 81 : 81INERT.3 (SECID)	● 81INERT.3_SECID
PART → 82 : 82BAFFLE_VENT_SAMLL.4 (MID)	● 82BAFFLE_VENT_SAMLL.4_MID

Figure 2: OPTIMUS for LS-DYNA

Thirdly, the standard LS-DYNA environment does not support studies with different crash scenarios. Using Process Integration software, studies with different crash scenarios can be performed while taking into account different government regulations. Furthermore, post-processing tools and other simulation codes, like NVH and static analyses can be integrated as well. Once the simulation process is defined, the simulation codes can executed automatically for new sets of parameters values. An example of a multi-discipline flowchart is shown in Figure 1.

Design Improvement Studies

Once the simulation process is automated, various methods can be used to improve the design. Methods like Design of Experiments, Response Surface Modeling techniques, Single and Multi-Objective Optimization and Design for Six Sigma are all available in OPTIMUS. Together with included powerful post-processing tools, PIDO software enables the user to find the best possible design.

Design of Experiments

The engineer selects a pre-defined experimental plan to sample the Design Space. The design space is determined by the ranges of the Design Factors. There are many different methods to distribute the values of the input variables. Well known Design of Experiments methods are 2-level and 3-level Full Factorial, Taguchi, Box-Behnken and the Latin Hypercube method. Some of them are shown in Figure 3.

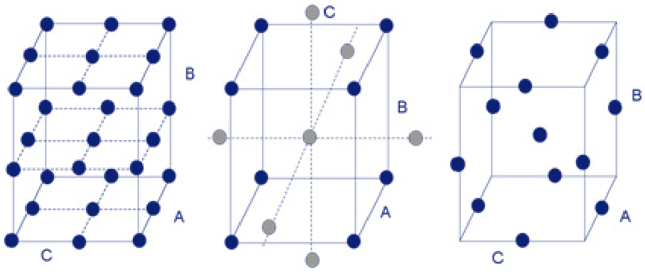


Figure 3: Some of the Design Space Sampling Plans

Response Surface Modeling

The obtained results from a Design of Experiments can be used to build an approximation model or a Response Surface Model. A response surface is a mathematical model which describes the relationship between the experimental factors (inputs) and the values of one or more experimental responses (outputs). Subsequently, the Response Surface Model enables rapid analyses to get a better insight in the design problem. An example of such Response Surface Model is shown in Figure 4.

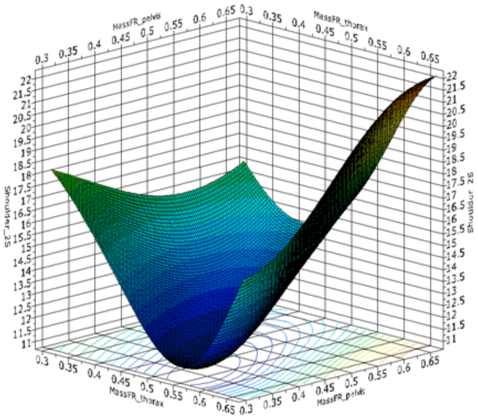


Figure 4: A Response Surface Model Example

Optimization

Optimization algorithms change the design parameters to improve the design requirements. A single objective optimization, a target optimization (calibration) or multi-disciplinary optimization can be possible. If required, the user can define constraints which identify the feasible domain. The design parameters of the optimization can be continuous or discrete. Various different optimization methods are available like local (gradient-based) or global (evolution or genetic-based) algorithms.

Reliability-Based Design Optimization

The traditional deterministic optimization model is used to systematically improve the system design process, yielding a reduction of the costs and an improvement of the final quality of the products. However, variation in either engineering simulations and/or manufacturing processes can exist. A reliability-based design optimization (RBDO) for robust and cost-effective designs is defined by using mean values of the random system parameters as design variables and optimizing the cost subject to prescribed probabilistic constraints (e.g. a maximum on the allowed probability of failure). As a result, the RBDO solution provides not only an improved design but also a higher level of confidence in the design, as is shown in Figure 5.

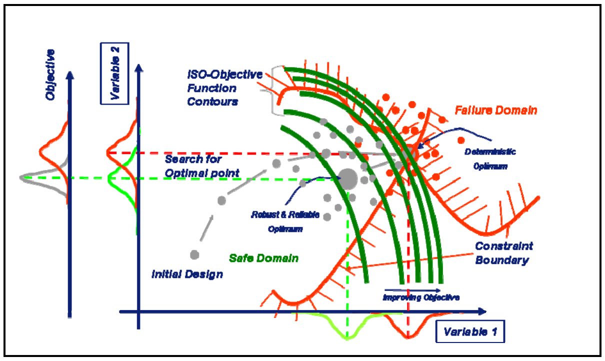


Figure 5: The Reliability-Based Design Optimization effect

Application Case 1: Multi-Disciplinary Optimization

The first case describes the optimization of a side impact occupant restraint system to meet performance requirements for the New FMVSS 214, the SINCAP and the SICE crashworthiness test modes. The parameters of the air bag and the door liner are optimized for the restraint system. The complete details of this application case can be found in reference 1.

The first step is the integration of the different crashworthiness test modes in OPTIMUS in order to automate the crash simulation process. If a new set of design parameters is defined, these values are automatically added to the LS-DYNA input decks, submitted to the 256 CPU cluster and executed, and the occupant injury criteria are extracted from the different result files.

