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Title Story // Bosch – first key user of optiSLang

Methods for optimization of air cooled surface topologies

optiSLang v5

Robust optimization of automotive suspension designs

Model calibration for analyzing film copper

Optimization of valve geometries in the launcher Ariane 5

RDO-JOURNAL

optiSLang

multiPlas

ETK

SoS

CAE-BASED RDO – AN ESSENTIAL PART OF COMPETITIVE PRODUCT DEVELOPMENT

Already in 2002, Dynardo's first key customer, Robert Bosch GmbH, started with initial parametric optimization and robustness analysis using optiSLang to partially replace expensive hardware tests and to gain more product understanding.

Nowadays, our customers face an ever increasing complexity in product development which demands new effective simulation based approaches regarding quality aspects, robustness, production cost and time to market. The variety of manufacturing, assembly and condition has to be considered with sufficient reliability under scattering environmental circumstances. In order to cope with these requirements and to stay competitive on the international market, the engineer has attractive options at a comparatively low cost level by using the advantages of parametric simulation based RDO. It can be used to better understand the design by conducting a sensitivity analysis, to improve the design by using methods of optimization and to validate the product quality by conducting a stochastic analysis. If CAE-based optimization and robustness evaluation are combined, we are speaking of Robust Design Optimization (RDO), which may also be called "Design for Six Sigma" (DFSS) or just "Robust Design" (RD).

In this process, it is crucial to connect parametric CAD and CAE to one parametric multi-physics simulation workflow with provided interfaces and a flexible integration of different CAX environments. Then, connected with state-of-the-art algorithmic implementations, best practice defaults and wizard-guided procedures, an improvement of the product combined with quality assurance will be achieved.

The openness of Dynardo's software optiSLang regarding parametric modeling environments as well as the automated algorithmic modules of sensitivity analysis, multi-objective optimization and robustness evaluation provide the user with a maximum amount of potential for product improvement, process traceability and quality monitoring. Furthermore, optiSLang provides unique algorithms like the Metamodel of Optimal Prognosis (MOP) to determine the most important correlations between parameter input variation and output results. This can be used as a meta-model for CAE-calculations in optimization procedures or robustness evaluation. The Coefficient of Prognosis (CoP) assures a predictable and reliable forecast of response variation and minimizes necessary solver calls.

In this edition, we would like to share the practical experience of our long-term customer Robert Bosch GmbH regarding the application of CAE-based RDO and the process implementation of optiSLang. For more than 13 years, Bosch has been gaining an extensive knowledge in parametric optimization and stochastic analysis in virtual product development.

Apart from that, we again have selected case studies and customer stories concerning CAE-based Robust Design Optimization (RDO) applied in different industries.

I hope you will enjoy reading our magazine.

Yours sincerely

Johannes Will
Managing Director DYNARDO GmbH

Weimar, October 2015

CONTENT

ROBERT BOSCH GMBH – FIRST KEY USER OF OPTISLANG

For more than 13 years of application, Bosch has been gaining an extensive experience of parametric optimization and stochastic analysis in virtual product development.

Methods of CAE-based optimization and stochastic analysis have become key technologies in parametric simulation. Thus, designs can be already tested and improved under the consideration of scattering properties in the development phase in order to reduce the number of hard ware tests and time to market. Beside parametric CAE models, state-of-the-art algorithms, a high degree of automation and the availability of powerful hardware is a crucial requirement for a successful implementation of parametric optimization in CAE - processes.

In an interview given in 2004 (first published in Simulation, 1/2004, page 78-79), Roland Schirrmacher (Corporate Sector Research and Advance Engineering at Bosch) defined the requirements for CAE software as follows:

The most important criteria are the functionality and the features of the software followed by operating stability and user-friendliness. The complex industrial tasks require sophisticated methods using various approaches and achieving a significantly improved design with a minimum number of iterations.

At that time, Mr. Schirrmacher said about the application of optiSLang at Bosch:

In the field of optimization, all methods implemented in optiSLang have been used successfully. As a first step, a Design of Experiment (DoE) scheme is often generated to obtain initial information about component behavior from the response surfaces and to possibly eliminate unnecessary parameters. Utilizing these response surfaces, several improved designs are simulated afterwards by using gradient or evolutionary strategies. These can be taken as starting designs for a gradient-based optimization or as an initial population. This procedure has proven especially successful in an optimization using improper initial designs and under highly nonlinear conditions.

The graphical user interface of optiSLang is designed intuitively and does not make high demands on the user providing a step by step procedure of necessary input. The most complex part of the task definition is to build the parameterized model and to connect all programs or commands associated to the workflow in one script. Bosch insisted to reference only this script during the development of optiSLang in order to guarantee the flexibility for a variety of tasks.

Robert Bosch GmbH was the first key customer in the industrial use of optiSLang. The application started in 2002

as a research project and since has been developed over the years to an integral part in the virtual development process at Bosch. Applications include et al.:

- Simulation of loads and durability regarding electric drives in vehicles
- Simulation of the behavior of design elements exposed to thermal loads
- Reliability analysis
- Realistic simulations of dynamic designs including material models
- Robustness evaluations toward scatter, such as manufacturing tolerances
- Parameter identification for the calibration of material models
- Optimization and robustness evaluation during the simulation of mechanical systems
- Virtual product design
- Sensitivity analysis of product life based on parametric models
- Multiobjective optimizations

In May 2015, Dynardo visited Mr. Schirrmacher and two of his colleagues in Stuttgart to take stock again regarding the use of optiSLang and the cooperation between Dynardo and Bosch.

**Since when have you been using optiSLang in the product development process at Robert Bosch GmbH?**
The test phase of optiSLang started in 2002 with basic research and setting up software tools like ETK, optiPlug for ANSYS or Optiqus-Plugin for coupling parametric CATIA-Models with Abaqus/CAE. After this phase was successfully finished, we began to implement the software into the product development process at Bosch. The first fields of application dealt with injector development and power tools. Meanwhile, optiSLang has been utilized in almost all business units of Bosch.

What were the reasons for Bosch to decide in favor of optiSLang?
optiSLang was chosen out of three software products after a benchmark in the automotive industry in 2001. At that time, a major reason was that optiSLang had already implemented all essential methods, for example, Design of Experiment, meta-models or procedures of optimization, robustness and reliability. This also applied to the design variable types which could be processed ranging from binary to real and integers. Another reason for our decision was that Dynardo allowed us to directly influence the software development combined with a fast and service-oriented support. The contact with the development department and the resulting short paths of communication are still reasons for the close and successful cooperation. We also appreciate the flexible and open licensing models provided by the company.

What are the most important applications of optiSLang at Bosch?

The first fields of application were in structural mechanics combined with the CAE programs Abaqus and ANSYS. Later projects were added in electrodynamics, fluid dynamics and thermodynamics. In recent years, optiSLang has been increasingly used regarding multibody simulation models as well as system models from Matlab or AMESim. Besides the application to product development, optiSLang is often used for parameter identification of material properties. Also
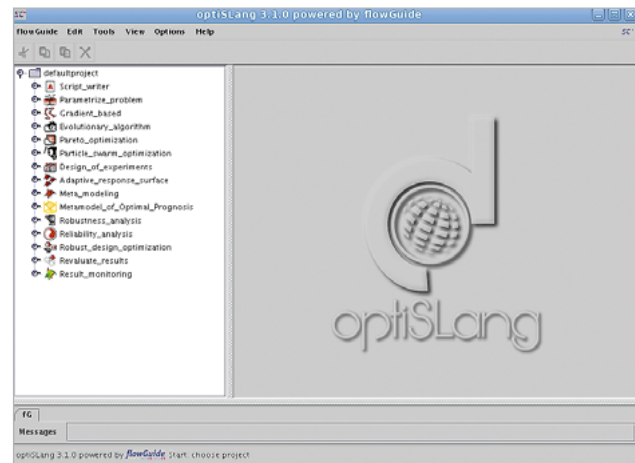

Start window of optiSLang 3

in the advanced development, optiSLang workflows are implemented for model development, pre-standardization by tolerance analysis, functional analysis as well as robustness evaluation. In the design of electric motors, optiSLang is part of the standard process for sensitivity analysis, optimization and robustness evaluation of, for example, eccentricity, brush running or other motor characteristics. In collaboration with the manufacturing, investigations of production tolerances along with evaluations and data analyses regarding correlations and parameter dependencies are conducted.

Which methods and workflows are used most intensively?
The most common applications are sensitivity analyses and robustness evaluations. optiSLang is also increasingly used for the generation of meta-models in order to efficiently describe the phenomena occurring in complex and extensive simulation tasks, to use them in system simulation as well as to draw conclusions for the optimization. During the advanced development process, sensitivity analyses regarding scattering parameters are conducted for a better product understanding and for setting the base to conduct multi-objective optimizations.

What are the main benefits from the use of optiSLang in the virtual product development at Bosch?
By using optiSLang, we obtain a much better product understanding regarding the product robustness, sensitivities as well as the potentials for optimizations and their boundaries. Thus, we can specifically improve the product performance during the development stage to come up with an already optimized initial
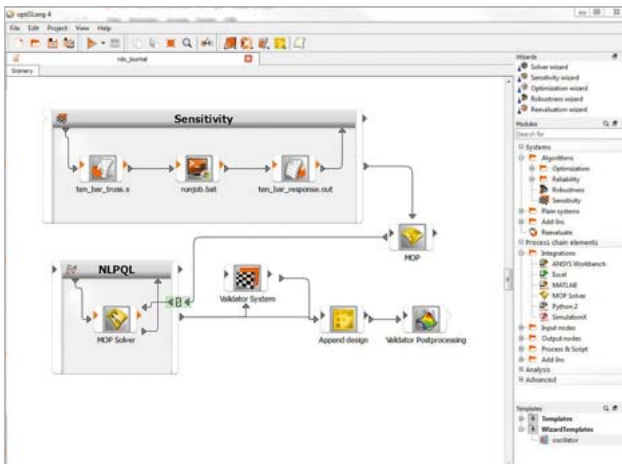
Graphical user interface optiSLang 4

sample saving a lot of time and money in prototyping. In complex multi-domain application, optiSLang also finds optimal designs which have not been found by experts. By taking into account scattering effects, which is hardly or not at all possible in hardware tests, we can determine and evaluate product robustness and limiting samples a lot more accurately and faster. The saving of extensive tests regarding product life and durability especially accelerates our development process considerably.

How important are the issues of process automation and integration?

Due to the importance of these issues, there has been a cooperation to improve process automation and integration capabilities in optiSLang between Bosch and Dynardo for quite some time. The main benefits are the control of system complexity and the standardization of the workflow management. Here, the intention at Bosch has always been to have a one-software-solution for all the different CAX processes. The multi-functionality of optiSLang has fulfilled this expectation. The aim is to generate interfaces for process integration with little programming effort. The implementation of simple standard templates must be possible without special knowledge. This is the only way to cope with the rising demand for simulations by the same human resources.

What other areas of application in the product development at Bosch can you imagine in the future?

In the future, we consider improvements in the visualization of correlations and results, for example, Pareto fronts in multi-objective optimizations, as an expandable application of optiSLang. In addition, the software will be increasingly used in sensitivity analyses of signals. Also the issue of meta-models is of crucial importance in order to obtain greater efficiency and opportunities in the approximation and evaluation of, for example, several operating points or characteristics. These meta-models can be stored as basis product knowledge for further modeling.

How important is the issue of Robust Design Optimization at Bosch?

Robustness of designs is a very important issue for Bosch. Proving the design robustness during virtual prototyping is one of the most important applications of optiSLang, because the optimal nominal design does not represent an optimum in reality. However, the automatic combination with optimization procedures make high demands on the parametric modelling process. Today it is only applicable for some modules but not for the whole CAX portfolio. The qualification of parametric modeling and the automation of CAX processes as requirements for a more frequently use of Robust Design Optimization will be an important point on the agenda for the next years.

Which "bottlenecks" appear during the implementation of robust design optimization with optiSLang today?

We are constantly working on expanding and assessing our product knowledge regarding scatter conditions in manufacturing, material properties and environmental circumstances. In this process, a close cooperation between development and manufacturing departments plays a major role. Respectively, the interfaces between CAD and CAE process parameters and the transfer of geometric tolerances must be further improved and optimized. Another key point is the availability of efficient and powerful hardware in the CAE process in order to keep the overall response time as moderate as possible. In this context, it is still a major challenge to handle the complexity of 3D parametric CAE modeling. This includes constraints, loads and contact as well as the associated model size taking into account meta-models and a high number of parameters. Here, the license models of all commercial CAE codes used must ensure a simple availability of parallel computing and processes, storage management as well as bundling of calculations.

What can Dynardo do to overcome these obstacles?

In this context, we expect from Dynardo further development and improvement of automatic generation of best possible meta-models out of simulation or measurement data bases as a very important strategy of reducing the complexity of CAE-based simulations. In order to minimize the manual transfer of parameters or processes, the approach of generating transferable, reusable template structures inside optiSLang should be expanded. Here, of course, the compatibility between platforms and interfaces plays a crucial role. Also, the increased complexity of post-processing much more parameters, responses and objectives must be constantly monitored regarding the prevention of a decline in the software's performance capacity.

