

ISSUE 1/2016

Title Story // Correlation analysis in time and space

Sensitivity analysis of several body-in-white parameters
Model-based optimization of vertical axis wind turbines
Impact analysis of joining distortion
Optimization of fiber composite components in yacht racing
Feasibility study of large gas turbine outer casing bolts

RDO-JOURNAL

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CORRELATION ANALYSIS IN TIME AND SPACE – NEW METHODOLOGY FOR EXTENDED EVALUATION OF DESIGN PERFORMANCE

A large amount of customer value in using variance based design evaluation with optiSLang is driven by correlation analysis helping to increase the understanding of designs. Dynardo's MOP technology represents the leading edge methodology for correlation analysis between scalar input and output variables. In recent years, Dynardo has been developing intensively the application of random fields and field meta-models to extend the capabilities of correlation analysis from scalar values to field quantities, such as one dimensional fields in time or frequency as well as two or three dimensional fields at surfaces or in 3D space.

Nowadays, in the age of Industrial Internet of Things (IIoT), known as Industry 4.0 in Germany, we are looking forward to getting access to a lot of real time machine and design data, including spatial distribution of material or signal-based properties. There will be a race for the best algorithms to process "Big Data" and to use it for product life cycle management, design and optimization. For virtual prototyping, this means plenty of data in time and space will become accessible requiring extended methods of correlation analysis for evaluations of the design performance.

First industrial projects have shown that Dynardo's application of random fields and field meta-models are very appropriate for the modeling of correlations in time and space. Field meta-models are especially useful whenever distributed or location-varying quantities have to be considered for correlation and sensitivity analysis, robustness evaluation as well as design optimization.

Another interesting industrial application of the technology is the calibration of so called digital twins regarding signals in time and space for monitoring, diagnostics and prognostics of product designs or systems. Further applications are in tolerance analysis or shape optimization.

The title story of this journal will give a brief overview on the methodology and application areas of random fields and field meta-models using the software Statistics on Structures (SoS).

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, Juni 2016

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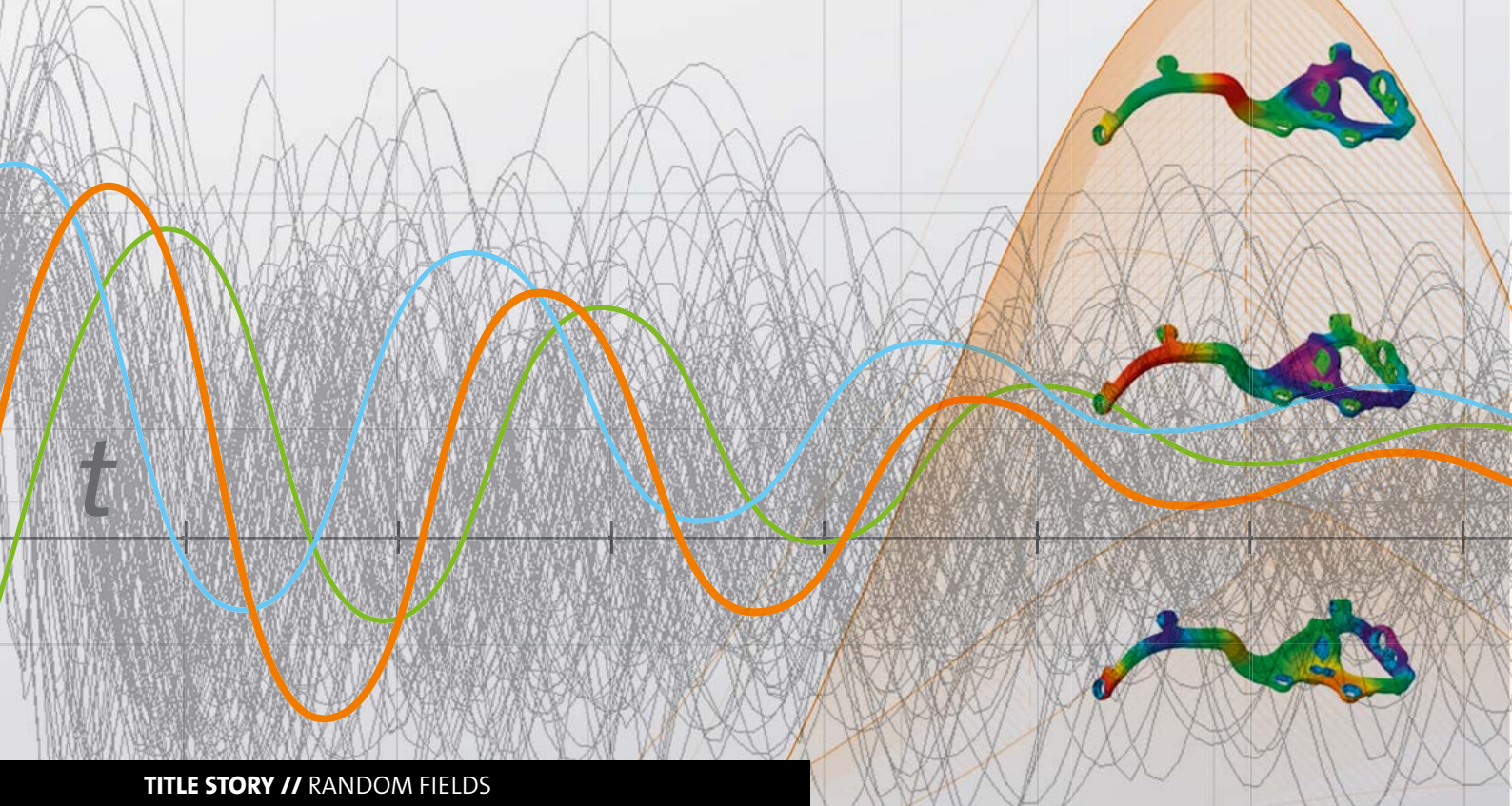
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TITLE STORY // RANDOM FIELDS

