MASTER OF DESIGN – CAE-BASED
ROBUST DESIGN OPTIMIZATION WITH OPTISLANG

Sensitivity analysis, optimization and robustness evaluation with a minimum amount of user input and solver runs for your effective virtual product development.

optiSLang as algorithmic toolbox for RDO

In the field of product engineering, the introduction of technical innovations as well as the requirements for improvement of product performance are accelerating and increasing. Thus, product life cycles and development times are constantly getting shorter. Therefore, there is a high demand for virtual product development (Computer Aided Engineering, CAE) and CAE-based optimization tools. At the same time, quality requirements of reliability and robustness are increasing. Robust and optimized product designs are needed. Considering this, CAE-based Robust Design Optimization (RDO) becomes more and more important. To address these challenges, optiSLang offers you an algorithmic toolbox to meet all requirements.

With optiSLang you are able to:
- couple any (CAE) solver software to your workflow and use it for automation of your process chain
- manage an unlimited number of parameters due to automatic input reduction
- handle design failure up to 50%, non-linear CAE-problems and noisy responses
- standardize your process for quality assurance

- perform variant studies, sensitivity analysis, optimization, robustness and reliability evaluation within a single workflow

The general RDO methodology which will be discussed in this article is the following:
1. Sensitivity analysis to focus on important inputs
2. Deterministic optimization to find the optimal design
3. Robustness evaluation to evaluate input tolerances of the best design by stochastic methods

Parametric modeling, process integration and automation

To solve RDO tasks, the availability or generation of a suitable (CAE) parametric model is a key requirement. Parametric modelling environments like ANSYS are very powerful and can be easily integrated with optiSLang. Even a full integration of optiSLang into ANSYS Workbench is available. In principle, any other solver can be easily coupled to optiSLang. We offer you a great variety of supported integrations which includes, amongst others:

- any solver that can be executed in batch-mode handling ASCII-input and -output files
- ANSYS Workbench and ANSYS classic
- Abaqus
- FloEFD
- AMESim and Simulation X
- Python, Matlab and Excel

After your process is integrated, it can be automated and used as standardized process. The process chain can be expanded by additional solvers or pre- and post-processing tools within a single workflow. For any time- or frequency-dependent RDO task, optiSLang's functionality of signal processing significantly helps to extract particular responses out of signal data.

Best practice modules

One of the main innovations of optiSLang v4 is the availability of best practice workflow modules with wizard guidance to choose the most appropriate algorithms with robust default settings. With the help of the following three modules:

- **Sensitivity analysis** to understand the design, to reduce the input parameter space to the most important inputs, to check the prediction quality of response variation and to automatically generate the optimal meta model
- **Optimization** to improve design performance
- **Robustness evaluation** to check design robustness exposed to scattering material parameters, production tolerances or scattering environmental conditions

The user input is minimized to define the parameter ranges and their scattering, as well as objectives and constraints. All modules can be applied via drag and drop into the scenery of the project page.

Focus on important design parameters

As a first step before the actual optimization procedure, it is always recommended to perform a sensitivity analysis. With this analysis, you can study how the output variation is affected by different sources of input variation and thus, to reduce the input parameter space for the RDO task.

The most relevant methodologies for a global sensitivity analysis implemented in optiSLang are:
1. Scanning the input parameter space with advanced Latin Hypercube Sampling to avoid clustering and to cover optimally the input parameter space.
2. Identification of the most important input parameters and quantification of their contribution to response variation using optiSLang's **Metamodel of Optimal Prognosis (MOP)** algorithm and variance based sensitivity analysis.

The main benefits of optiSLang's sensitivity analysis are:
- Automatic identification of the MOP with maximal prognosis quality by determination of best approximation model (e.g. polynomial, Moving Least Squares) for each output in the optimal subspace of important input parameters
- Automatic reduction of inputs of those being important to describe the output variation
- Assessment of the prediction quality of the MOP by optiSLang's **Coefficient of Prognosis (CoP)** including quantification of input importance
- Quantification of numerical noise of the outputs
- Estimation of the optimization potential: are the chosen input parameters in the right range to achieve the objective? Are objectives conflicting? Can the MOP be used to approximate the solver output for further optimization?

Design optimization

Within the optimization framework, several algorithms for single and multi-objective optimization are available:
- Gradient-based methods
- Adaptive Response Surface Method
- Nature inspired algorithms such as evolutionary algorithms or particle swarm optimization

The choice of the most suitable and efficient optimization method is automatically provided by optiSLang workflow wizards. This choice is based on the results of the sensitivity analysis and the optional user-defined input, like the number of objectives, parameters and failed designs as well as the level of solver noise.