Author // H. Schwarz (Dynardo GmbH)

The interview was given on Mai 13th in 2015 in Stuttgart by:
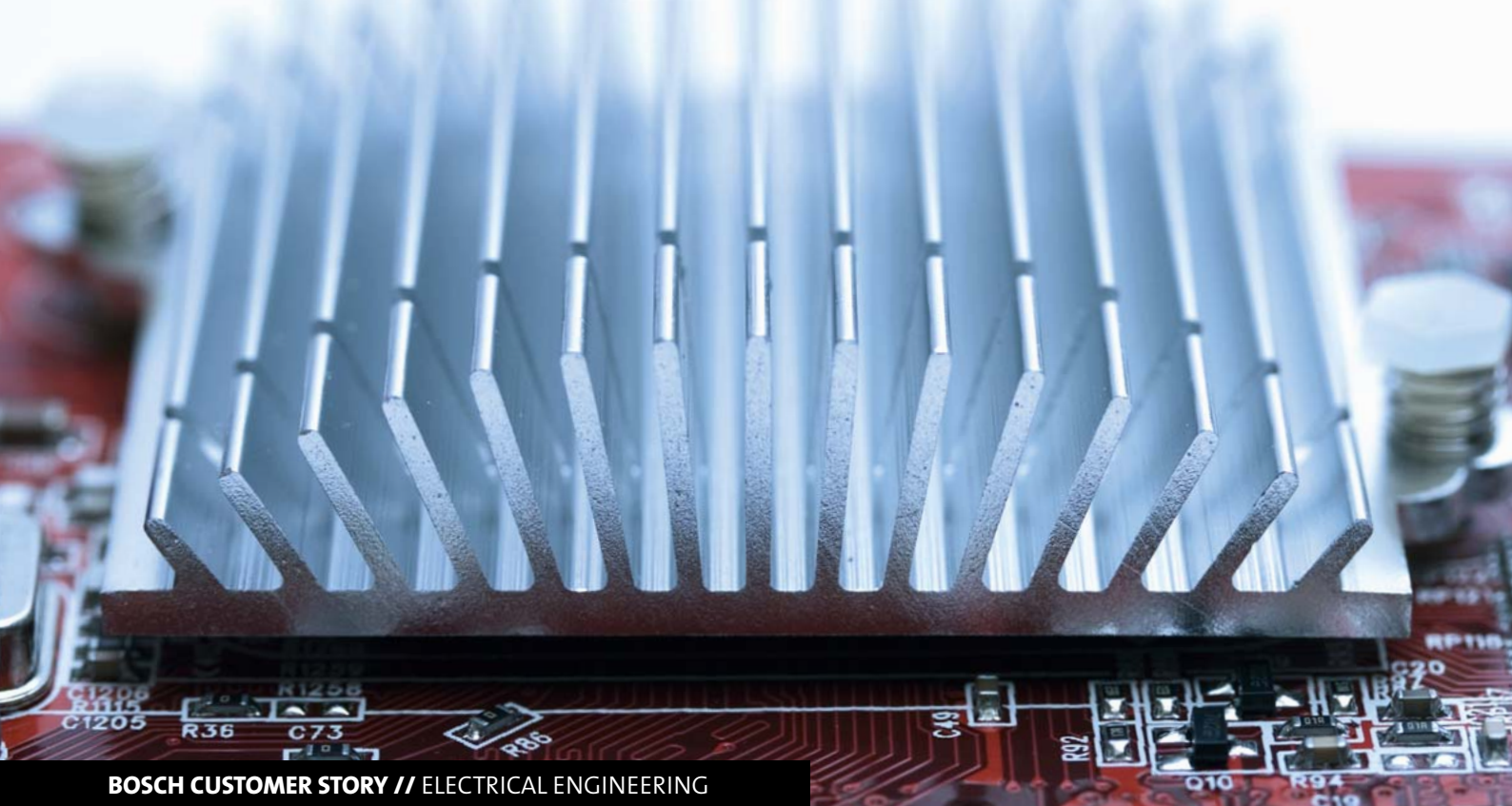**Dipl.-Ing. Roland Schirrmacher**
Corporate Sector Research and Advance Engineering
Dipl.-Ing. Henning Kreschel
Diesel Systems, Common Rail Injector Development
Dr.-Ing. Olaf Schönrock
Advanced Development

METHODS FOR OPTIMIZATION OF AIR COOLED SURFACE TOPOLOGIES

optiSLang is used at Robert Bosch GmbH for optimizing the surface topology of heat sink geometries to enhance their convective heat transfer to the ambient air flow.

Motivation

The thermal performance requirements of air cooled electronic control units (ECUs) increase continuously due to the growing extent of implemented functionality and thus higher power loss density and the trend of miniaturization. To meet these targets, it is mandatory to enhance the convective heat transfer to the ambient air flow by means of optimizing the surface topology of heat sink geometries.

Introduction

In order to quantify the cooler performance for a given power loss P_v and air flow, either the cooler temperature or the derived scalar quantity Thermal Resistance "R_{th}" is usually chosen as a primary output variable:

$$R_{th} = \frac{T_{surf} - T_{amb}}{P_v}$$

with the heater surface temperature T_{surf} and the constant ambient temperature T_{amb}. Furthermore, the objective material volume of the heat sink as an indirect estimation

for the manufacturing costs is of relevance and used as secondary output variable. It is not unusual that optimal cooler design and low cooler mass are in conflict with each other, therefore, a multi-objective optimization has to be performed in order to compromise for a design.

Realization

In order to tackle this task, several different approaches were implemented in both, optiSLang and optiSLang inside ANSYS Workbench utilizing different computational fluid dynamics programs (CFD), namely scStream (Cradle), FloEFD (Mentor Graphics) and CFX (ANSYS) as it can be seen in Fig. 1 (see next page). These procedures all have their own benefits and draw backs. In standalone optiSLang for example any scriptable software can be used as shown in Fig. 1a) - c) (see next page). The method shown in Fig. 1b) (see next page) even relies on implementing Excel with its powerful Visual Basic utilities in order to control calculations, simulations and several batch scriptable programs. In this case, VBA, VBS, windows batch, scStream, ANSYS APDL and Python was used.
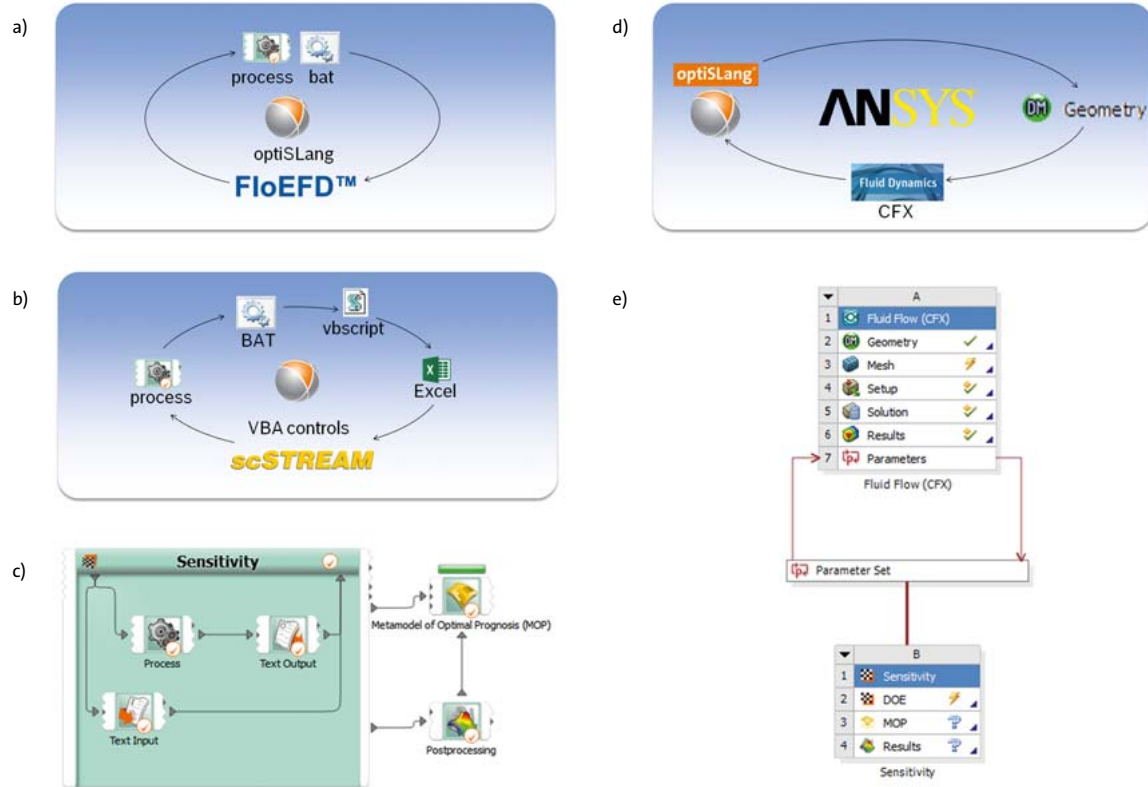
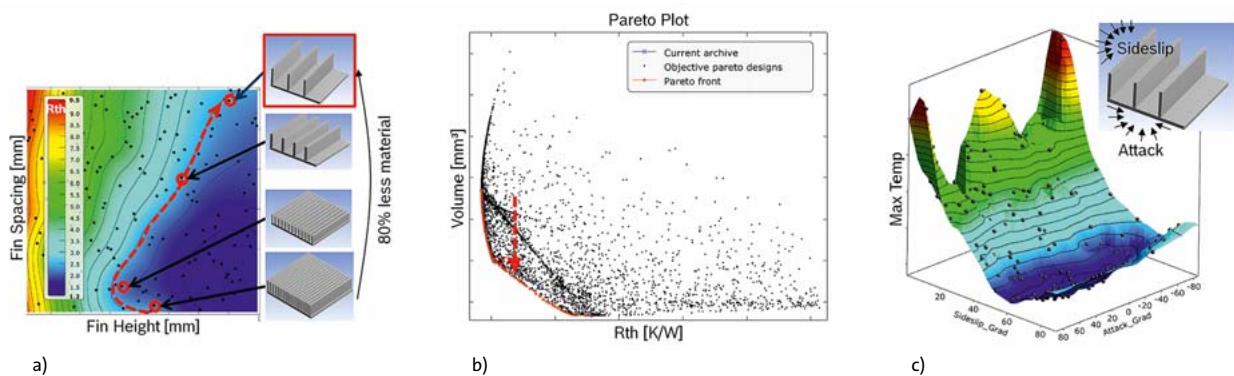Figure 1: Implementation of workflows. a) - c) standalone optiSLang, d), e) optiSLang inside ANSYS Workbench.

Figure 2: a) Rth value of cooler with fins depending on geometry with indicated isoline, b) Pareto plot depending on cooler volume and c) sensitivity analysis of air flow vector depending on maximum cooler temperature

This approach is functional, but includes the handling of several interfaces introducing a high level of complexity. In Fig. 1d) − e) ANSYS Design Modeler and CFX was used in order to generate and calculate parametrized geometries controlled by optiSLang inside ANSYS Workbench. The benefit of this approach is that geometry generation, calculation and result evaluation is done in one framework. With this solution however, the user is obliged to use CFD solutions implemented into ANSYS.

Results

The examined geometry in the following results is a simple solid metal fin-heatsink structure with a heating boundary condition at the base. In Fig. 2 the sensitivity analysis of the cooler R_{th} is shown for fin height, fin spacing and air flow directions, all varied according to an Advanced Latin Hypercube algorithm. In Fig. 2a) the R_{th} is plotted as a function of fin height vs. fin spacing for a fixed air flow direction. It is evident, that the R_{th} gradually improves with increasing

fin height. Several designs are displayed near an isoline of the R_{th} revealing that the mass of the cooler can be reduced by 80% while maintaining the same thermal performance. This is achieved by increasing the fin height and fin spacing. In Fig. 2b) the corresponding Pareto front is shown giving insight in the multi objective optimization.

In Fig. 2c) the geometry was fixed and the air flow angle was varied. In this analysis the maximum temperature of the cooler is evaluated. Local and global minima are present depending on alignment of the air flow. Based on these sensitivity analyses, a subsequent optimization based on a Metamodel of Optimal Prognosis (MOP) can be performed without the need of additional CFD simulations.

Summary

The presented workflows and results serve as a proof of concept study. It has to be verified that this approach is also suitable for complex geometries.

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DYNARDO GMBH // SOFTWARE & DEVELOPMENT

OPTISLANG V5

From expert tool to standard application – CAE-based Robust Design Optimization (RDO) with optiSLang in industrial product development.

Optimization in virtual prototyping aims at achieving the best possible product features with minimal resource consumption. Here, product optimization often approaches limits of tolerable load or deformation. Guaranteeing robustness against scatter is increasingly becoming a focus in the development process. With the help of CAE-based Robust Design Optimization (RDO) and optiSLang, the robustness can be analyzed and proved against scattering material parameters, geometry changes or environmental conditions. Innovative methods as well as a simple and intuitive user interface are crucial for a successful implementation of CAE-based product optimization in order to gain:

- Time-efficiency by Automatization
- Higher quality in V-PDP by standardization
- Assurance of innovation by individualization of flexible flows, combination of CAx tools and algorithms
- Extensive usage of expert know how by collaborative work

optiSLang's efficient sampling and optimization methods allow to solve even highly complex, non-linear tasks. Meta-models with optimal prognosis quality are automatically generated taking into account a maximum of potentially affecting variables while minimizing CAE solver runs. For the best possible user friendliness in building up a CAE process chain, the operator is supported by predefined and task-oriented workflows. An expert knowledge on stochastic or statistical analysis is not required anymore to routinely use RDO in industrial product development.

Postprocessing

One of the most important parts in optiSLang is its post-processing. Based on requests from our customers, Dynardo's development team widely enriched the functionality in version 5. The access to all plots in all standard modes is now possible, e.g. for approximations, optimizations or statistics. Therewith, users are provided with a high flexibility when exploring the data of the parametric studies. For a better monitoring during a running analysis, e.g. conducting an optimization, the automatic update of the plots can be chosen now. Thus, for instance, the convergence of the optimizer can be directly tracked while all plots keep their position and size. Furthermore, the postprocessor has been opened for customization. Besides the standard modes of approximation, optimization and statistics, users now can

define their own standardized way to explore the data. This includes, for example, which plots should be displayed when the postprocessing opens or which designs should be highlighted. Additionally, the export of plots as pictures (png, jpg etc.) and, thus, the examination and report generation can be automatized and standardized.

