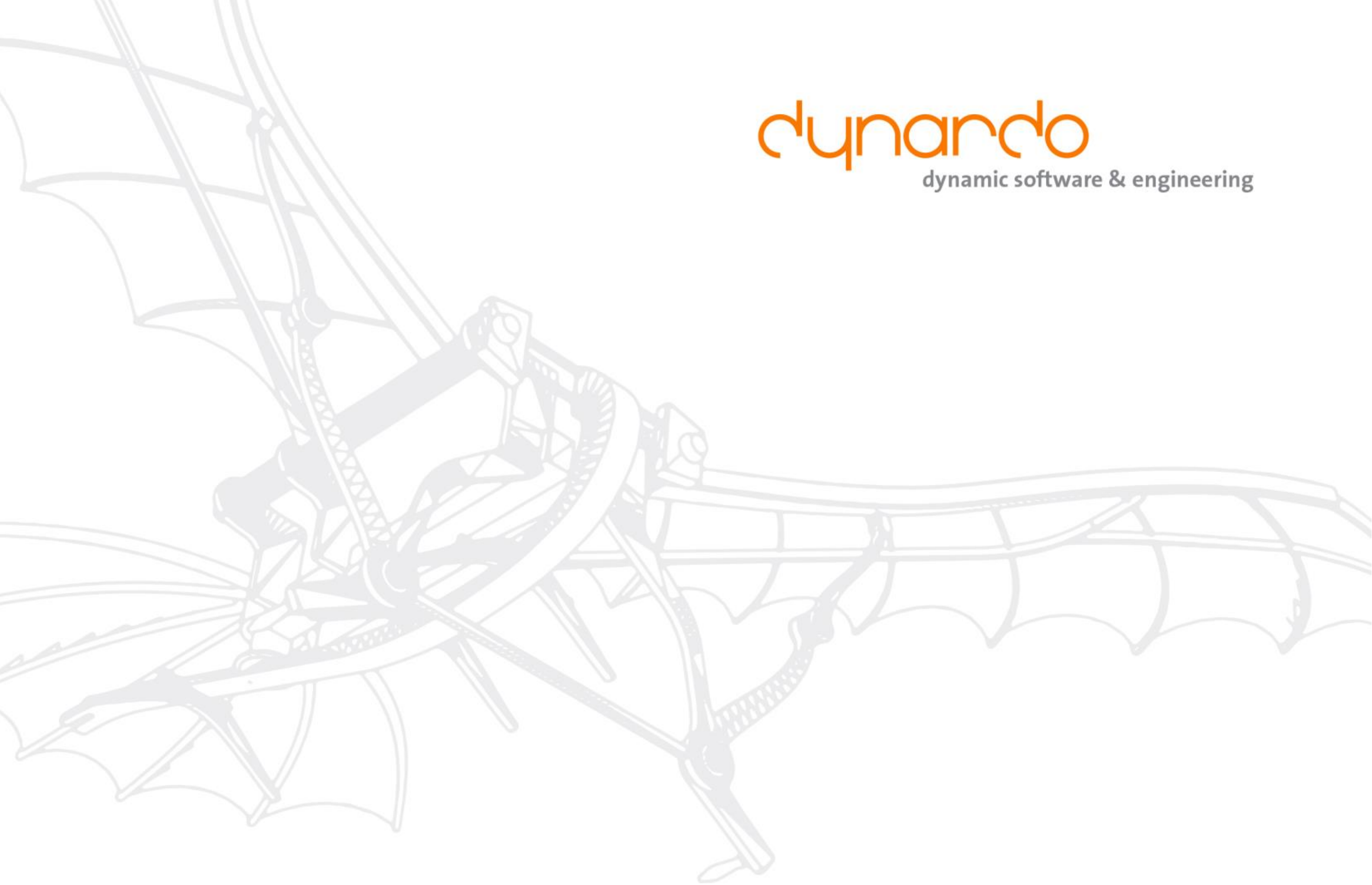

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Lectures

Calibration of Field Data and Simulation as an Optimization Task with Signals

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CALIBRATION OF FIELD DATA AND SIMULATION AS AN OPTIMIZATION TASK WITH SIGNALS

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Dynamics and Testing: Combining Physical & Virtual Testing

SUMMARY

Signals are characteristic system responses that are a critical help to understand, validate and improve the physical model of the system as well as the system design itself, by understanding the important parameters.

Calibration, in the sense of using field observations and simulation runs to estimate simulation model parameters or to update the uncertainty regarding these parameters, can be formulated as an optimization task where the output parameters are signals and the target function is for example the sum of the square deviations of the signal from the testing and the signal from the simulation.

The optimization task of identifying the right input parameters can then be formulated for example to minimize the value of the target function by selecting the appropriate values for the input parameters. A simple example however shows that this can lead to a non-unique solution for the input parameters. Therefore additional boundary conditions for the calibration can be very useful.

Knowing from the calibration the significance and sensitivity of input parameters, further optimization can be used to improve the system or product design. With the information from the calibration the design space can be adapted and appropriate surrogate models can be used, that also respect nonlinear system behaviour.

In the case of strong scattering of the test and/or simulation results the identification task must be enhanced by stochastic analysis as the fit of single signals by design variables are no longer sufficient. Then a parameter space has to be used, where the input variables have also stochastic elements, like a stochastic distribution.

The technique of identifying the input parameters within an optimization task for the calibration of field data including measured signals and signals generated from the simulation can be used across all industries where virtual prototyping is important.

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In this paper we first introduce and discuss some methods and measures used for sensitivity analysis and optimizations, than the parameter identification as a special optimization task is shown by using two theoretical examples followed by two industrial applications.