There are two main optimization strategies:
1. The search of the best design is performed on the MOP as a very efficient pre-search without any additional solver calls. Then, the best design of the MOP can be used as the final design after validation with a single solver call or as a start design for a subsequent optimization
2. Standard optimization with direct solver calls using the reduced input parameter set of the sensitivity analysis

Evaluate tolerances

To match quality requirements of designs exposed to given material and environmental variations or geometry tolerances, their scatter of all important responses needs to stay within acceptable ranges. To prove that, a variance based robustness evaluation can be performed.

In this context, the first step is the assignment of scattering input parameters by definition of their scatter range, distribution and correlation among each other. Then, the robustness space is scanned by advanced sampling methods and the resulting response scatter is quantified. By using the MOP ap-

proach, we can additionally identify the most important scattering input prameters and quantify their importance.

Several strategies for robustness evaluation are possible to be realized in optiSLang:
1. Robustness evaluation after determination of the best design
2. Sequential optimization and robustness evaluation
3. Fully coupled robust design optimization

Example: Tuning Fork in ANSYS classic

Introduction
With the simple example of a tuning fork, the whole workflow will be presented comprising integration, sensitivity analysis, optimization and robustness evaluation in optiSLang. A modal analysis with a fixed support of the tuning fork and an undamped oscillation is performed within the parametric modeling environment ANSYS classic.

Integration
The integration is created via batch-script that executes ANSYS classic in batch mode and ASCII-input and –output files. This integration is fully supported in optiSLang and therefore very simple to generate.

Definition of input and output parameters
For the sensitivity analysis and optimization, six input parameters were considered. Namely, these are the geometry parameters rod length, rod width, grip length, grip width, radius and depth (Fig. 1). At the same time, four output parameters are evaluated: the frequencies obtained by the modal analysis (frequency 1, 2 and 3) and the mass.

Optimization task
The aim of the optimization was to equalize the main frequency 1 to 440 Hz and the higher frequencies to their duplicates and triplicates respectively. Thus, a single objective target optimization was performed by taking the quadratic deviation to the target value and by weighing the importance of the targets. The objective function which should be minimized is (frequency_1-440)^2 + ((frequency_2-880)/2)^2 + ((frequency_3-1320)/4)^2. As a constraint, the mass should be lower than 12 g.

Sensitivity analysis
As a pre-optimization step and for the identification of the most important inputs, a sensitivity analysis was performed. By obtaining an MOP for each output, an input parameter reduction is possible. Figure 2 (top) shows the CoP matrix as a result of this procedure. For instance, 98 % of frequency 1 can be explained by the MOP with only five inputs (rod width, rod length, grip width, grip length and depth) instead of six considered input parameters. The MOP for frequency 1 is illustrated in Figure 2 (bottom).

Optimization
After choosing the appropriate optimization algorithm by optiSLang's workflow wizard, the optimization can be performed based on the reduced input parameter set. First, a gradient-based optimization on the MOP with best design validation was chosen using
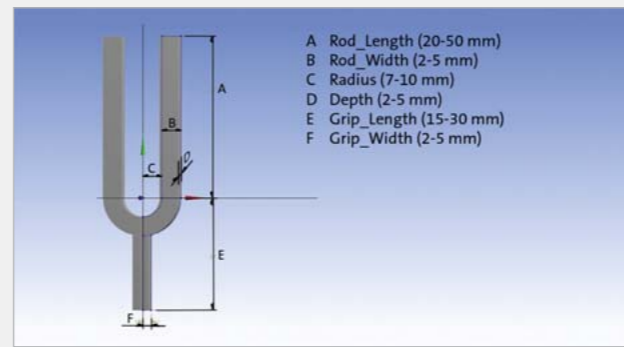

Fig. 1: Geometry input parameters of the tuning fork design

predefined settings of the optimizer. 200 design points were evaluated until the algorithm was converging. In a second step, the best design of this MOP pre-search was used as a start design for an optimization with Adaptive Response Surface Method (ARSM) with direct solver calls. The search window of the start range for the ARSM was reduced to 10 % to generate a local search. The post-processing window of these results is illustrated in Figure 3.