MOP®

The technology using DOE, the Metamodel of Optimal Prognosis (MOP)® and the Coefficient of Prognosis (CoP)® is one key to a successful performance of parametric studies. Dynardo's development and research teams continuously work to improve this technology in order to provide more possibilities for design understanding. Based on a research project with Fraunhofer ITWM, the MOP algorithm was re-implemented to achieve an optimized performance in searching for the best meta-model and for its use in an MOP-solver. Thereby, it is, for example, possible to parallelize the search. Thus, the time to create and search the MOP can be divided by the number of CPUs. Additionally, because of this gained optimized performance, two new meta-model types could be added to the list of options: Kriging and Anisotropic Kriging.

Following the motto "from expert tool to standard application", the user is now supported by "Automatic settings" in the MOP dialog. Therein, users have just a few clearly arranged settings to generate the MOP analysis. Those provide proven default settings for the most common applications. Detailed settings are still possible in the advanced section.
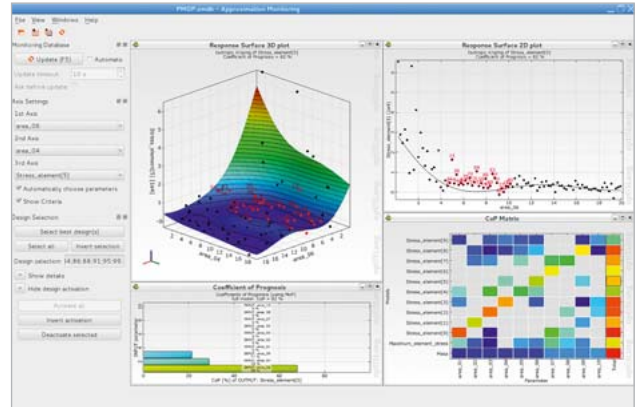
Robustness wizard

CAx based tolerance analysis needs algorithms covering a range from 1 to 8 sigma. Based on Dynardo's tradition and 30 years of experience, those have been provided since the first versions of optiSLang. This includes algorithms for all sigma levels as well as the proof of quality of an optimized design in an RDO flow.

As users know from the optimization wizard, based on underlying information about the task, the robustness wizard now helps to select the suitable algorithm. All algorithms for variance based and reliability based analysis are now available in optiSLang and in optiSLang inside ANSYS. By the help of the decision helpers a detailed expert knowledge is not needed to set up a Design for Six Sigma project.

Workflows

Besides the wizard based and best practice set up of RDO tasks, the convenience to create very complex flows was also increased in version 5. By the enlarged functionality of data-mining, it is now possible, for example, to quickly build optimization workflows which consider the performance of multiple operational points (sweep) or larger

grids (n-dimensional). Quick geometry pre-checks help to decide whether the meshing and solving is appropriate or not. Thus, it is possible to define sub-flows which only start an evaluation if a precondition is fulfilled. A lot of unnecessary analysis time can be saved and the total execution can be extremely accelerated.

Approximation postprocessing in optiSLang v5
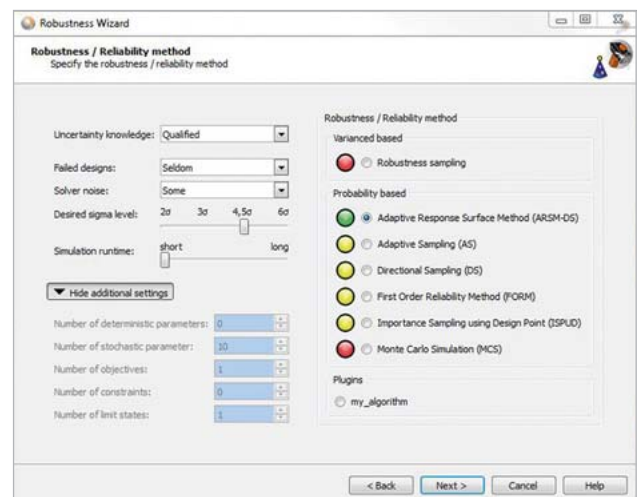
Wizard for robustness and reliability evaluation in optiSLang v5

Openness

optiSLang supports both the parametric and non-parametric interfacing to almost any CAx tool and fulfills the requirements of running in batch. Algorithmic building blocks are provided for an automatized and standardized RDO in virtual product development. Over the last years, a lot of successful implementations of optiSLang into company solutions have been realized including MS Excel interfaces as well as custom or even web applications. The openness provides the customers with the ability to use their own integration nodes, algorithms and meta-models as plug-ins in optiSLang flows.

Author // David Schneider | Product Manager optiSLang (Dynardo GmbH)
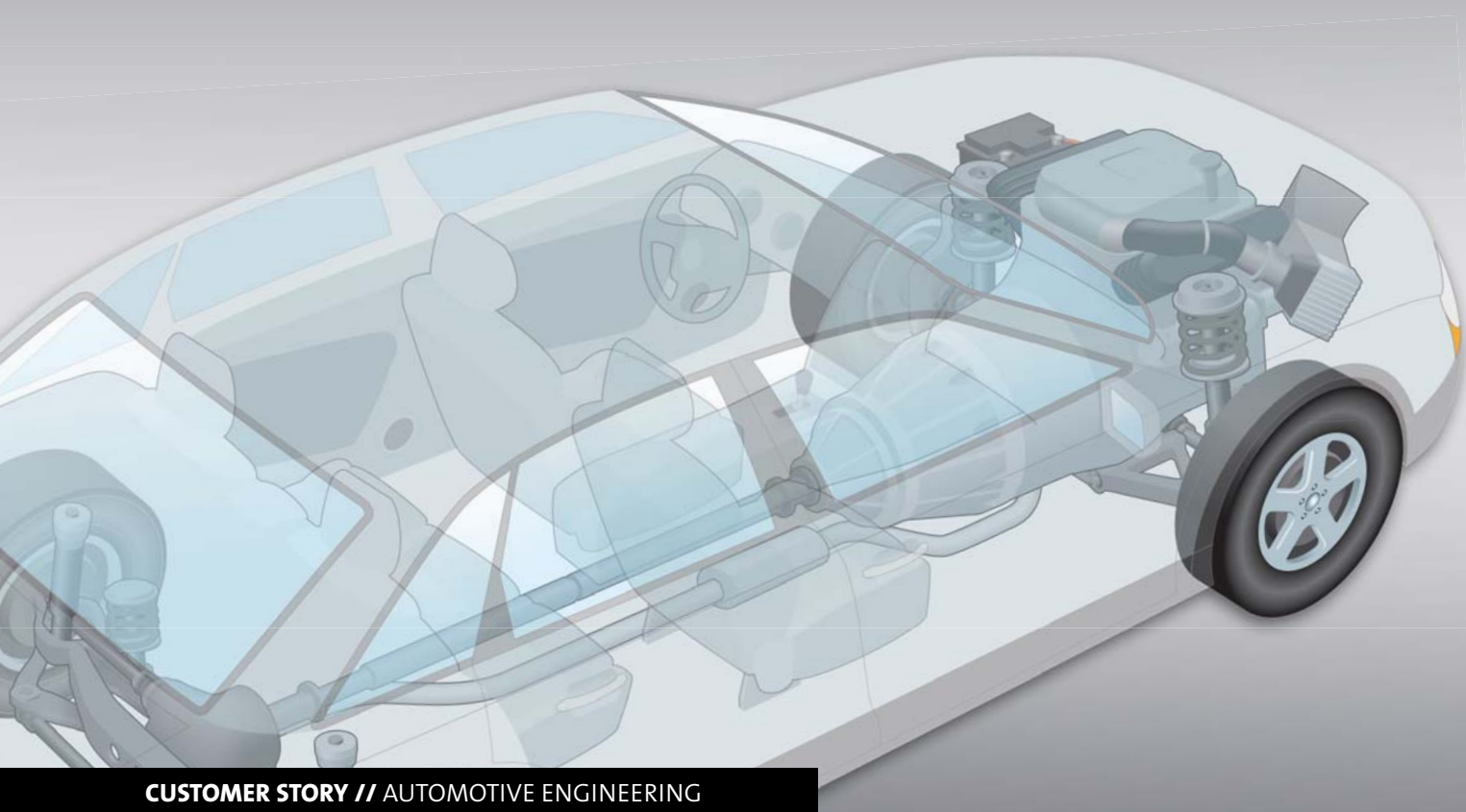
ROBUST AUTOMOTIVE SUSPENSION DESIGN USING MULTI-OBJECTIVE OPTIMIZATION

A Robust Design Optimization (RDO) approach with optiSLang is used to implement further improvements in car suspension design with respect to model transferability and a wide spectrum of load variations.

Introduction

For decades, automotive experts have gained a profound level of knowledge in the field of conventional suspension design leading to a high degree of maturity of current car suspensions. To carry out further improvements, it is inevitable to increase complexity by introducing more sophisticated designs. In parallel, the needs with respect to robustness are dramatically increasing due to a still growing number of derivatives on the one hand and a wider spectrum of wheel load variations by introducing electric batteries for plug-in and pure electrically driven cars on the other hand. Under these circumstances, optimal solutions are hard to find by human search. Computer-based optimization used in the digital phase of suspension development may help to improve insight into the system and to implement better designs. Besides optimizing individual car suspensions, however, it is also desirable to ensure consistent ride and handling behavior for a whole car segment including different engines, extra equipment, plug-in batteries and customer loading. Thus, a suspension system should be designed so that it can be used in several derivatives such as sedans, station wagons, coupes, etc. This may be achieved by using RDO as it will be shown by an approach based on optiSLang.

Robust Design Optimization

Generally, RDO is an optimization performed under consideration of uncertainties. Typical tasks are to optimize a given objective while fulfilling constraints with a specified safety margin or minimizing the variance of responses with respect to uncertainties.

Because robustness measures (variances and mean values) are used in the presented optimization loop, the procedure is considered as an integrated variance based RDO. For each design generated by the optimization algorithm, mean value and variance need to be estimated. Because this procedure needs a vast amount of CPU-time for expensive direct function evaluations, an efficient design evaluation process using an adaptive Response Surface approach is needed if time-consuming simulations are involved.

Adaptive Response Surface Based RDO

As mentioned above, the Response Surface Method (RSM) offers an opportunity to minimize the amount of CPU-time needed for the RDO process. Here, an aRSM based multi-objective RDO is used and explained in the following.

The goal is to optimize a system in terms of minimizing mean and variance of an objective function with a given set of design parameters between some upper and lower bounds and with normally distributed stochastic variables representing uncertainties. The solution process consists of two parts: an initial sampling and the main RDO loop consisting of different process steps, see Figure 1.
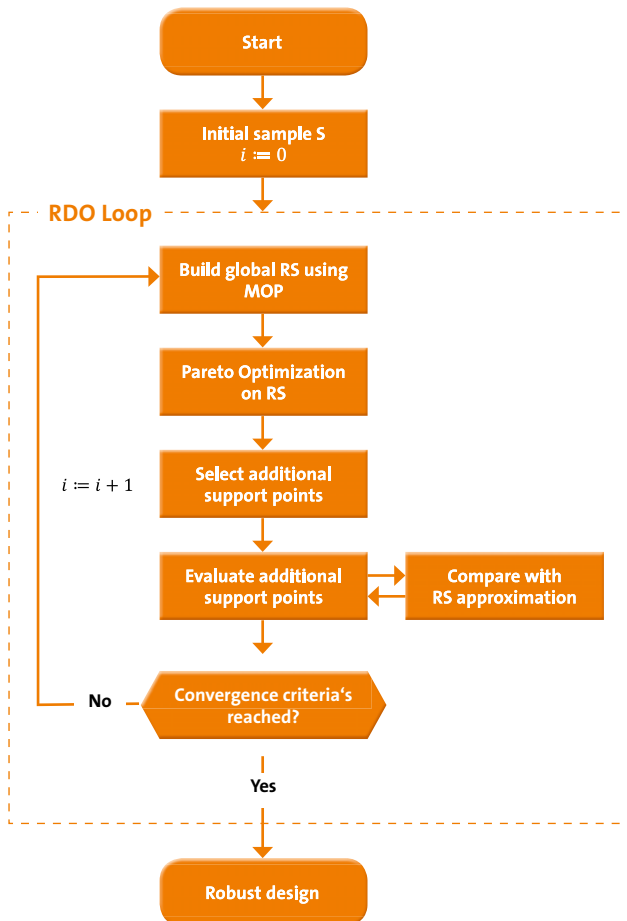

Fig. 1: Flow chart of the adaptive response surface based RDO

In the first step, a predefined number of design points are generated in the design space of the optimization. For every point in the optimization space, a sampling within the space of uncertainties is done. To avoid purely distributed inputs, particularly for a small amount of samples, advanced Latin Hypercube Sampling (aLHS) is used for initial and uncertainty sampling. The resulting set of sample points in the design space of optimization acts as a set of support points for generating response surfaces for mean and variance estimation. These robustness measures are evaluated by solving the sampling in uncertainty space of every support point. In the first step of the main RDO loop, response surfaces are built up from the actual set of support points and associated response values. To build up the response surface, the Metamodel of Optimized Prognosis (MOP) is used. Briefly said, MOP is an automatic approach which searches for the best subspace of important optimization parameters and the best response surface approximation

for a given dataset with respect to a specific validation method. For the developed process, parameter filtering is disabled and the MOP is only used for metamodeling. Polynomial least squares approximation, moving least squares and ordinary Kriging have been currently implemented in optiSLang. After generating the response surface, the optimization problem is solved on the response surface. A global evolutionary optimization algorithm based on the Strength Pareto Evolutionary Algorithm (SPEA2) is used. The algorithm generates a Pareto-front of optimal compromises between low mean value and low variance dominating the remaining designs. The result of the optimization is a set of non-dominated compromise designs and a remaining set of dominated designs.