KEYWORDS

Dynamics and Testing: Combining Physical & Virtual Testing; Calibration, Parameter Identification, NVH, nuclear waste depository

1. Model Validation and Calibration with the Parameter Identification as an Optimization Task

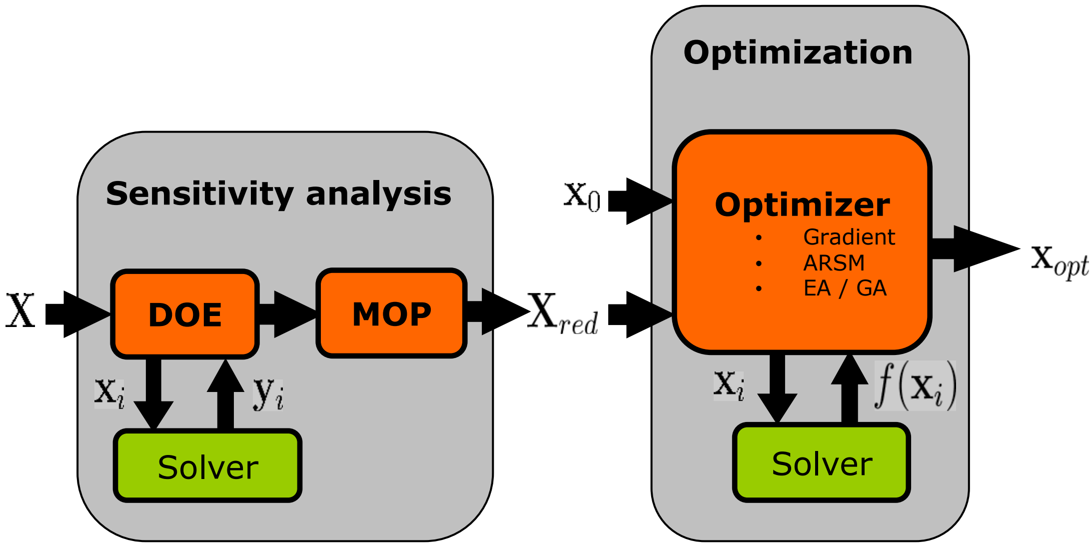
Optimization using numerical simulations can in general be classified into two different categories: the first category is associated with the target to improve the functionalities of the product and the second category is to test and improve the model to fit in a better way the reality.

While the optimization is already in wide spread usage for the improvement of product functionalities the potential for the usage of similar optimization techniques to improve the quality of the model, typically with parameterization and calibration, is often not realized. Therefore the main aim of this paper is to clarify that potential.

The workflows that are used for the calibration of a model are similar to those used for the improvement of functionalities of the product.

In both cases it is recommended to start with a sensitivity analysis, especially if handling with a larger number of parameters. A sensitivity analysis is used to study which input parameters have significant importance for which output parameters. These studies are also used to establish a meta model, that approximates the output parameters as functions of the input parameters. This step can help to reduce the design space to the important parameters. For the criteria of importance of parameters and quality of the meta model different statistical measures have been established (Most and Will, 2011). It is important that these meta models also include nonlinear dependencies of the parameters and that the prognosis quality is quantified. For the quantification of the quality of prognosis of such a model in (Most and Will, 2008) the coefficient of prognosis, CoP, is introduced. With these CoPs a nonlinear meta model can be selected, that provides the best model with respect to the ability for the best prognosis, not only the best fit for the data. Trying to provide only a model that best fit the data easily can lead to an overfitting, however unable to explain further data. This model based on the best CoPs is the meta model of best prognosis, MOP.

Figure 1: A typical workflow for an optimization, starting with a sensitivity analysis for selecting the important parameters, followed by the optimization.



A typical workflow for the optimization of product functionalities is shown in Figure 1: After the definition of the Design Space X (the parameterization), during the design of experiment (DOE), designs with different input parameters X_i are created. These different designs are solved, generating the values for the output parameter Y_i. These data samples can be used to establish the MOP, that can significantly reduce the design space to the important variables X_{red}, including nonlinear dependencies. Also from the sensitivity analysis a good initial parameter set X_0 for the optimization is selected. For the optimization it is necessary to define at least one optimization function $f(X_i)$. Several optimization methods are available like gradient based, adaptive response surface, or evolutionary and genetic methods (Will, 2006). Finally an optimized set of input parameters X_{opt} is found.

The workflow for the calibration can be just similar, using as an optimization function a difference to the measurements, i.e. the sum of squared deviations of measured and calculated data for the corresponding time steps, and the identified parameter set is than the optimized set of input parameters X_{opt}.

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2. Two theoretical examples

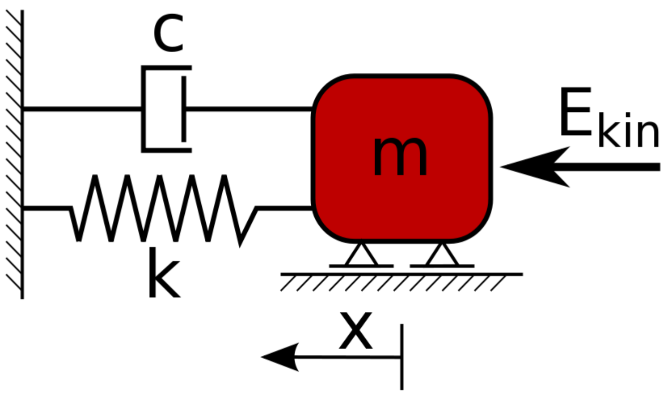
That the potential of using optimization for the parameter identification is currently not realized is also associated with the fact, that there are not many optimization tools available that can handle different field measurements, i.e. time series for a pressure, or in general have the ability to include signals from the real test environment in an easy way for the target function of the optimization.