RANDOM FIELDS AND FIELD META MODELS – CORRELATION ANALYSIS IN TIME AND SPACE

The extended capabilities of Statistic on Structures can process and analyse spatially or temporally distributed product parameters for a realistic simulation and evaluation of the design performance.

Introduction

Progress in measurement technology makes it possible to capture accurate data of real component geometries. This also includes the recording of spatial distribution of material or signal-based properties, such as dynamic processes in time, frequency fields or load-displacement curves. Computing-based manufacturing technologies (Industry 4.0) provide such spatially or temporally distributed product parameters in large quantities. To use this data (Big Data) for a realistic simulation and evaluation of design performance, extended methods of correlation analysis are required.

Random fields and field meta models, which Dynardo has been developing intensively in recent years, are suitable for the modeling of correlations in time and space. Using random fields, parametric models for arbitrary geometries and signals will automatically be generated and can be directly used for the process of optimization, model calibration or robustness evaluation. For example, the generation of random imperfections will be possible with the help of random fields. Field meta models can be used, for instance, to approximate the result of an FEM solution including spatial and temporal distribution. Thus, the accuracy of the meta

modeling and the sensitivity analysis of distributed values will be increased while simplifying the effort of processing such parameters.

This article gives a very brief overview on the methodology and application areas of random fields and field meta models.

Methodology

Typically, the variation of a parameter can be described by a representative value (e.g. statistical mean), the magnitude of variation (e.g. statistical variance) and even more detailed by its statistical distribution type. This can be applied directly to distributed quantities, where one can describe the variation by the statistical parameters - for each point - in time or space. Further and most importantly, the correlation among all individual points in time/space need to be specified. In practice, however, one can hardly specify the whole covariance matrix of a spatial or temporal field. However, it is possible to approximate the covariance matrix through a truncated series expansion as shown in Figure 1. This series represents the correlation structure of a field in

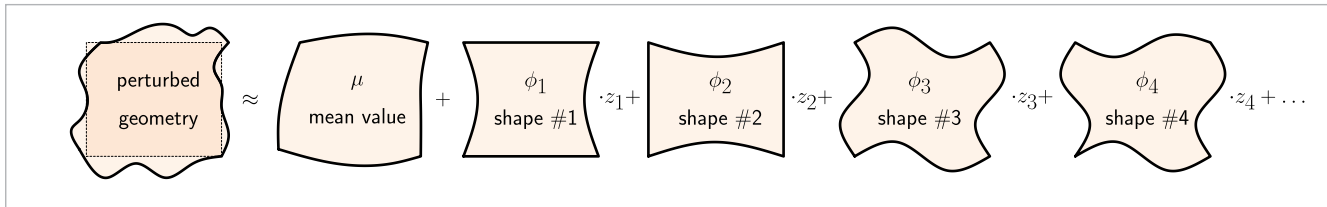


Fig 1: Representation of a random field (e.g. a geometric perturbation from a CAD model) based on mean value and a linear combination of deterministic scatter shapes and associated random scaling factors (random field amplitudes) z_i .

sparse memory layout. It is defined by “scatter shapes” and associated “amplitudes”. The scatter shapes are typically determined by analysis of a test set. The amplitudes are a sub space representing the total field variation in terms of a few scalar parameters.