In the next step, proper sample points for the adaption of the response surfaces have to be selected, which is briefly explained in the following. At first, minimum distances between non-dominated designs and all points of the actual set of support points are calculated. The design with the maximum distance is then chosen as a new potential RS support point and removed from the set of non-dominated designs. In order to prevent the selection of new support points lying too close to others or being even identical to an already existing support point, a characteristic distance criterion is introduced which needs to be fulfilled. If the characteristic distance criterion cannot be satisfied by enough Pareto optimal designs, the set of non-dominated designs is extended by the set of dominated designs, forcing the algorithm to globally update the meta-model. This process repeats itself until a predefined number of new support points are found. After updating the set of support points, design evaluation is performed for all new support points. Based on the new set, response surfaces are updated and the RDO loop in Figure 1 repeats itself until a maximum number of iterations or a convergence criterion is fulfilled.

To check for convergence, approximation quality of the new support points is assessed in the criterion space, meaning that the relative differences between objective values gained from response surfaces and originally evaluated values are assessed: if this error rate is smaller than a predefined error tolerance, the algorithm is assumed to be converged and the RDO procedure finishes.

Implementation in optiSLang

The proposed process is implemented in the commercial optimization tool optiSLang by combining the described algorithms with existing process nodes out of the optiSLang library. The implementation of the RDO process in optiSLang is shown in Figure 2 (see next page), where the different process nodes are numbered and will be explained in the following.

The first node in the blue box (1) in Figure 2 (see next page) is a sensitivity node used for initial sampling. Here, a predefined number of sample points are generated and evalu-
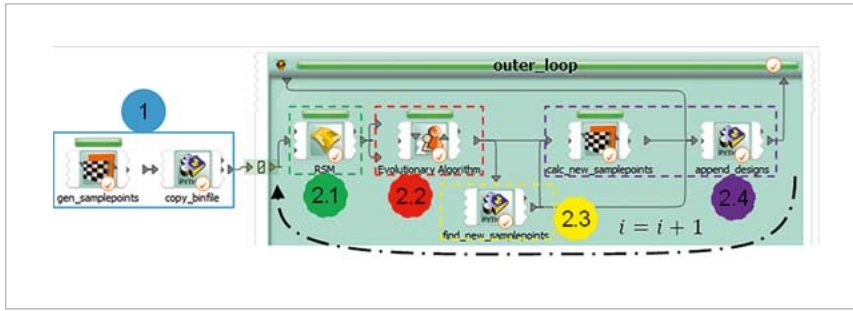
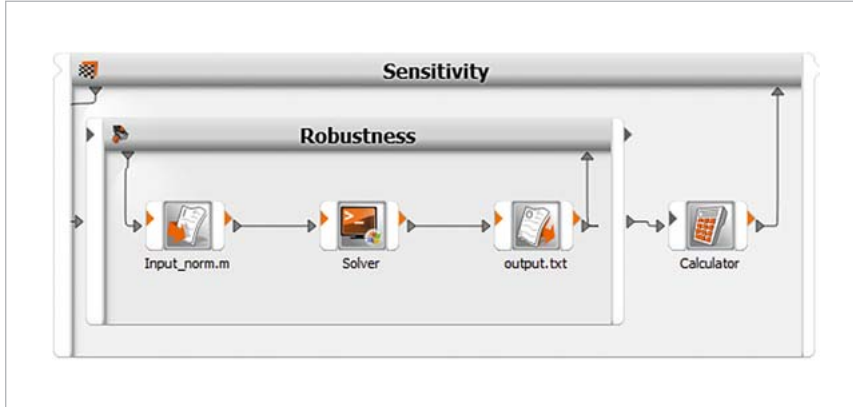Fig. 2: Implementation of the proposed method in optiSLang

Fig. 3: Sensitivity analysis with nested robustness analysis

ated to be used as support points later. In order to determine robustness measures, a nested robustness analysis is performed for each design generated by the sensitivity node as shown in Figure 3.

The results are stored in a single file which is relocated to a specified folder by the second node. This is done by a simple script written in Python-code which can be directly executed in optiSLang by using the Python integration node.

In the first step of the main RDO loop (see the green dashed box 2.1), response surfaces are built up from the actual set of support points by using the MOP node. To get the set of actual support points, the MOP node reads the file mentioned above that is stored in a standardized location. Again, as explained for the sensitivity node, the MOP node is only used for metamodeling, meaning that filters and post processing are deactivated. After generating the metamodels, the multi-objective optimization problem is solved on the response surfaces via the EA node shown in the red dashed box (2.2). In the next step, proper sample points for the adaption of the response surfaces are selected, which is done by a script executed in the Python node in the yellow dashed box (2.3). Evaluation of the new support points and check for convergence is done by the nodes in the purple dashed box (2.4). The first node, a sensitivity node, acts similarly to the node used for initial sampling in the blue box (1). Here, the chosen points are evaluated by using the nested robustness analysis. The last node then appends the evaluated designs to the set

of support points. It checks for convergence and stores the new set of support points to the standardized location as mentioned above. Now, the next iteration is performed starting with the metamodeling of the MOP node. This process repeats itself until one of the stop criteria defined above is fulfilled.

Application to Suspension Design

The proposed method is applied to Robust Design Optimization of a suspension of a full vehicle model. The vehicle, a luxury passenger car, is modeled as a multibody system (MBS) with 112 rigid bodies and 111 degrees of freedom (DOF). Model components are suspension links, wheel carriers, bushings, spherical joints, springs, dampers, wheels, tires, steering system, as well as subframe at the rear axle and the main body. Two different comfort oriented load cases are investigated. The main goal is to find a bushing setup which has the best robust performance with respect to the specific objectives and uncertainties. The uncertainties shall emulate different car derivatives which have the same track width, wheelbase and kinematic hard points, but different mass and size.

Design Goal

Design goal is to minimize the oscillation intensities of two typical driving maneuvers. The first load case is called axle tramp which is a coupled oscillation between wheel and axle appearing while a car is accelerating or braking. In this article, only the axle tramp during braking is investigated. Depending on axle kinematics, the wheel moves backwards and upwards due to the applied braking force which leads to a loss of road contact and, thus, a reduction of the friction force on the tire. This, however, lets the wheel swing back gaining more road contact again. Repetition results in the oscillation are illustrated in Figure 4. The most sensitive parameters for this scenario are the tire mass and stiffness as well as the bushing stiffness and damping where a certain amount of damping should be realized in particular.

To get a reproducible axle tramp behavior in the simulation, an initial vertical force impulse is applied to the rear wheels while the car is braking. The resulting longitudinal and vertical accelerations of the rear wheels in the time-domain are squared, integrated, normalized to a reference car and chosen e.g. as characteristic response criterion f_2 to be minimized, see Figure 5.

In the second load case, the vehicle is driving with constant speed on a straight road while a single step-shaped roadway excitation occurs at the rear axle. Here, the acceleration of the driver's seat in the opposite driving direction is investigated in the time-domain and transformed to criteria f_5 similarly to f_2, which should be minimized, see Figure 6.

The first acceleration peak can especially be recognized by passengers and, therefore, is of particular interest. To minimize the seat acceleration in the x-direction, the axles should provide enough longitudinal compliance and little damping.

For each of the altogether five response criteria, mean value as well as variance are calculated, normalized with respect to a reference car and partly summed up to finally achieve two objectives for each load case. The different needs of both load cases regarding stiffness and damping should lead to compromised bushing setups forming a Pareto-front. These tradeoffs are hard to find by human search which is why the proposed computer based optimization procedure is used.
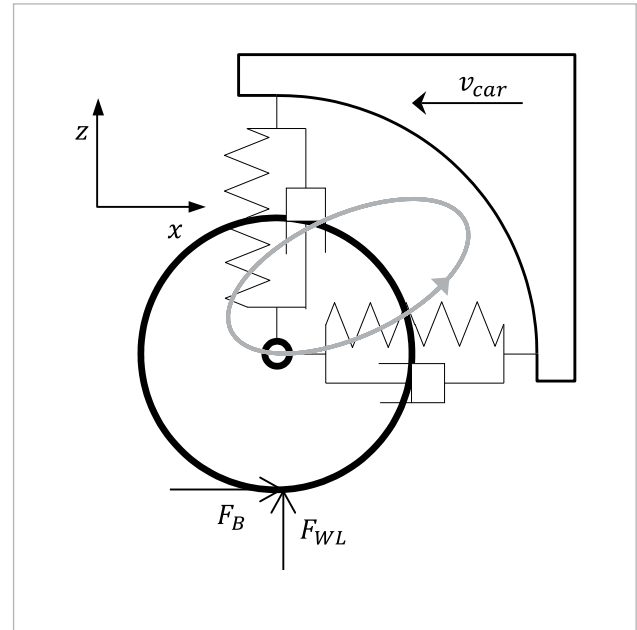

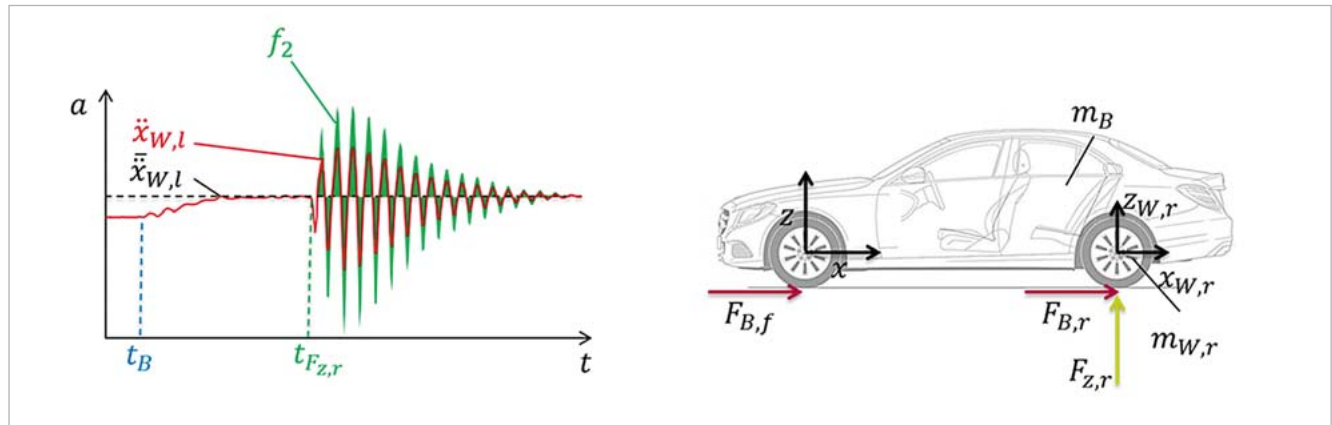Fig. 4: Schematic tire movement during tramp oscillation

Fig. 5: Schematic representation of one of the axle tramp responses (green curve) for the rear left wheel acceleration in x-direction (red curve)
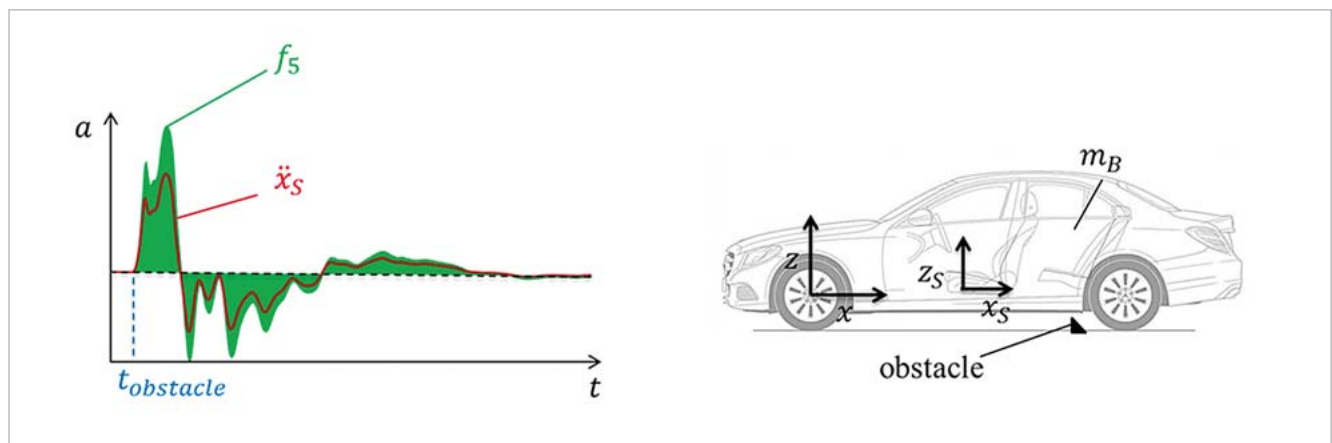

Fig. 6: Schematic representation of the obstacle crossing response (green curve) for the driver's seat acceleration in x-direction (red curve)

Design Parameters

The stiffness and damping characteristics of the suspension bushings are chosen as design parameters where the bushings are represented by a Kelvin-Voigt (KV) model as shown in Figure 7 (see next page). This model is limited in terms of approximating real bushing behavior, but it only needs two
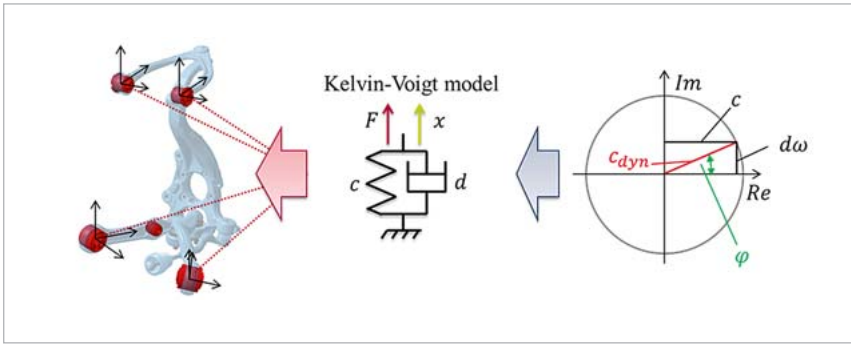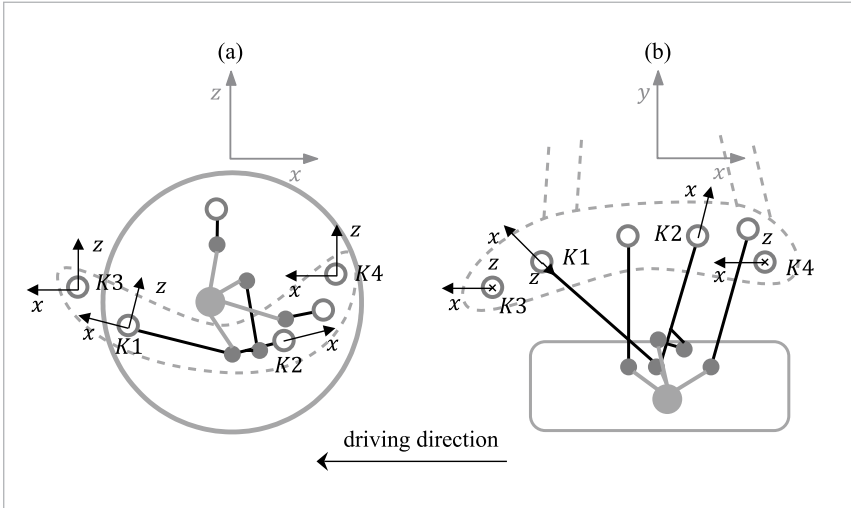
Fig. 7: Schematic bushing parameterization process