During the development of such a model for the simulation the parameterization is the key to ensure a realistic behavior of the model.

Our first example is a simple damped harmonic oscillator. This example is used to understand how signals can be handled and also that that different optimization runs can lead to quite different values for the parameter, due to the fact that the solution can be realized with different values of the input parameters.

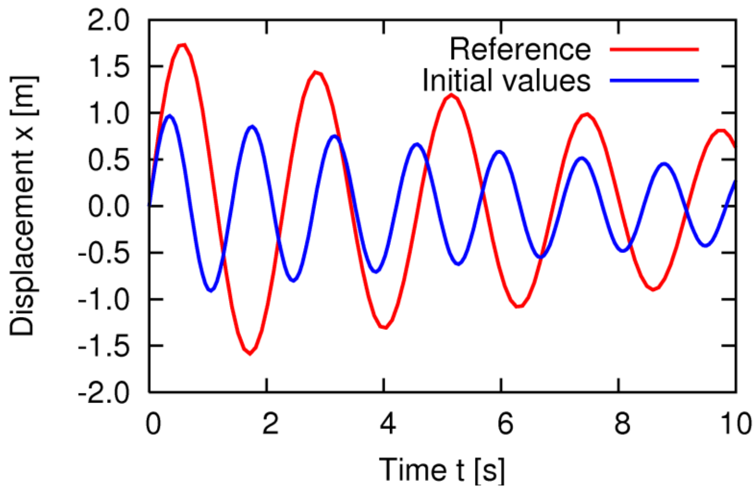
The basic input parameters for the calibration of the damped oscillator are the mass m, the initial kinetic energy E_{kin}, the damping c and the stiffness k.

Figure 2: The damped harmonic oscillator.



The reference signal is from the displacement x over time for some parameters, that are the unknown parameters in this example (red curve):

Figure 3: The reference signal and the signal calculated from the initial values.



The equations for the damped oscillator are:

$$m\ddot{x} + c\dot{x} + kx = 0$$
$$\ddot{x} + \frac{c}{m}\dot{x} + \frac{k}{m}x = 0$$
$$\ddot{x} + 2D\omega_0\dot{x} + \omega_0^2 x = 0$$

and they have the analytic solution for the displacement

$$x(t) = e^{-D\omega_0 t}\sqrt{\frac{2E_{kin}}{m}}\frac{1}{\omega}\sin(\omega t),$$

With the undamped eigen-frequency ω_0:

$$\omega_0 = \sqrt{\frac{k}{m}}$$

Lehr's damping ratio D:

$$2D\omega_0 = \frac{c}{m}$$

and the damped eigen-frequency ω:

$$w = w_0\sqrt{1 - D^2}$$

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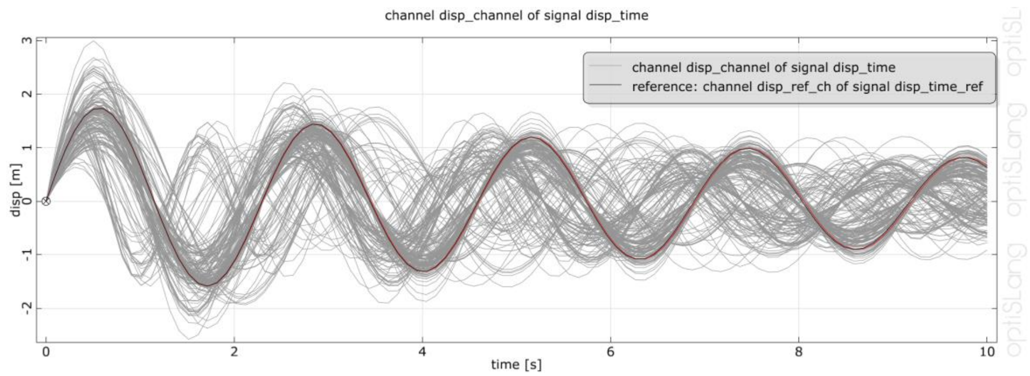
The target for the optimization is to identify input parameters, that generate a signal very close to the reference signal, therefore the objective function is the sum of squared differences between the displacement of the reference x* and the displacement of the calculated solution x at n discrete time steps (signals are in general discretized due to the measurement)

$$f(m, k, D, E_{kin}) = \sum_{i=1}^{n} (x_i^* - x_i)^2$$

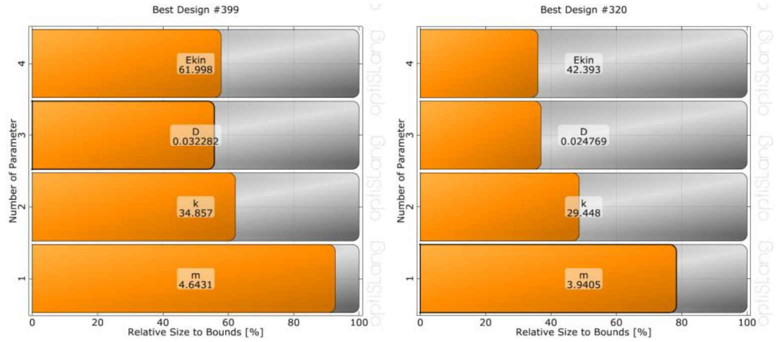
The sensitivity study for this case shows that all input variables are significant. Showing the solutions for all the initial parameters of the sensitivity study, that are all the signals from the designs of the design of experiment, like in the figure below, often already provides for real world applications insights into interesting frequency ranges as well as some information about the feasibility of the parameter identification itself.