The methodology ensures that a minimum number of parameters yields a certain accuracy in describing spatial or temporal variation patterns. Hence, **it can be used to identify an optimal parameterization of a variation in space or time based on analysis of measured or virtually created data.**

An extension of the random field parameterization is field meta modeling. Therein, one does not represent the field variations in terms of a new parameter space, but in terms of the original input parameters. The field meta models are nonlinear functions that are chosen to approximate the average field response in an optimal way through variations of the input parameters as illustrated in Figure 2. Therefore, these surrogates are called field meta model of optimal prognosis (F-MOP). They also allow to compute sensitivity indices based on prognosis quality (field coefficient of prognosis – F-CoP).

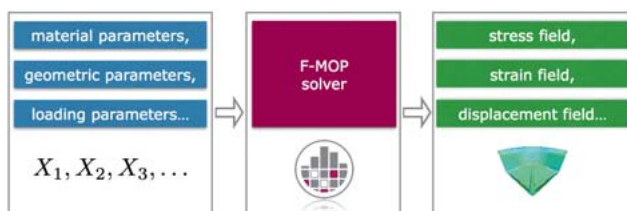


Fig 2: Approximation of FEM solutions by field meta models replacing the original CAE solver

Correlation analysis of signals

Signals are data being distributed in a one-dimensional space. Signals are, for example, dynamic processes (time, frequency), load-displacement curves, transient external loading and boundary conditions, etc.

Case 1: Parameterization of a dynamic process

This example represents a simple dynamic process defined by a damped harmonic excitation in time. Although the mechanical model is very simple, the task of finding a good parameterization is a challenge: The response changes its magnitude, its damping ratio and its frequency as illustrated in

Figure 3. Based on the analysis of a design of experiments, a random field model is established. Only 7 parameters can be used to explain nearly 80% of the whole variance observed in the DoE, while already 11 parameters represent more than 90% of the variance. The scatter shapes are wavelets as seen in Figure 4. This result can be confirmed to be an optimal parameterization by analytical solutions.

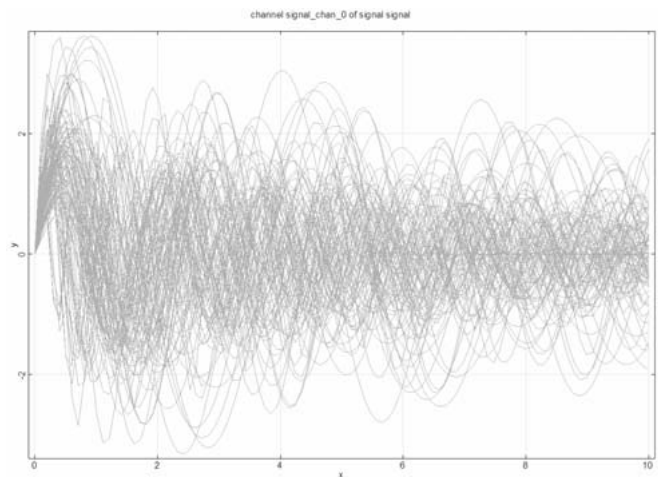


Fig. 3: Observed variations of a dynamic process in a design of experiments

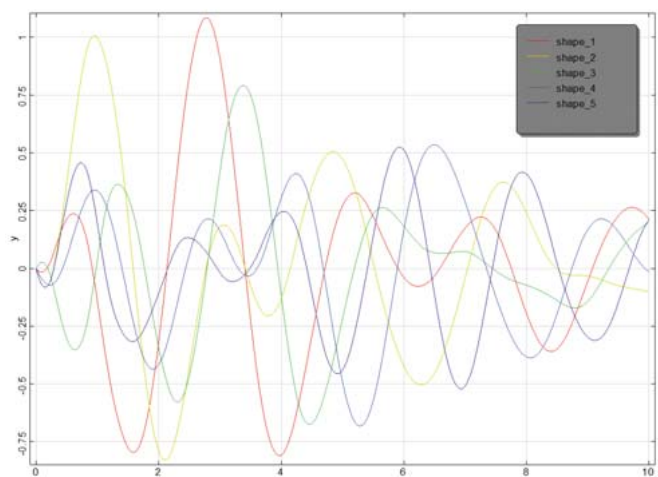


Fig 4: Identified scatter shapes describing variations of a dynamic process

Case 2: Modeling ad-hoc variations of signals

Sometimes, one wants to study the performance of a numerical model given some variations of input signals. If measurements are available, the random field parameterization can be used to create an accurate statistical model for the

observed signal variations. Typically, however, no or only a few measurements are existing during the design process.