Fig. 8: Side (a) and top view (b) of investigated rear axle with wheel carrier (grey), linkages (black), bushings (white circles) and subframe (gray dashed)
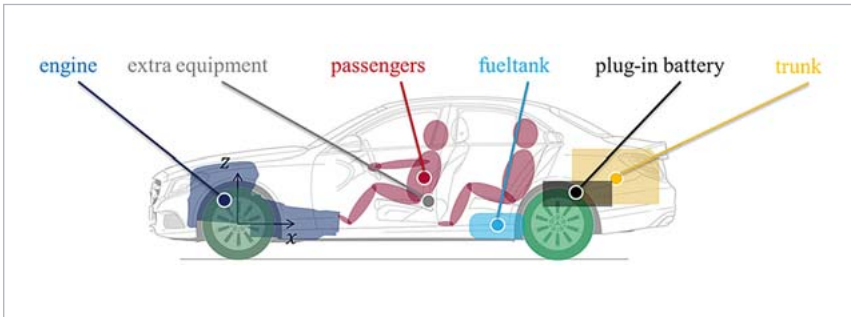

Fig. 9: Sources of uncertainties and representation within the MBD model

translational bushing characteristics are changed. C_{dyn} and φ for each coordinate direction of each bushing accumulates up to 60 parameters that may be considered. To minimize the amount of design parameters, a sensitivity analysis was performed resulting in only 11 important parameters which are varied between predefined bounds. The associated bushings and their individual coordinate systems $K1$ to $K4$ are visualized in Figure 8.

Uncertainties

A passenger car underlies several uncertainties. In this article, the scatter of mass properties of loading and bodies is investigated according to Figure 9. More precisely, the variation of passenger numbers, fuel level, boot loading, extra equipment, engine and battery type are taken into account where positions are assumed to be given. Due to the lack of statistics for the masses described above, they are assumed to be normally distributed within given ranges and independent. For sampling purposes, a truncated standard normal distribution is used for each parameter and generated with aLHS for predefined bounds.

Optimization Results

The RDO is performed subjected to design objectives, normalized design parameters and uncertainties. For the evaluation of robustness measures, a sample size of 20 is used for uncertainties. The initial set contains 30 support points. In each iteration, 5 new support points are added to improve the RS. The SPEA2 performs an optimization on the RS with a maximum of 150 generations using 20 new individuals in each generation. The RDO procedure is limited to 40 adaptions of the RS resulting in a maximum of (30+40×5)×20=4600 original design evaluations. While running 10 simulations in parallel, the overall RDO took 6 days and 9 hours until it converged after only 38 adaption iterations. The evaluated support points are shown in Figure 10.

It is clearly visible that all criteria improve simultaneously resulting in a rather narrow Pareto-front which indicates that mean objectives are not as contradicting as assumed. Nevertheless, both criteria could be enhanced with respect
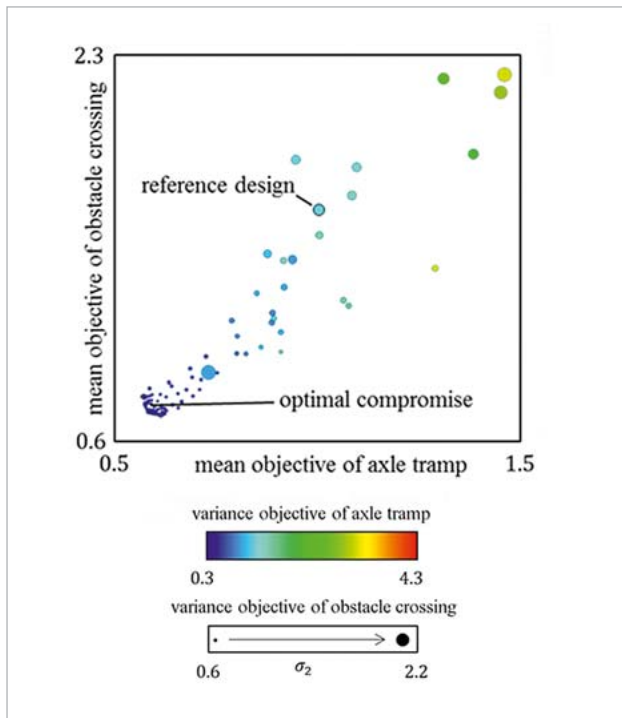
parameters which is efficient. The main drawback of the model is the incapability of reproducing the real amplitude and frequency dependencies of rubber material used for vehicle bushings. To overcome this lack of approximation quality, the KV model is parametrized to match the real bushing behavior only for a specific excitation frequency. This has been possible since the two considered load cases, i.e. axle tramp and free vibration after obstacle crossing, have well defined excitation frequencies. Briefly said, dynamic stiffness c_{dyn} and loss angle φ are calculated from design variables and converted to specific model parameters c and d, see Figure 7. In total, the vehicle model has 10 bushings where here only

Fig. 10: 4D-Pareto plot of support points

Fig. 12: Frequency plot of objectives f_2 (top) and f_5 (bottom) for optimal compromise design (red) and reference design (black)

to the reference vehicle setup and also the robustness seemed to be improved. For better visualization of the improvement, histograms of two specific objectives of a Pareto-optimal design lying on the knee of the front are shown in Figure 12. They have been compared to the reference set-up. It can be easily observed that mean value and variance are both significantly improved. The corresponding accel-
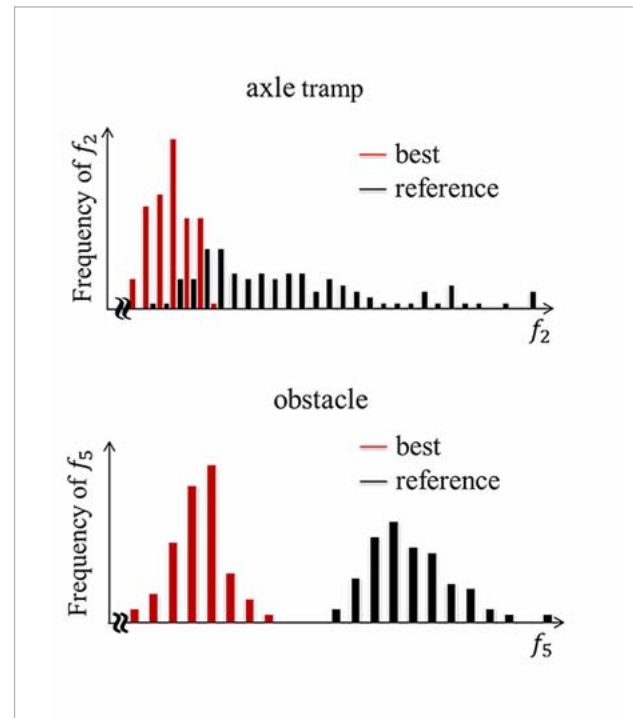
erations determine f_2 and f_5 as the acceleration of the left tire during tramp (Figure 11 top) and the driver's seat after obstacle crossing (Figure 11 bottom) in x-direction. They confirm the histogram information in Figure 12 in the time-domain. The large scatter in tire oscillation of the reference car during axle tramp can especially be observed.

Conclusions

The article demonstrates an efficient multi-objective robust design optimization procedure. The implementation of an adaptive response surface modeling strategy significantly reduces computational effort compared to direct optimization. This is proven by optimizing a simple test function. An application of the proposed method to vehicle suspension design by using multibody system simulations and optiS-Lang is successfully performed. The optimization is done in terms of minimizing predefined accelerations measured throughout the load cases, which are axle tramp and single step-shaped roadway excitation for a given range of bushing stiffnesses as well as damping parameters under presence of scattering vehicle masses. Although both load cases need contrary bushing characteristics, optimal compromise designs could be found where mean value and variance of the vehicles dynamical behavior are significantly improved compared to a reference design.
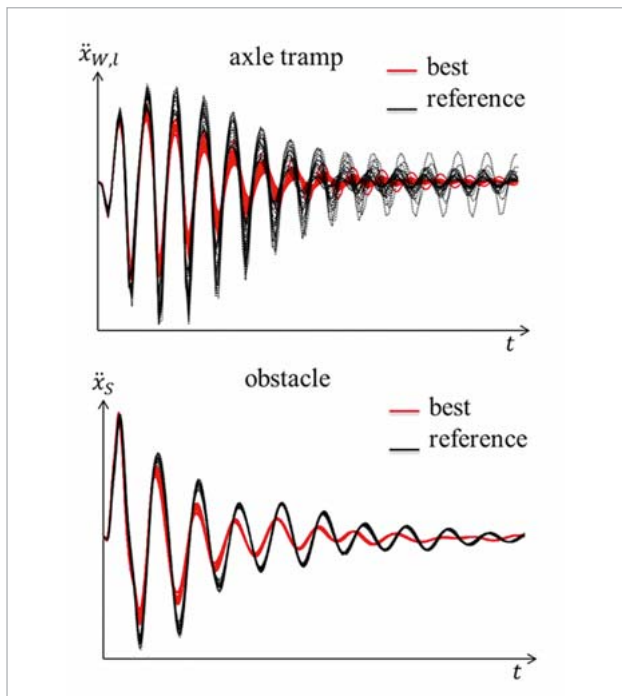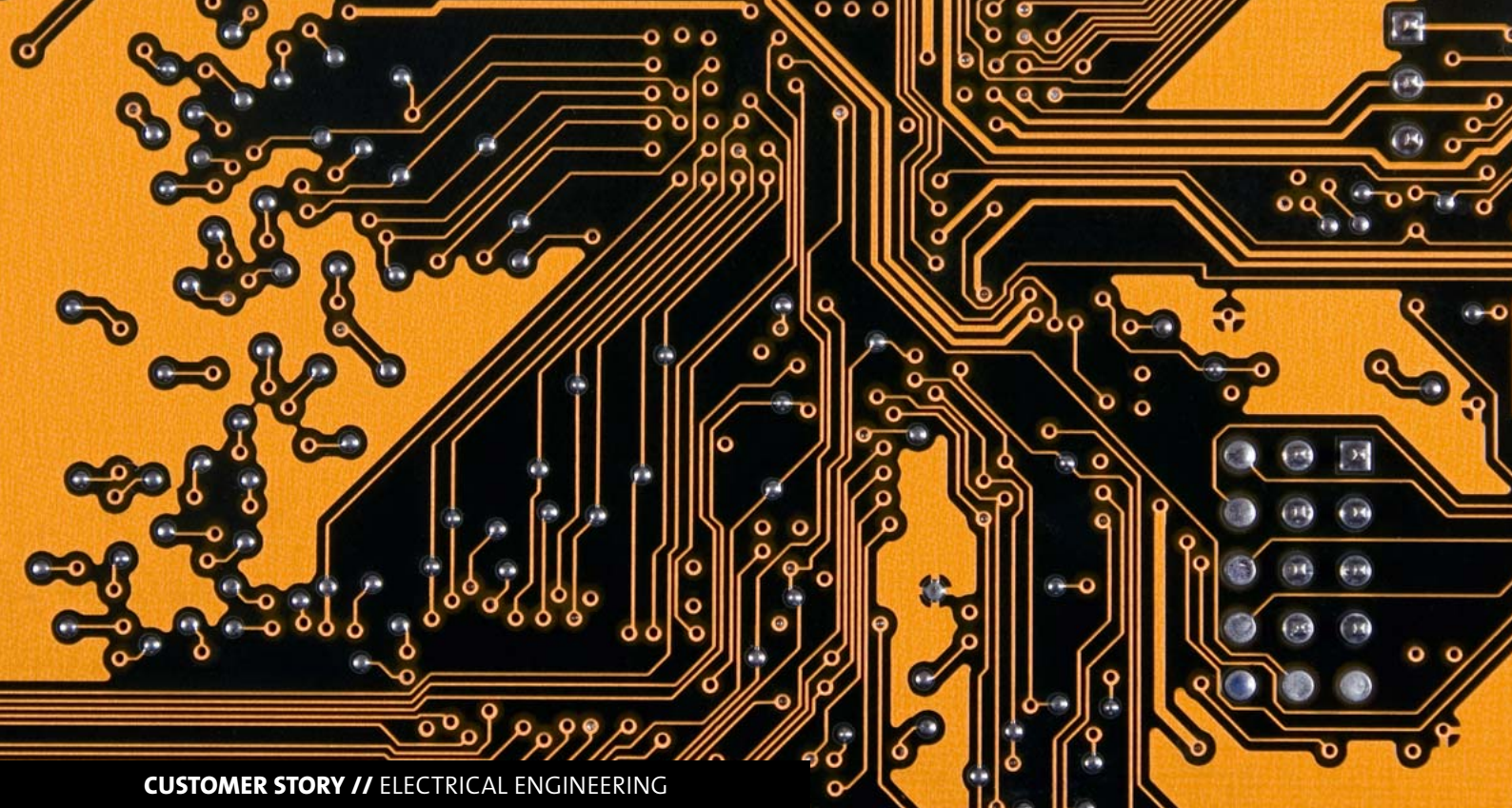

Figure 11: Time plots of tire acceleration during tramp oscillation (top) and driver's seat acceleration after obstacle crossing (bottom) of optimal design (red) and reference design (black)

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OPTIMIZATION OF MODEL CALIBRATION FOR ANALYZING THE BEHAVIOR OF FILM COPPER

optiSLang provides effective methods of parameter identification to optimize the analysis of film copper produced by Electro-Chemical Deposition (ECD) in the semiconductor industry.