Figure 4: The reference signal together with all signals from the sensitivity analysis.



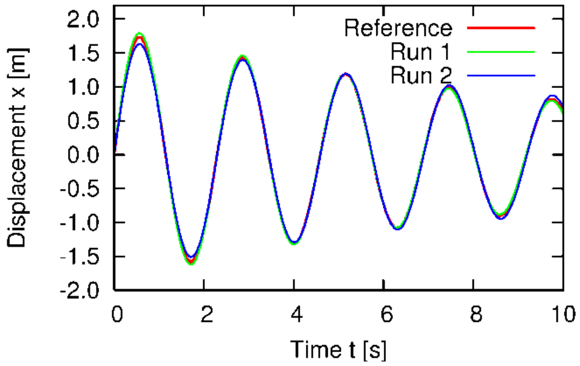
Running different optimizations lead to different set of initial parameters like show in figure 5.

Figure 5: Two different optimizations lead to rather different identified parameter values.



Where both optimization runs lead despite the different values for the parameters to good results with small differences to the reference signal.

Figure 6: The identified parameter values from both optimizations lead to a good approximation of the reference signal.



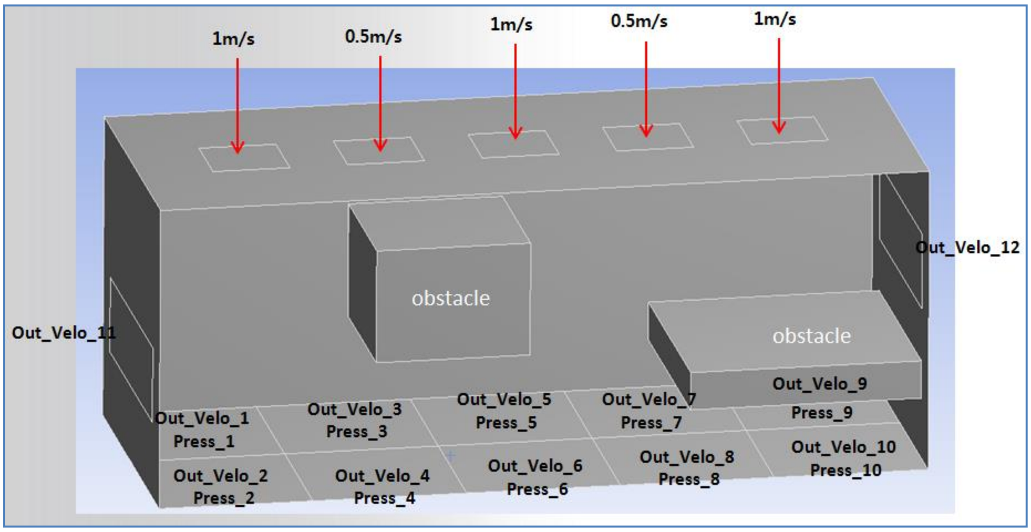
This non-unique solution for the identified parameters is due to the fact that the parameters E_{kin} and m as well as m and k appear only pairwise in the solution for the displacement and it is only their ratio that matters for the solution.

Therefore a unique solution can be generated by having for example a constant mass value for the optimization.

This example is shown in more details also for training purposes with signals in an optiSLang tutorial, available from Dynardo and currently included in the software delivery of optiSLang.

The second example is a simplified CFD test model, where a reference vector of the 12 outflow velocities exists and the task of the optimization is to find the set of 10 input parameters for the pressures (Press_1 … Press_10), that come close to the outflow velocities.

Figure 7: A CFD example of a box with two obstacles.



The optimization function to minimize, similar to the signal function for the damped harmonic oscillator case, is the squared deviation of the reference velocities Ref_Velo_i and the velocities Out_Velo_i from the calculated solution:

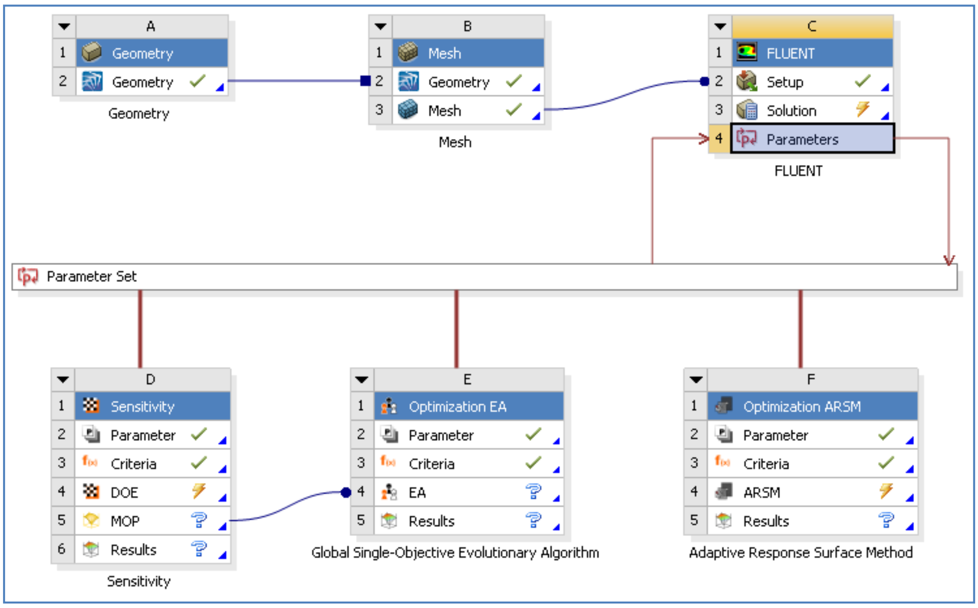
$$\sum_{i=1}^{12}(Ref\_Velo_i - Out\_Velo_i)^2$$