The benefits of using optiSLang for this optimization are:
- The optimization was performed much faster: without the MOP, 200 solver calls would have been necessary for the first optimization step. This results in 33 minutes of time saved with calculation durations of 10 seconds per design.
- The properties of the best design were considerably improved. By comparing with the original design, the mass was reduced from 29.2 g to 9.9 g and the frequencies matched the target values (Figure 3). The starting values were 414, 417 and 959 Hz.
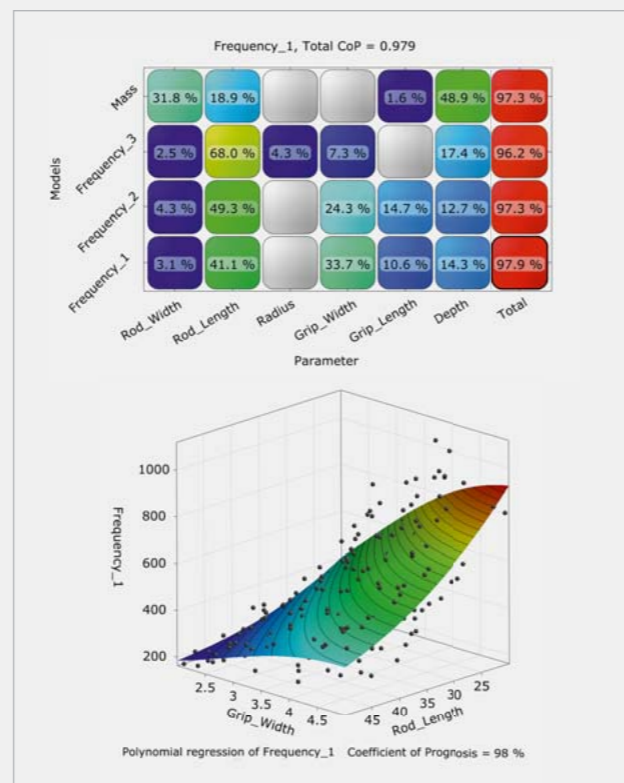

Fig. 2: Results of the sensitivity analysis: CoP matrix (top) / Metamodel of Optimal Prognosis for frequency 1 in dependence of the two most important inputs (bottom)
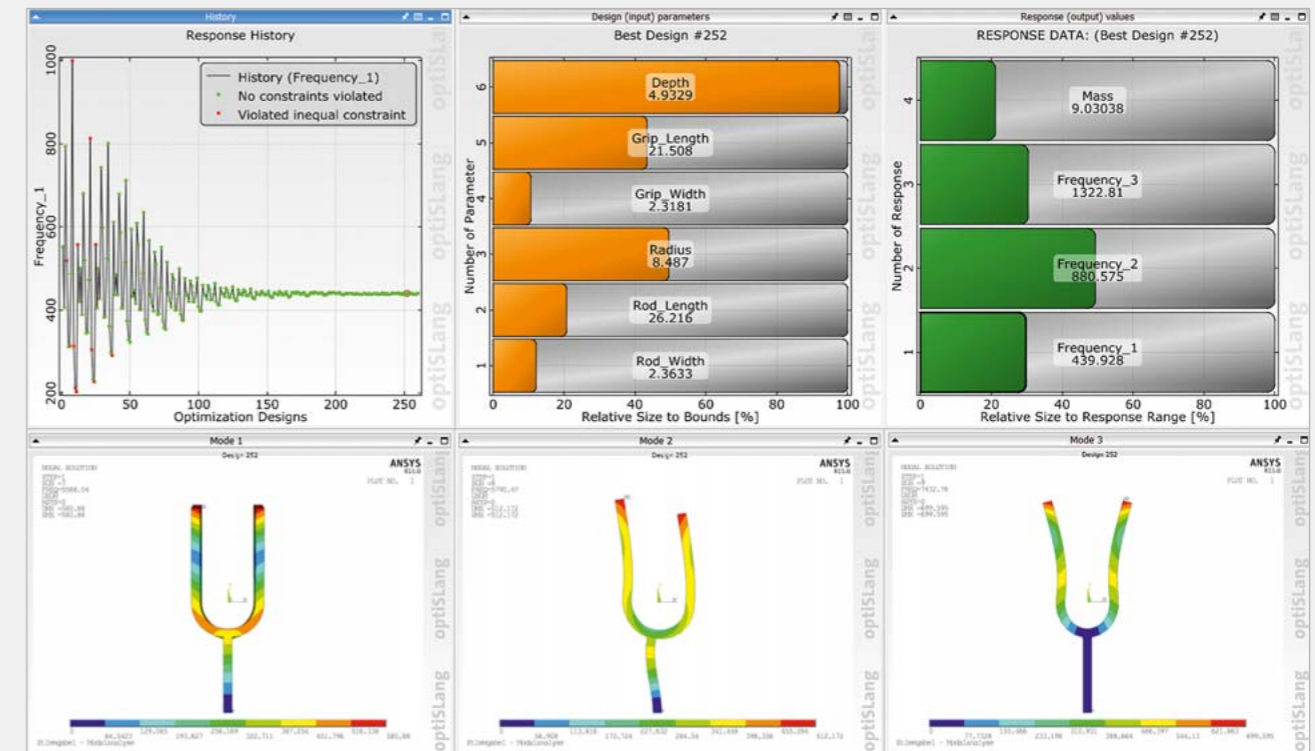