Optimization Task

Metallic thin films often show a different physical behavior than bulk solids made of the same material. This requires the determination of new parameters of corresponding material models. Thin film copper produced by ECD is widely used in the semiconductor industry because of its excellent electrical and thermal conductivity. The functionality of semiconductor products depends strongly on the mechanical performance of ECD-Cu under a broad temperature range. Therefore, the stress-strain response of this special copper is measured at different temperatures. The aim of the optimization was to match the reference signal (bow vs. time) from the experiment with the simulated signal from the FEM calculations.

Methodology

The stress-strain response of this special copper is measured at different temperatures. The wafer curvature approach serves as a standard method. It measures the change of curvature radius due to mismatch in thermal extension coefficients between the film and substrate for a temperature profile. Silicon is often used as a substrate since its mechanical properties are defined and sufficiently known.

In this example, an inelastic material model consisting of seven parameters was validated for ECD copper subjected to cyclic thermal loading (see Fig. 1).
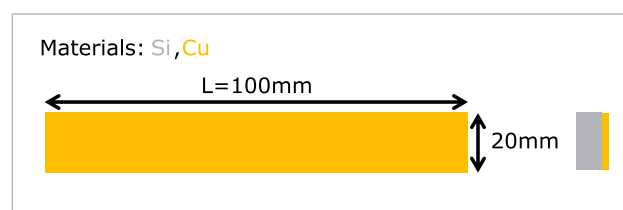

Fig.1: Bimetallic strip in top view and cross section, silicon in grey, copper in yellow

The raw measured quantity was the curvature radius (see Fig. 2). It is usually used for the calculation of the bow (maximal deflection of sample) and stress in the film using Stoney's formula which is valid for the elastic and non-elastic range:

$$\sigma_{Cu} = \frac{E_{Si} h_{Si}^2}{6 h_{Cu}} \frac{1}{R}$$

where σ_{cu} describes the average film stress in the direction of the length side of the strip, h_{si} is the substrate thickness, R is the radius of the curvature and E_{si} is the Young's modulus of the substrate.

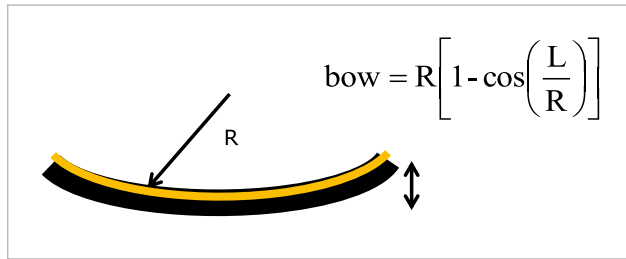$$\text{bow} = R\left[1 - \cos\left(\frac{L}{R}\right)\right]$$

Fig. 2: The Curvature radius of a Cu-Si bimetallic strip is the raw measured quantity. The bow is calculated afterwards and compared with simulation results.
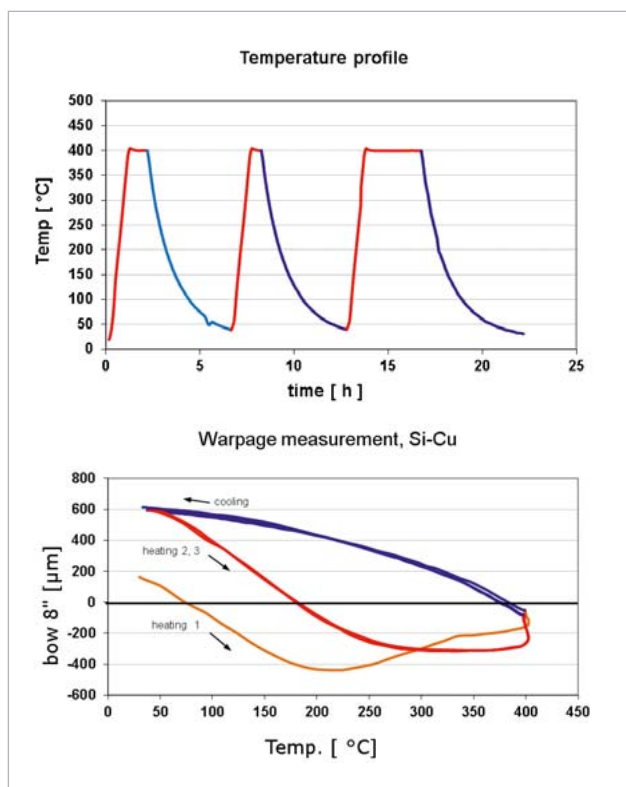

Fig. 3 top: A typical cyclical heating and cooling process during a measurement of a Cu-Si bimetallic strip | bottom: The bow evolution displayed as a function of temperature clearly demonstrates the complex inelastic behavior of ECD copper.

The measurement of the mechanical properties of the Cu-Si bimetallic strip was performed by a cyclical thermal exposure that is illustrated in Fig. 3 top. The corresponding measurement data deduced from the curvature of the substrate is shown in Fig. 3 bottom. Before running the calibration procedure, it had to be decided in which extent each parameter should be changed. For this purpose, gradients of the objective function were manually built as sensitivity measures using MS Excel. Even after achieving a satisfactory result with this method, it was not clear whether the parameter set could be further improved or not. For comparison, the optimization was also conducted with optiSLang applying the least squares approach.

Within one day, the automated optimization was finished after 284 runs of simulation. It could be seen that the agreement of the curves of the automated optimization was significantly better than the agreement of the manual optimization (see Fig. 4).
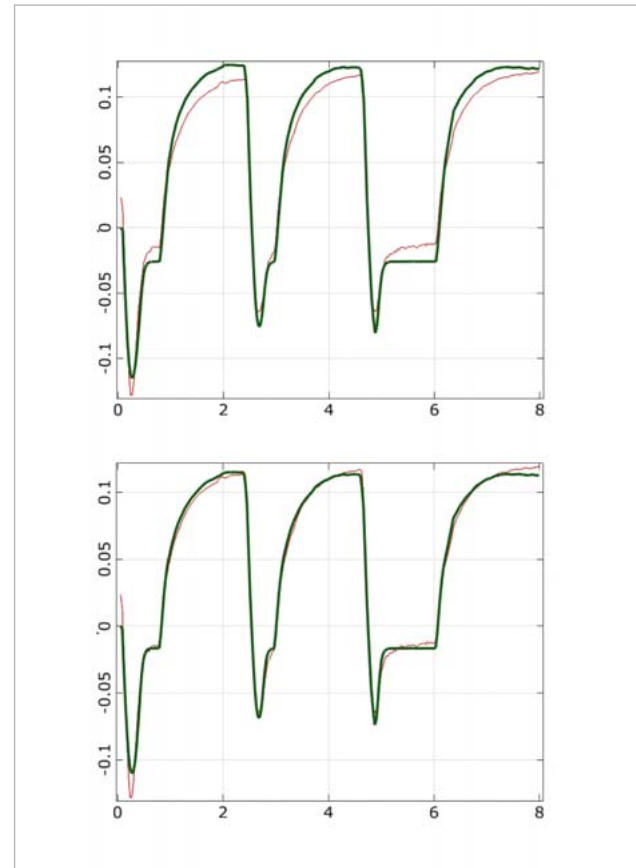

Fig. 4: Bow vs. time. Top panel: The outcome of the manual optimization was a good agreement between reference and simulation signal but with much effort. Bottom panel: The automated optimization resulted in an almost perfect match within a shorter time (green -simulation, red -experiment).

Customer Benefits

A "manual" validation was extremely time-consuming: it took about 3 weeks for 70 simulations. The problem was not necessarily the time needed for one run (it was less than 10 min), but the analysis of results and decision making how to change the parameter values in order to achieve a better calibration to the experimental results. With optiSLang, this procedure was optimized regarding time efficiency and result quality. An additional advantage of using optiSLang was the possibility to repeat the parameter fitting, for example, in the case if some model parameters were deduced from independent experiments. For manual validation, such a situation would be a real no-go criteria, because the simulation engineer would have to start the whole procedure over.

Publication by courtesy of Infineon Technologies AG
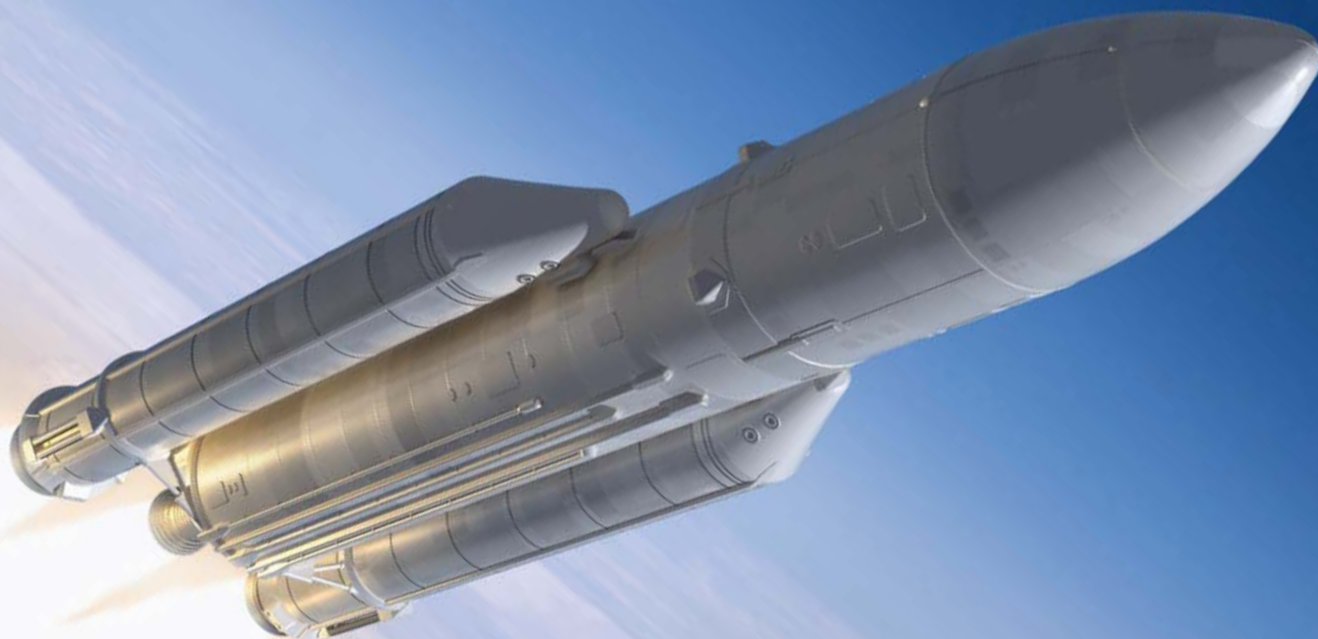
OPTIMIZATION OF VALVE GEOMETRIES IN THE ENGINE SYSTEM OF THE ARIANE 5

optiSLang is used to generate a transferable automatic and efficient RDO process to reduce the weight of casted valve nozzles as components in the upper stage Midlife Evolution (ME) of the launcher Ariane 5.

Fig. 1: Upper stage Midlife Evolution (ME) of the launcher Ariane 5

Introduction

The efficient use of materials is really important in many different settings, especially in the aerospace industry. Structures are subjected to many extreme conditions and at the same time, must be as light as possible. In this article, a highly automated optimization process for the weight reduction of casted support structures will be presented. The structural component to be examined is the oxygen/hydrogen balancing nozzle (TEO/TEH) situated on the upper stage Midlife Evolution (ME) of the launcher Ariane 5 (see Fig.1).

The optimization is carried out using ANSYS Workbench as a solver and the software optiSLang for the sensitivity analysis and optimization. After finalizing the first optimization, the workflow is tested on a second structure.

Parametric design optimization

For a parametric design optimization, this article discusses an approach based on the Design of Experiments (DoE) and the Response Surface Method (RSM) to improve the design and to carry out a fully parametric optimization process. The initial design is parametrized and the user decides which dimensions can be changed in which variation window of each parameter in order to modify the shape of the structure during the optimization process. The second step is the setup of the simulation sequence in order to investigate the mechanical behavior of the structure and to extract the output parameters, such as stresses, displacements or eigenfrequencies. Then the DoE generates a set of design points which represent possible combinations of the input variables. Each design point represents a specific shape of the structure and all of them must be solved in the simulation model. Once all the design points are solved and the outputs are extracted, the RSM allows to express the variation of each output pa-

rameter as an explicit function to the variation of the input parameters. In this way, it is possible to investigate the correlation between variation of the input and output parameters. The user can now understand the model behavior and explore improvement possibilities for the optimization process. Moreover, a sensitivity analysis is carried out in order to identify the most influential input parameters, to reduce the optimization problem and to improve the accuracy and efficiency of the RSM approach. Finally, objectives and constraints are defined and the optimization algorithm is chosen to find the best design improvement which satisfies goals and constraints.