Also in this case it is important to have additional constraints, we choose that each output parameter is close enough within 10% to the corresponding reference output parameter:

$$abs\big((Ref\_Velo_i/Out\_Velo_i) * 100 - 100\big) < 10$$

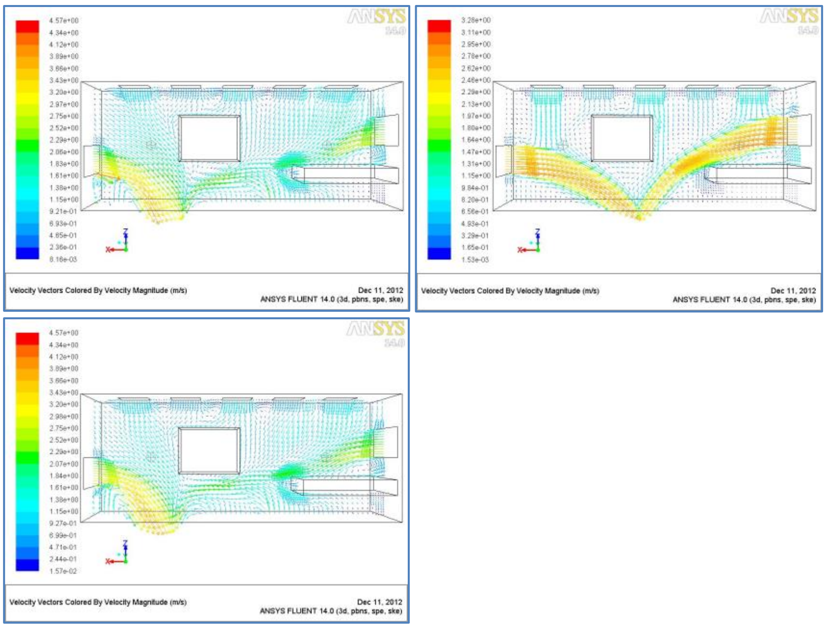
This problem was solved with optiSLang inside of ANSYS Workbench, the complete workflow is shown in figure 8:

Figure 8: The ANSYS Workbench set up with optiSLang inside ANSYS Workbench for the CFD example of a box with two obstacles.



and the solution was found with an Adaptive Response Surface Method (in general this method is recommended for a small number of continuous input paramaters).

Figure 9: Reference Solution (top left), Initial Solution (top right) and Optimized Solution (bottom right) showing the velocity vectors colored by velocity magnitude.



3. Practical Applications

The field of practical applications for model calibration by parameter identification cover a broad range. Some publications are available from the online library of Dynardo, showing applications from different industrial areas like civil engineering (Zabel and Brehm, 2008), automotive (Will, 2006) and oil & gas (Will, 2010). In this paper we focus only on two applications with signals, some progresses we made for a NVH automotive application and a new model calibration for a nuclear waste depository analysis.

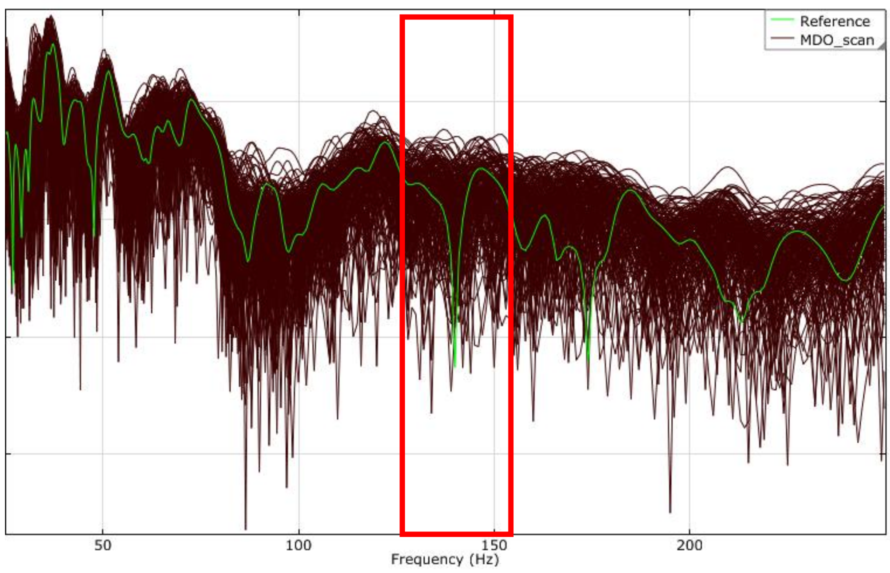
Calibration and Optimization of Driving Comfort Behaviour

In product development of luxury cars Noise Vibration Harshness (NVH) plays a very important role. Driver, co-pilot and passenger on the back seats should feel very comfortable during any driving conditions. Therefore the calibration of virtual models to available test data and the reduction of noise levels inside the car cabin is an important task of the virtual prototyping.

For the formulation of a successful calibration design space as well as a successful objective function two challenges needs to be met. First a very large number of variables may have an influence on the passenger car air vibration and second the frequency signals show a very large number of vibration modes.