After the automation of the workflow, a Design of Experiments study was performed to screen out the most dominant input variables. After the completion of this study, 33% of the parameters are removed from the optimization problem, as they didn’t have a big effect on the injury criteria.

The final step of the project is the optimization of the occupant restraint system. The purpose of the optimization is to find a design that meets all the injury criteria. At the end of the optimization, 11 designs are identified which meet the requirements. In total 72 different designs were evaluated, which means in total 216 different LS-DYNA runs.

Application Case 2: Reliability-Based Design of Automotive Interior Trimming

Problem Description

Currently, the automotive industry is dedicating much attention to improve product quality and reliability through a virtual simulation environment. Safety and robustness are becoming of increasing importance for the customer who is paying much more attention to these issues than in the past. Also the non-structural components, like interior trimming elements, are relevant to reduce the possible damage to the vehicle passengers. More details of this application case can be found in reference 2.

This paper presents an industrial example of an A-pillar trim design optimization for occupant head safety based on standard regulations, taking into account typical variability. Focus is given to the polymeric material variability, which originates mainly from slight variations in production and manufacturing processes, from the challenging testing conditions at high speeds and from large deformations. The structural part of the vehicle body is modeled as a fixed metal part, and the A-pillar is constrained rigidly at the joint locations, which have not been modeled in detail (see Figure 6). However, this does not pose restrictions on the validity of the simulation results for the particular analysis case.

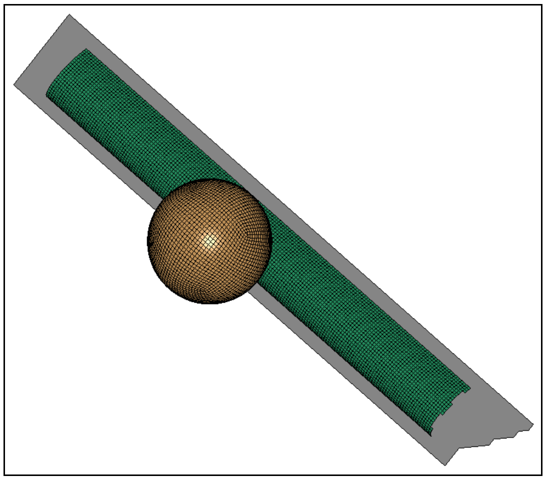


Figure 6: Trim Pillar/ Headform FE Model

Reliability Based Design Optimization Problem

It is always necessary to achieve a compromise between the number of parameters and the desired accuracy of the results. For the considered analysis model, this section describes the set of inputs and output which have been selected for further use, and gives some details on the process workflow.

Table 1 shows the three probabilistic variables that are modeled. Two of these variables, namely the stress-strain curve scale factor and impact velocity, are considered to be environmental variables, for which the mean value cannot be changed in a design process. Therefore only the mean value of the rib thickness has been considered as a design parameter in the reliability based optimization.

Designation	Distribution	Mean Value	Standard Deviation
Ribs thickness	Normal	1 (mm)	0.031
Stress-strain curve scale factor	Normal	1	0.017
Impact velocity	Normal	6700 (mm/s)	70

Table 1: Probabilistic Description of the Inputs

The objective is the HIC(d) value, on which the following constraint is imposed:

$$\text{HIC(d)} < 1000$$

Process Integration and Design Optimization

The process integration chart with OPTIMUS is shown in Figure 7

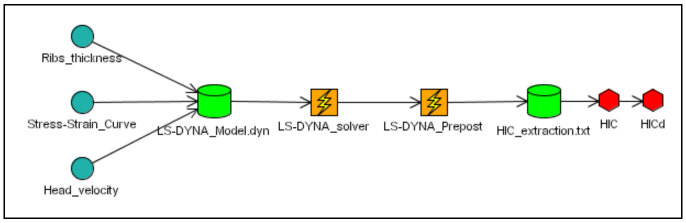


Figure 7: The Crash Simulation Process

The following procedure has then been used for the analysis

1. Compute the response behavior of the structure with DOE;
2. Compute the best fitting Response Surface Model (RSM) using DOE results;
3. Reliability assessment of the nominal design point using the RSM;
4. Reliability assessment of the nominal design point using FE simulation;
5. Deterministic Optimization on the RSM;
6. Reliability assessment of the optimal design point using the RSM;
7. RBDO using the RSM;
8. Results comparison.

The details of the results can be found in reference 2.

Summary

In this paper, the advantages of a using a dedicated Simulation Process Integration and Design Optimization package for LS-DYNA simulations are illustrated with two case studies.

In the first application case, a multi-disciplinary crash optimization case for an automotive company is discussed in detail. It illustrated that the without the help of the process integration and design optimization tool OPTIMUS, the execution of 216 different LS-DYNA runs over a cluster required optimization study would have been an impossible and unmanageable challenge. In addition, it was possible to take into account multiple different government safety regulations and manage and visualize the obtained data effectively.

In the second application case, an industrial example of an A-pillar trim design optimization for occupant head safety was presented. During the optimization the variability present in actual testing conditions was also taken into account. The analysis was mainly aimed at minimizing head injury. This application case illustrated that the use of OPTIMUS with LS-DYNA simulations enables efficient reliability studies that can take into account a probabilistic constraint formulation.

References

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[4] LS-DYNA version 970 Keyword user's Manual