TEO/TEH Valve geometry

The geometry in exam is the TEO/TEH. This valve is situated in the upper stage ME of the launcher Ariane 5. This component is integrated inside the Elongated Lower Skirt (ELS), symmetrically positioned to the oxygen/hydrogen purge connector (CPO/CPH) and it provides longitudinal thrust to balance the nozzle (TCPO/TCPH). At the other side, the TEO/TEH is connected to the Cryogenic propulsive stage (EPC) attachment bracket via a rigid rod. The complete system and the valve geometry in exam marked in red is illustrated in Fig. 2.
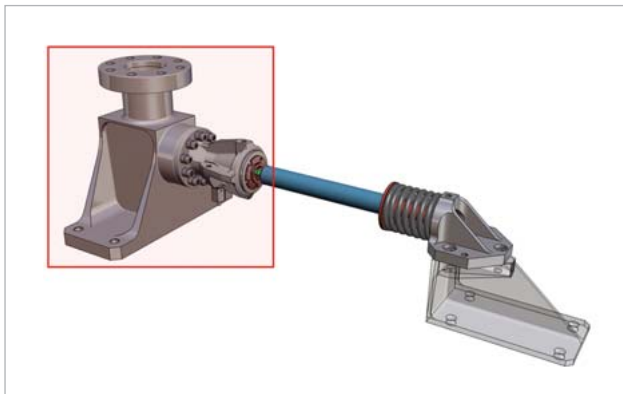

Fig. 2: TEO/TEH Complete system

The used material is Aluminum 3.3214 and the proprieties are shown in the Tab.1. This material is a heat-treatable aluminum alloy of medium strength especially used in applications requiring good weld ability and corrosion resistance.

Design constraints

The first step is to create the parametric model on the initial design in order to change the shape of the structure during the optimization process. In Fig. 3, the initial design of the Tex valve is illustrated.

Fig. 3: Initial design

Input design parameters

The parametric model is generated inside ANSYS Design Modeler by using sketches and plans. In this way, all the generated dimensions are automatically selectable as input parameters for the optimization process. In the following, the input design variables are described:

- Thickness upper flange – by increasing the parameter, the thickness of the upper flange decreases (see Fig. 4a next page)
- External diameter upper flange
- Mass - for reduction the value of the external diameter of the upper flange is decreased (see Fig. 4b next page)
- External diameter interface towards nozzle (see Fig. 4c next page)
- Thickness base (see Fig. 4d next page)
- Central pocket – the central part of the geometry is the only area where it is possible to create a pocket. By drawing the sketch shown in Fig. 4e (see next page), the length and the radius of the pocket are selected as input parameters in order to change the shape of the pocket during the optimization process.

Simulation model

The structure is subjected to several forces and moments which are defined in their coordinate system as shown in Fig. 5 (see next page). The definition of the load vector orientations leads to 64 possible load case combinations.

Furthermore, it must be considered that a pressure load has to be applied on all the internal surfaces of the structure (see Fig. 6 next page).

Material	Temper	E (MPa)	G (MPa)	α (1/K)	R_{p02}(MPa)	R_M(MPa)	ρ (g/cm³)
Al	T6	63300	26200	2.28E-5	230	255	2.71

Table 1: Material proprieties
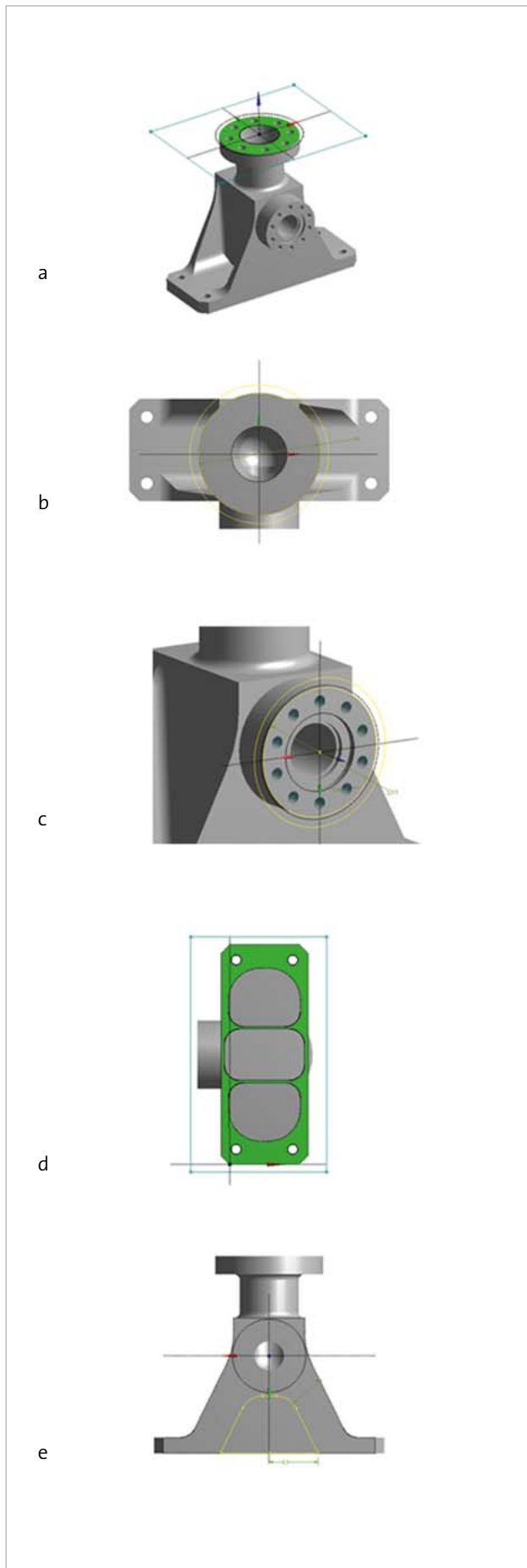
a

b

c

d

e

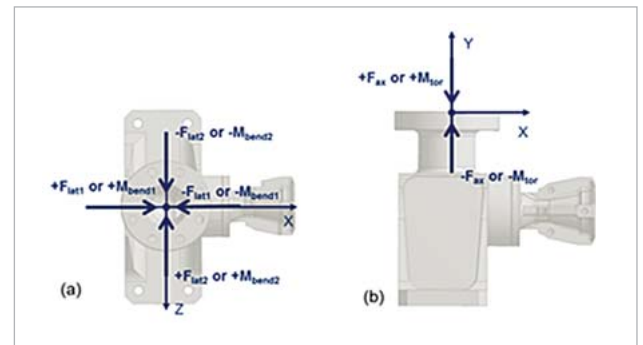Fig. 4: Input design parameters

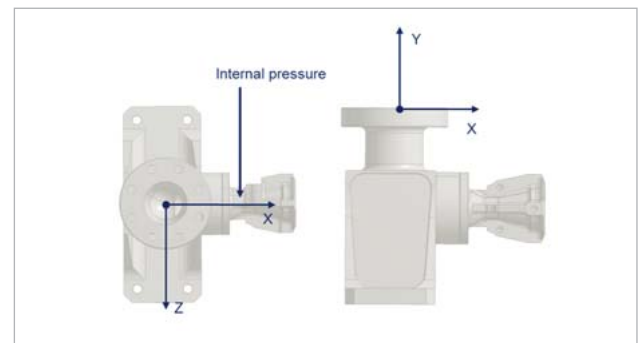Fig. 5: Orientation of load vectors – (a) lateral force or bending moment / (b) axial force or torsional moment.

Fig. 6: Pressure load

Input Parameter	Min Value [mm]	Max value [mm]
Length Pocket	37	62
Radius Pocket	10	22
Diameter upper flange	80.5	88
Diameter flange towards nozzle	56	60
Cut material from upper flange	0.1	4
Cut material from base	0.1	5

Tab. 2: Defined ranges for input parameter variation

The structure is constrained at its 4 interface points with fixed constraints towards the ELS. In Fig. 7, the positions of the fixed constraints S1, S2, S3, S4 are illustrated.
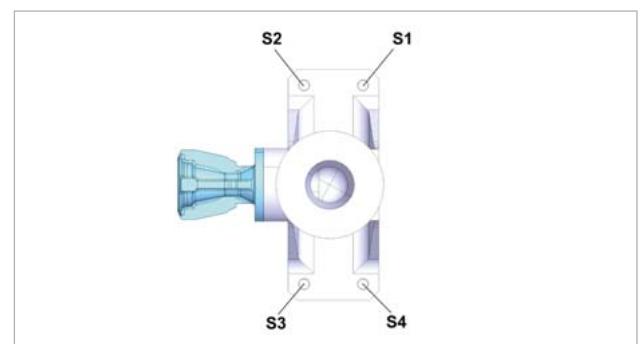

Fig. 7: Fixed constraints location

To reduce the computational time, 7 elementary load cases (ELCs) are solved and then all the 64 LCs are calculated from the post-processed results of the ELCs by using linear superposition of the nodal stress.

The von Mises equivalent stress for all nodes of the structure are calculated according to the specific LC combination. Finally, the maximum stress for the worst LC is selected as an output parameter.

Furthermore, in the simulation model, the modal analysis in clamped configuration must be performed in order to calculate the first eigenfrequency in the range of 0 to 2000 Hz. By performing these operations, the user can investigate the following three output parameters during the optimization process:

- Mass value
- Maximum stress for the worst LC
- First eigenfrequency

The optimization aims at reducing the mass of the structure as much as possible while keeping the maximum stress under 225 MPa and the first eigenfrequency over 400 Hz.

Optimization in optiSLang

optiSLang provides a workflow for the automatic identification of relevant input and output parameters and quantifies the forecast quality of the response surfaces with the help of the Coefficient of Prognosis (CoP) and the Metamodel of Optimal Prognosis (MOP) workflow. To achieve an efficient optimization and reliable parameter reduction, a predictable prognosis quality of the response surfaces is incredibly important. With the availability of an automatic parameter reduction, optiSLang allows a "no run too much" philosophy in order to minimize solver calls. Furthermore, optiSLang automatically selects the appropriate algorithms for the optimization and supports the interfacing to almost any software tool which is used in virtual product development.

Sensitivity analysis in optiSLang

There is an integrated version of optiSLang inside ANSYS Workbench available where the following steps have already been performed:

- Parametric Model
- Definition of input parameters
- Simulation Model
- Definition of output parameters

After dropping the sensitivity wizard on the project page, optiSLang automatically shows all parameters defined in ANSYS. The user defines the optimization problem by assigning the specific range for each input parameter as well as goals and constraints for the outputs. The first and most important step for a successful and efficient optimization procedure is to analyze the global sensitivities of the design parameters of the initial design. By performing an optimized Latin Hypercube Sampling (LHS) with N=45 design points, the design space is scanned. Once all the design points indicated by the Coefficient of Prognosis measure are computed, the Metamodel of Optimal Prognosis detects the optimal approximation model using the optimal subspace of important variables for each specified solver response. The software directly shows only the most influential design variables for each output parameter. In the following, for each output parameter, the optimal approximation model and the most significant input parameters are identified (see Fig. 8 next page).

Looking at the graphs in Fig. 8 (see next page), it is interesting to note that the length of the pocket is at the same time the most influential input parameter regarding the mass and the first frequency reduction. This means that the optimization will be the best compromise between goal and constraints.

Optimization

Using an optimization wizard, optiSLang automatically suggests the most appropriate optimization algorithm in order to find the best design which satisfies goals and constraints. Here, the NLPQL is suggested as the most appropriate optimization algorithm. The quality of results obviously depends on the accuracy of the approximation which is influenced by the number of design points and the approximation functions used to generate all response surfaces. The algorithm converges after N= 91 design evaluations. The best design (#88) with its input parameters is shown in Fig. 9 left (see next page) with the associated responses shown in Fig. 9 right (see next page).

The best design is automatically verified in the ANSYS simulation model. In Fig. 10 (see next page), the optimum design is shown and compared to the basic geometry.

The optimization provides a final design which presents the minimum value for the thickness and the diameter of the flange according to the design constraints. In Tab. 3 (see next page), the geometrical characteristics and the mechanical performances of the optimum design are compared to the basic geometry values. The percentage of decreases or increases of the output parameters are also shown.