In this case, signal variations were modeled by a “synthetic random field”. Therein, the correlation is assumed using some autocorrelation model between the individual points in time. The distribution of mean and standard deviation can be either estimated from a few measurements or assumed as well. The results are typically sinus-like functions in 1D similar to the Fourier series, as being illustrated in Figure 5. Therein, a synthetic random field model is created with zero mean and constant unit standard deviation.

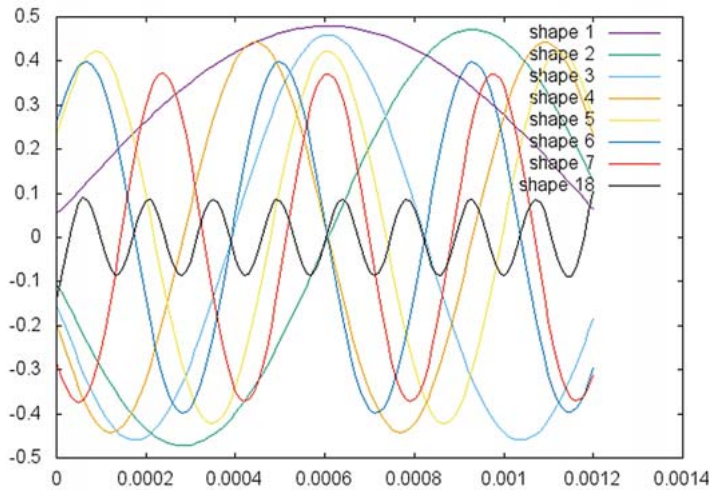


Fig 5: Scatter shapes of a synthetic random field model for mean=0 and std-dev=1 at all points

Case 3: Sensitivity analysis of a signal

The field meta models can be used to perform an extended sensitivity analysis based on signal data. They allow to identify which input parameter is responsible for the response variation for each individual point in time. It is recommended to perform a sensitivity analysis based on field meta models (in favor of the scalar MOP) if

- The location of hot spots is not yet known
- The location of hot spots is varying
- Hot spots do not exist since one is interested in a distributed effect (for example the shape of the signal in an interval)
- The accuracy of a scalar MOP is too small, but the reason is unknown.

The result of a F-MOP is the visualization of the Field-CoP describing the distribution of the CoP along the time axis. By that one can identify at which locations of the signal the meta model is able to predict the variations well (or not), and at which locations of the signal input parameters are of large or small influence onto the signal variation.

The following example is presented by Römelsberger et al [1]. Therein an optimization on a meta model was attempted in order to optimize the design of a dual band WiFi

antenna. The response of interest were the minima of the “return loss” in frequency domain. A scalar MOP obtained an accuracy of CoP=71% only. Using a field meta model for the return loss spectrum, however, one can identify the intervals in frequency domain, which are responsible for the low accuracy of the meta model. The signal responses of a design of experiments are illustrated in Figure 6. The corresponding F-CoP values are shown in Figure 7. The upper curve is the F-CoP of the whole model defining the model accuracy for the respective frequency value. For the right minimum the accuracy is sufficiently large, but the meta model cannot well predict the variations in the center and for the left minimum. The center is, however, not relevant for the optimization. The left minimum is, however, the reason why the scalar MOP cannot approximate the minimum value well: The position of the minimum is varying and, further, it is a true singularity being dominated by round-off errors in the CAE process. The other curves in Figure 7 denote the sensitivity of the individual input parameters which is varying in the frequency domain.

The advantage of a Field-MOP is that it captures automatically all support points of a signal. Alternatively, one needs to manually define few hot spots for which a MOP is evaluated, but still misses the shape of the signal in the interval between the selected locations.