Fig. 3: Results of the optimization with Adaptive Response Surface Method: the response history shows the iterative convergence to the target value of 440 Hz. The input and output parameter values can be monitored. Furthermore, images of the modal frequencies were displayed for each design.

Robustness evaluation
For the robustness evaluation of the best design, besides geometry parameters, material parameter variations (here: E-module) were also considered in order to recognize critical inputs and to reduce uncertainties. All geometry parameters were varied with 0.5 % scatter relative to the mean and 1 % for the E-module with normal distribution respectively.

For a robust design, ± 7 Hz variation of the first frequency were defined to be acceptable. As a result of the robustness evaluation (Figure 4 (A)), 13 % of the designs are not in this range indicating that the tuning fork design is not robust. To reduce the output variation, either the mean value of the output or the scatter of the most important inputs needs to be decreased. As the first option is meaningless for the frequency of a tuning fork, the second strategy was implemented here. The analysis of the importance of the inputs by their sensitivity measures (Figure 4 (B)) indicates that the scatter of the four most important geometry parameters (grip width, rod length, grip length, rod width) induce ~70 % of the total output variation whereas the E-module induces 26 % of the latter. Consequently, the scatter of these four geometrical inputs was reduced to 0.2 % and the E-module to 0.8 % relative variation of their mean in a second robustness analysis. Finally, only 1 % of the designs were not in the acceptable variation range of ± 7 Hz. Thus, by actively influencing only the most important inputs scatters, a robust design could be obtained.

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This tuning fork example can be provided to you as a tutorial with example files.
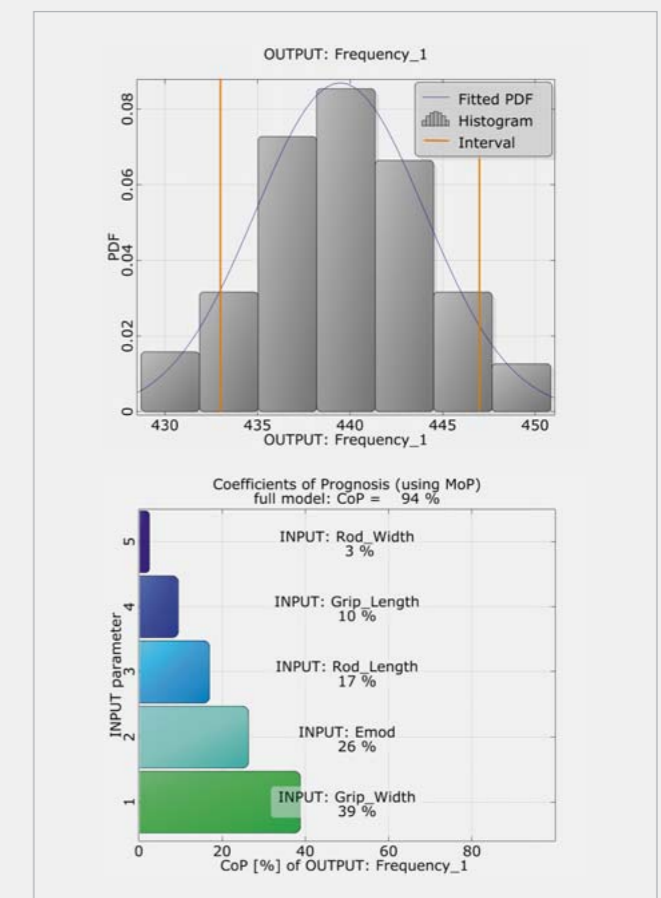

Fig. 4: Results of the robustness evaluation: probability density function of frequency 1 with the interval defining a variation of +/- 7 Hz (top) / CoP values as importance measure for all input parameters that influence frequency 1 (bottom).