As a result the selection of the main influencing parameters and the signal processing to extract response values which belong to one vibration mode are a very important part of the calibration process. In the example we start with a variation space of 485 sheet metal thicknesses of all body parts which might have an influence. Fig. 10 shows the variation of one of the sound pressure signals of 200 Latin Hypercube samples of the sensitivity analysis.

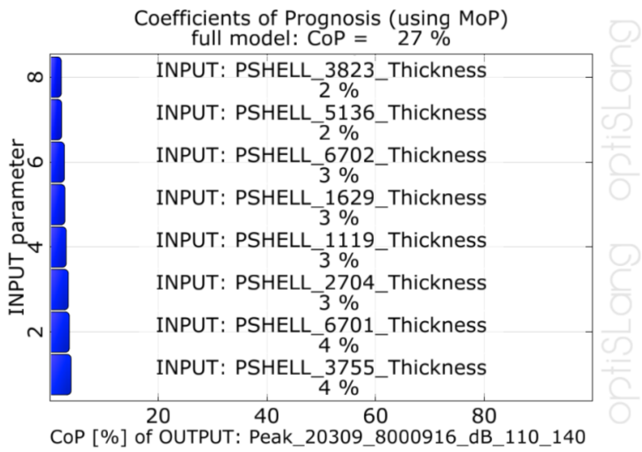
Figure 10: Variation of sound level, green – reference, black – 200 samples of the sensitivity analysis



Having the signal variation window we define the frequency window to extract the peak sound values which correspond to the vibration mode of interest. Note that because of stiffness variation the frequency and the sound value are varying at the same time and we need to adjust the extraction windows to avoid mode switch of important vibration modes within one extraction window.

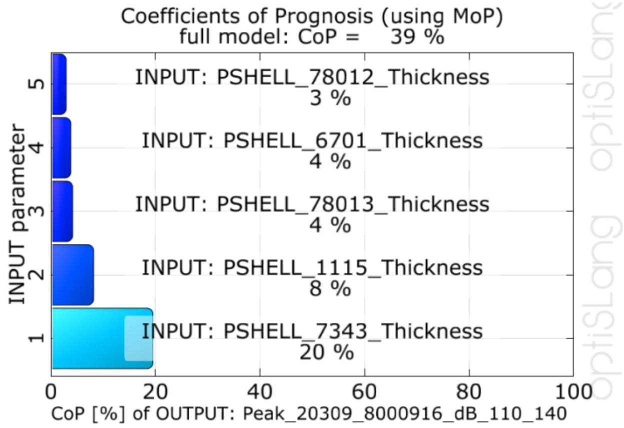
Unfortunately the CoPs for the variation of the peak sound level are below 30%, which indicate that only the important variables for less than 30% of the total variation were identified. It is our experience for this kind of identification task, that increasing of sampling to 300 or 400 designs or alternative extraction windows does not increase the CoP levels significantly. Main reason for the small CoP levels is that the pressure sound levels are influenced by mechanisms of 10..20 variables. To identify these mechanisms out of 500 variables a very large number of sample points will be necessary.

Figure 11: CoP value of the peak sound level in the frequency window 110 to 140 Hz, sensitivity study using 485 variables



Therefore we use the CoP values from the first sensitivity analysis to reduce the design space manually. We selected 37 variables which showed significant CoP for any of the response values of interest and repeated the sensitivity study in the reduced design space. The variation interval of the peak value in the frequency window 110 to 140 Hz at the second sensitivity study using 37 variables is 80% compared to the first sensitivity study using 485 variables. That approved our CoP based selection of important parameters. In the reduced space higher CoP value of the full model are close to 40% and higher CoP values of single variables are identified.

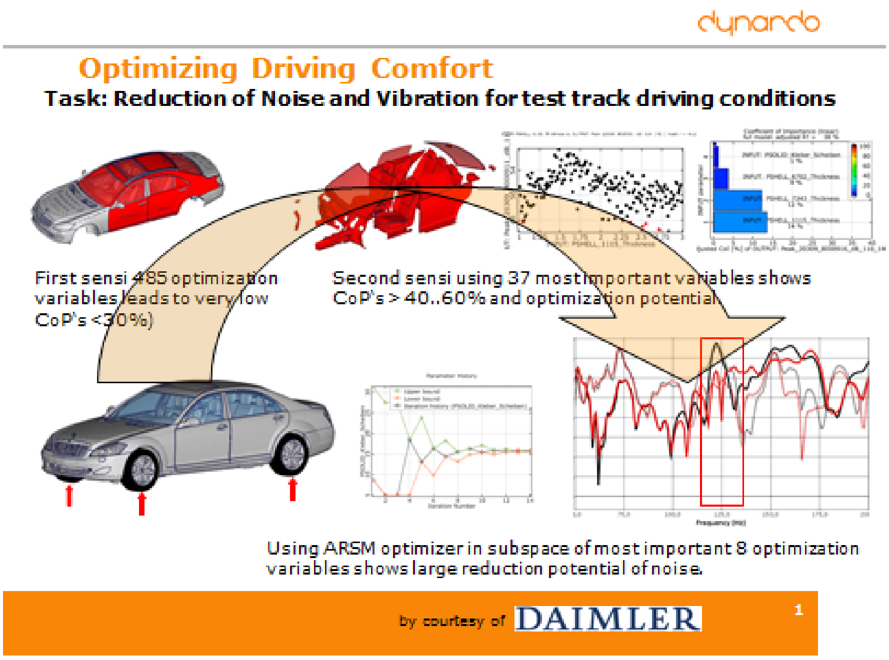
Figure 12: CoP value of the peak sound level in the frequency window 110 to 140 Hz, sensitivity study using 37 variables



In the reduced design space of 37 important variables also for the other important frequencies and positions the main contributors could be identified and the calibration to the reference signal was performed successfully.