It is proved that optiSLang allows to obtain a mass reduction of around 23 %. In this case, the final geometry also has a bigger value of stress and a lower value of the first frequency. However, all outputs satisfy the constraints. Furthermore, optiSLang allows working with much more than the investigated 6 input parameters without changing the process. The optimization loop in optiSLang is highly automated. The software independently reduces the optimization problem by choosing the best approximation model in
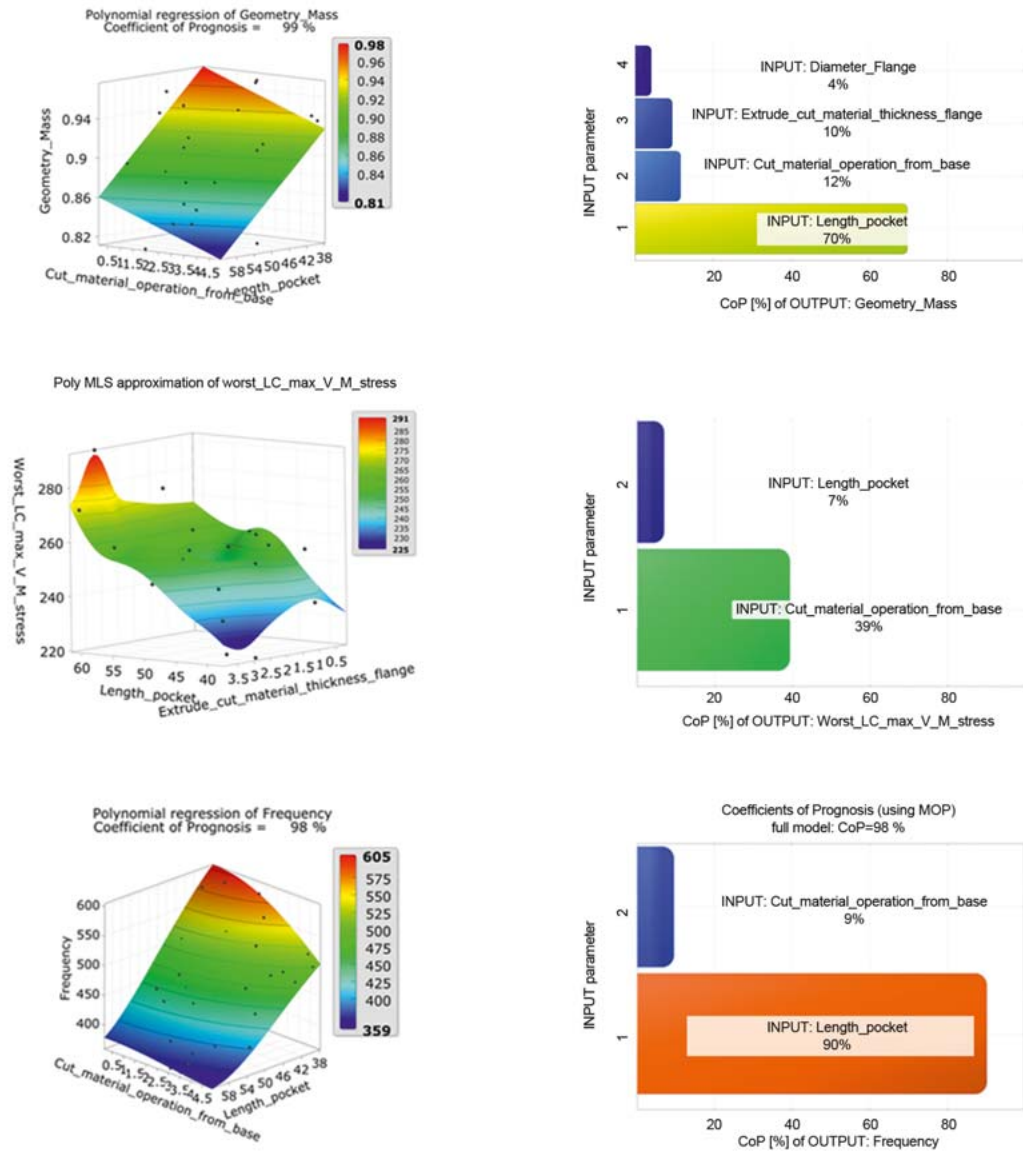
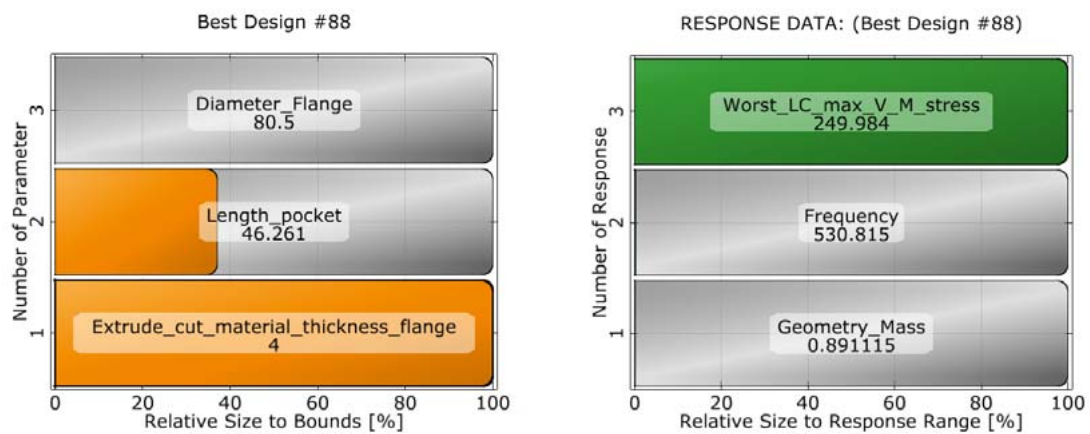Fig. 8: Most influent input parameters for each output

Fig. 9: Input parameters best design (left) and predicted output parameters best design (right)
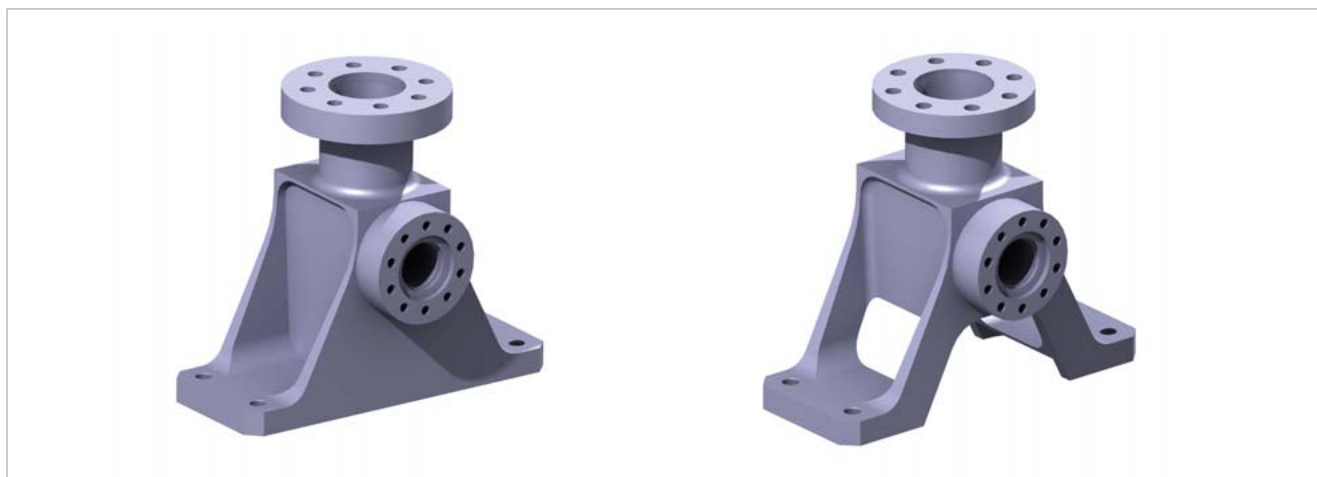
Fig. 10: Initial design (left) and optimum design (right)

		Basic Design	Optimum Design
Inputs	Diameter upper flange	88 mm	80.5 mm
	Length pocket	no pocket	46.26 mm
	Radius pocket	no pocket	20 mm
	Diameter flange towards nozzle	60 mm	57 mm
	Cut material from upper flange	no	4 mm
Outputs	Total Mass	**1.155 kg**	**0.89 kg = – 22,9 %**
	Maximum stress	**233.9 MPa**	**238.3 MPa = + 1,8 %**
	1st Frequency	**683 Hz**	**554.48 Hz = – 18,8 %**

Tab. 3: Results of the optimization in optiSLang

order to build the response surfaces. Also, the most appropriate optimization algorithm is suggested. In Fig. 11, the equivalent stress distribution for the worst LC, before and after the optimization, is compared.

Validation

The validation aims to demonstrate the possibility for an optimization of other cast components using the same workflow. Therefore, a much more complex geometry with a large amount of load cases was tested. The complex geometry examined is the pressurization and degassing plate for the hydrogen tank (PPDRH). The optimization goals and constraints are the same as previously described. The geometry presents 5 external mechanical interfaces and the simulation model consists of 320 load case combinations plus the modal analysis in clamped configuration.

By using the LHS method and 4 optimization parameters, 25 design points are generated and all of them are computed in the simulation model. Once the DoE is solved, optiSLang carries out the sensitivity analysis and generates all the response surfaces using the MOP. The NLPQL is again suggested as the most appropriate algorithm for the optimization because the number of inputs is low, the variables are continuous and the optimization problem presents one objective function. The algorithm generates 154 designs
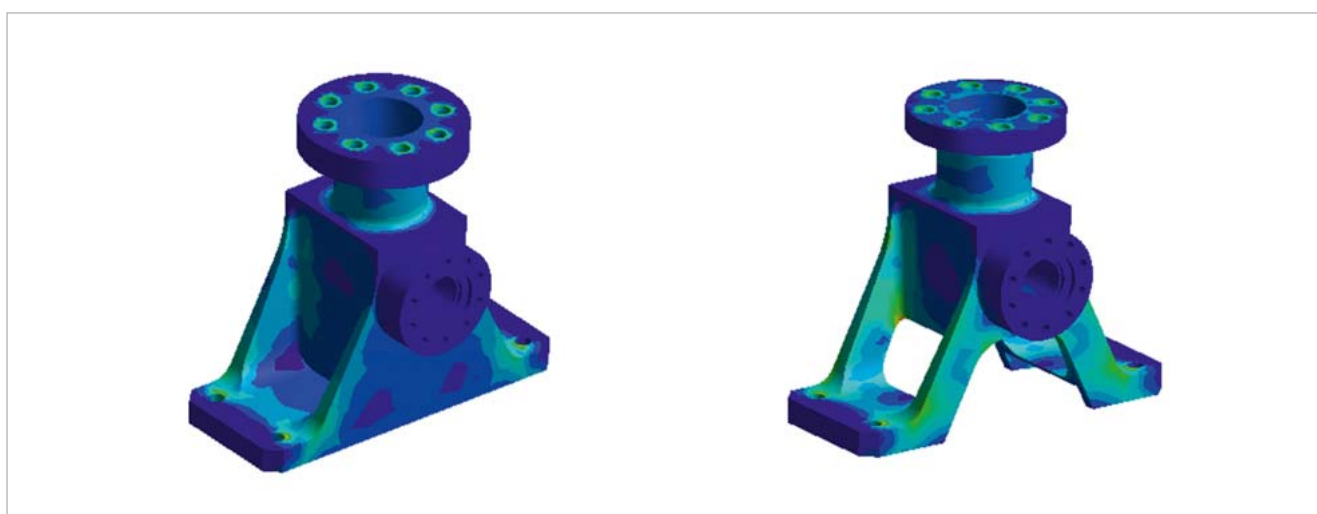

Fig. 11: Comparison of the equivalent stress distribution, initial (left) vs. optimum design (right)

and the best one is found. The final design is verified and, in the following, the output parameters are presented and compared to the initial design.

		Basic Design	Optimum Design
Inputs	Cut material IF5 IF3	no	6.97 mm
	Cut material IF1 IF2 IF4	no	11 mm
	Reduce thickness supports	no	3.96 mm
	Reduce thickness connections	no	7 mm
Outputs	Total Mass	**7.057 kg**	**6.580 kg = – 6,75 %**
	Maximum stress	**239 MPa**	**238 MPa = – 0,4 %**
	1st Frequency	**1150.7 Hz**	**1064.1 Hz = – 7.52 %**

Tab. 4: Results of the optimization in optiSLang

By looking at Table 4, it is possible to see that all the constraints are considered and the mass value has been reduced by 6.75%. In Fig. 12, the initial geometry and the final design are compared.

a valve geometry with the objective to reduce the structural weight as much as possible. The initial design was optimized using the three most importance input design variables and the mass was also significantly reduced by 23%. optiSLang is safe to use, minimizes the user input, automatically reduces the problem and suggests the best optimization algorithm. The software allows working with large numbers of optimization parameter, such as 50. Thus, the same design optimization process can be applied in order to optimize more complex geometries with a large amount of geometric parameter. In conclusion, the optimization process provided an efficient, flexible, suitable approach and allowed to explore possibilities of improvement in order to satisfy goals and constraints.

Outlook

The parametrical values of the design can be improved by using the parametric interface ANSYS space claim direct modeler which allows to automatically parametrize any kind of basic geometry STEP file. This is really suitable when the basic geometry becomes more complex. The optimization allows the user to perform a multi-objective optimization by using the possibility to consider different kinds of analysis
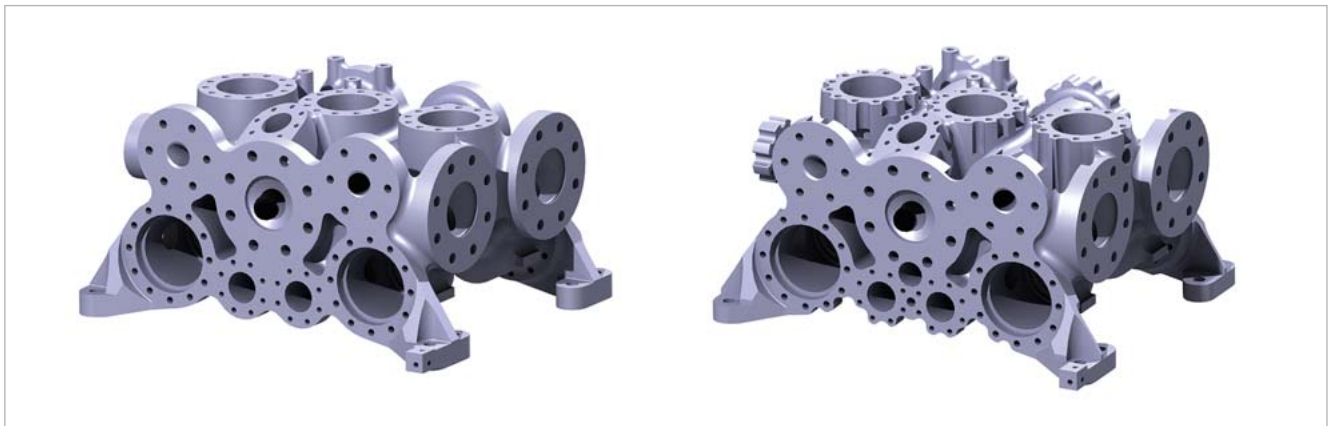

Fig. 12: Comparison of the initial (left) and the optimum design (right)

The validation demonstrates that it is possible to perform the design optimization process even for a much more complex geometry with a large amount of load cases. Thus, the presented process can be considered as appropriate for a standard optimization procedure of structural cast components.

Conclusions

The aim of the presented work was to develop a highly automatic and efficient design optimization process to optimize different structural cast components. A parametric approach based on the Design of Experiments and the Response Surface method was chosen to perform the optimization. The process was developed, implemented and validated successfully. The design optimization was applied for the redesign of

at the same time (such as: static structural analysis, modal analysis, fatigue analysis, thermal analysis, fluid dynamic analysis etc.). The power of this method is the improvement of the structural components in a multidisciplinary context in order to obtain a product with a high performance quality in several fields of application. A further step of an important improvement could be the performance of a robustness evaluation of the final design.

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