Of course, after having a model which shows sufficient forecast quality to measurements, the next step in the virtual prototyping will be the optimization, here the minimization of peak sound pressure levels as shown in Figure 13.

Figure 13: overview of the process for an optimization using the same sensitivity study but selecting only the 8 most important variables for the optimization.



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Calibration of a Nuclear Waste Depository Model

In the research for the safeness of nuclear waste depositories heating experiments are performed in underground laboratories in order to understand the thermal-hydraulic-mechanical (T-H-M) interactions.

In these experiments the change due to the heat energy input over time of temperature, pore water pressure and stress fields are measured.

The DBE TECHNOLOGIE GmbH develops in cooperation with the Dynardo GmbH simulation models that are able to comprehend these interactions in claystone.

An important component of these developments is the calibration of the models with respect to the results of the measurements.

The heating experiment has been simulated with a T-H-M coupled 3-dimensional finite element analysis with ANSYS and multiPlas.

Therefore special routines from the poro-elasticity theory, thermal-hydraulic coupling and thermal-mechanical coupling in isotropic and anisotropic claystone formations were developed and implemented in ANSYS.

For the sensitivity analysis and for the parameter identification optiSLang was used. Due to the complexity of the T-H-M phenomena about 30 model parameters are used.

In this case it was essential for the successful calibration of measurement and simulation to use the powerful algorithms and filter strategies for large parameter spaces of optiSLang and the achieved short calculation times due to efficient numerical algorithms of ANSYS with multiPlas.

In the sensitivity analysis the material parameters (including parameters for the coupling) have been varied within physical possible boundaries.

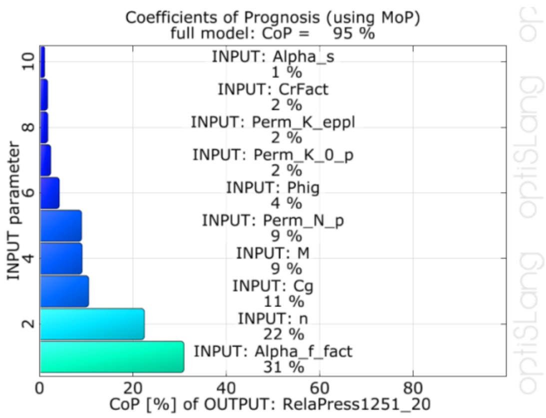
From the experiment temperature and pore water pressure data are available for 17 measurement points during the heating as well as before the heating.

Due to uncertainties in the process before the heating, the calibration and parameter identification was restricted to the heating process itself.

For the evaluation of the sensitivities the relative pore water pressures discrete time values are used. By the selection of these output values statements became possible for the sensitivity at the beginning and at the end of the heating as well as for the time when the pore pressure reaches the maximum.

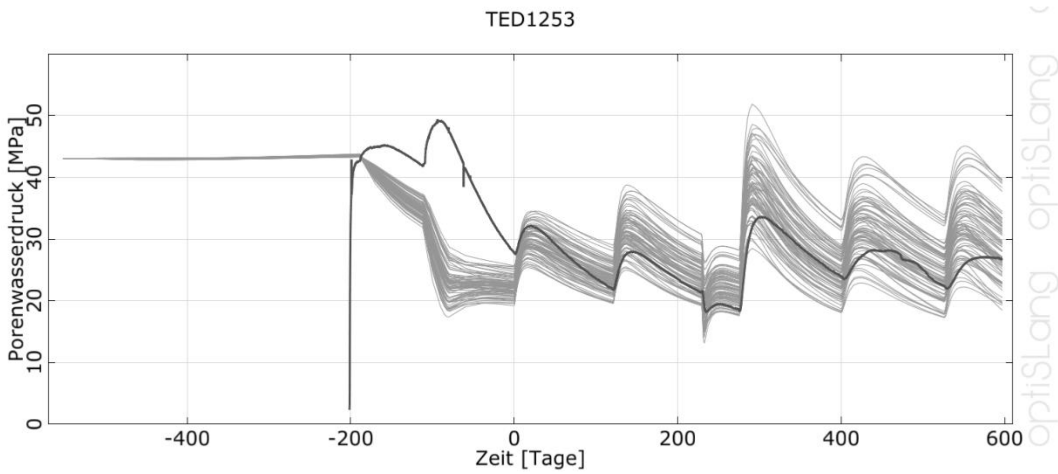
Without going here in further details for single sensitivities, it is important to note that the total CoPs show high values of above 85% (like in the figure below). This underlines that the physical phenomena are very good explainable through the identified correlations and also indicates that the right important parameters for establishing the model are used.

Figure 14: high CoPs are a good indicator for the quality of the model



By comparison of the scatter range of the calculated signals with the signals from the measurement (s. figure 15) statements about the quality of the model and the possible calibration of the model with the measurement are possible. If the scatter range of the calculated values is surrounding the measured values, then a successful calibration within the selected boundaries of the parameters can be possible. The figure shows, that this is possible from the start of the heating experiment (t=0).

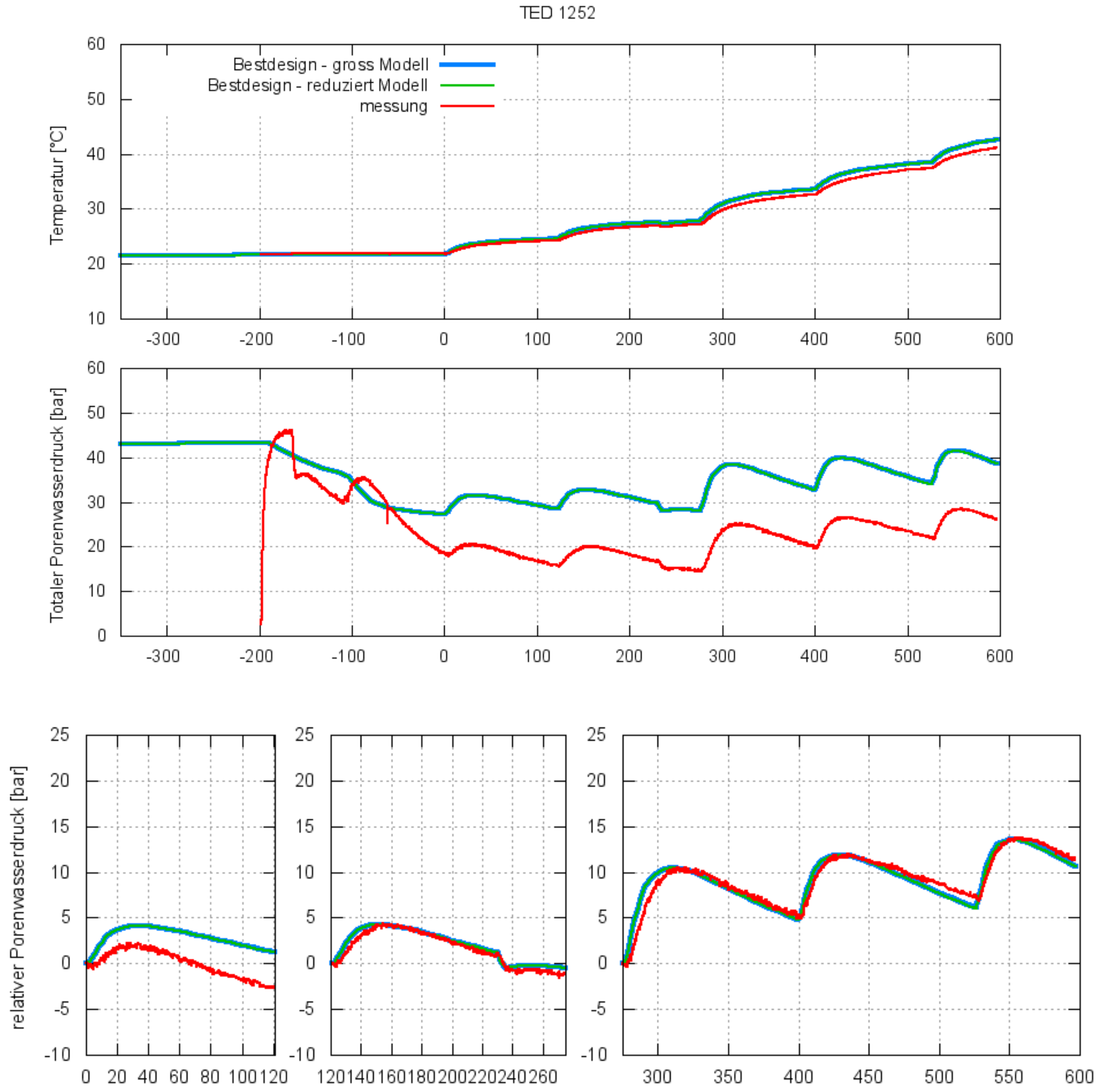
Figure 15: Pore water pressure at measurement point TED1253, as a signal over time, compared with the simulated signals of the sensitivity analysis.



For the parameter identification the optimization selected a set of input parameters, leading to a good approximation of the measured signals of the temperature and the pore water pressure over time. Parameters that only showed a negligible sensitivity have not been varied through the optimization for the parameter identification. They have been set to their reference values.

The comparison of the measured and calculated time signals of temperature and pore water pressure (s. figure 16) shows, that with the identified parameter for the model the physical phenomena could be simulated very plausible and a very good calibration with temperature and pore water pressure was reached.

Figure 16: Comparison of measurement vs. simulation at measurement point TED1252 after parameter identification. Top: temperature over time, middle: total pore water pressure, below: relative water pressure for the three phases of heating.



OUTLOOK

In this paper we demonstrated with theoretical and practical cases how the calibration of a model with parameter identification can be treated as an optimization problem including signals. These techniques will become most probably an important standard technology for the development of more accurate models for the simulation.

REFERENCES

T. Most and J. Will. Sensitivity Analysis using the Metamodel of Optimal Prognosis. In Proc. Weimarer Optimierungs- und Stochastiktage 8.0, Weimar, Germany, November 24-25, 2011. 2011.

T. Most and J. Will. Metamodel of Optimal Prognosis - an automatic approach for variable reduction and optimal metamodel selection. In Proc. Weimarer Optimierungs- und Stochastiktage 5.0, Weimar, Germany, November 20-21, 2008. 2008.

J. Will. The Calibration of Measurement and Simulation as Optimization Problem. NAFEMS Seminar Virtual Testing - Simulationsverfahren als integrierter Baustein einer effizienten Produktentwicklung. Wiesbaden, Germany, Mai 10-11, 2006. 2006.

Volkmar Zabel, Maik Brehm. System identification of high-speed railway bridges. In Proc. Weimarer Optimierungs- und Stochastiktage 5.0, Weimar, Germany, November 20-21, 2008. 2008.

J. Will. Optimizing of hydraulic fracturing procedure using numerical simulation. In Proc. Weimarer Optimierungs- und Stochastiktage 7.0, Weimar, Germany, October 21-22, 2010. 2010.