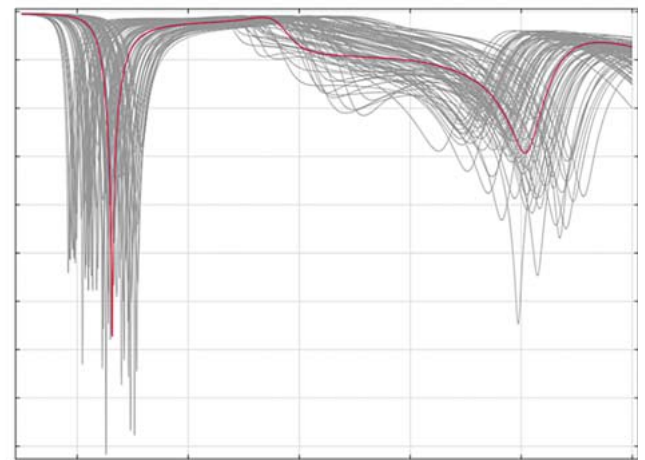


Fig. 6: Response signals of the “return loss” in frequency domain of a design of experiments

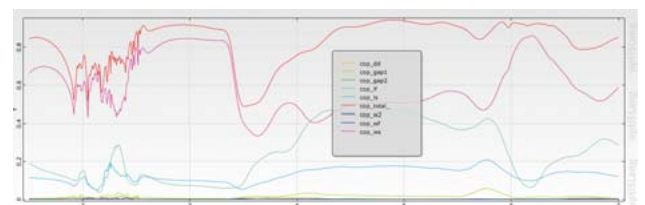


Fig. 7: F-CoP of the “return loss” in frequency domain

Case 4: Pre-Optimization on a signal meta model

A sensitivity analysis is an important part of the design process, typically being implemented before the actual optimization.

tion takes place. If the meta model is accurate enough, it can be used to “pre-optimize” the design without extra CAE solver run. The identified optimum of the meta model can later be used as a start point of the direct optimization.

Field meta models are recommended if the shape of the signal is of interest. This is the case in many applications of model calibration, e.g. the identification of material parameters based on measured load-displacement curves. The basic idea is that one approximates the whole load-displacement curve by a field meta model and then minimizes the error norm between the approximated signal and the reference curve.

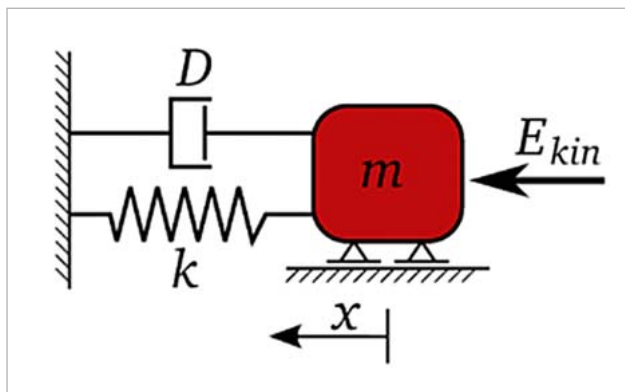


Fig 8: SDOF oscillator

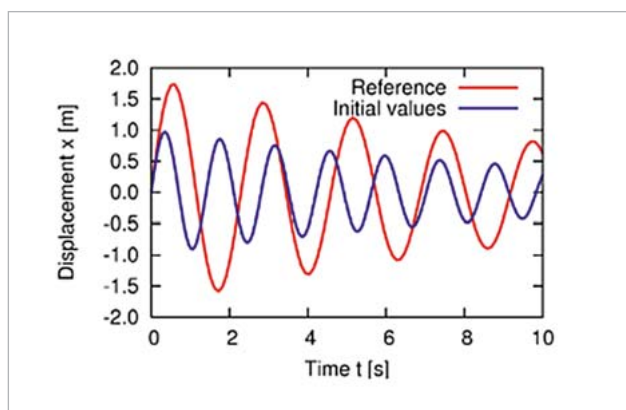


Fig 9: Response of a SDOF oscillator model (blue) and reference signal (red)

As an example, assume that the dynamic process of example 1 is the result of a numerical oscillator model as illustrated in Figure 8. The task is to identify the material parameters of a given measured reference signal as shown in Figure 9. In terms of scalar parameters one would need to identify the locations of the local minima and maxima and then minimize the position error with respect to the same extrema in the reference signal. The identification of these hot spots, however, needs manual programming and, thus, is prone to errors. Using a field meta model for the whole signal, one only needs to minimize the error norm between both signals. The result is shown in Figure 10 being very close to the true optimum.

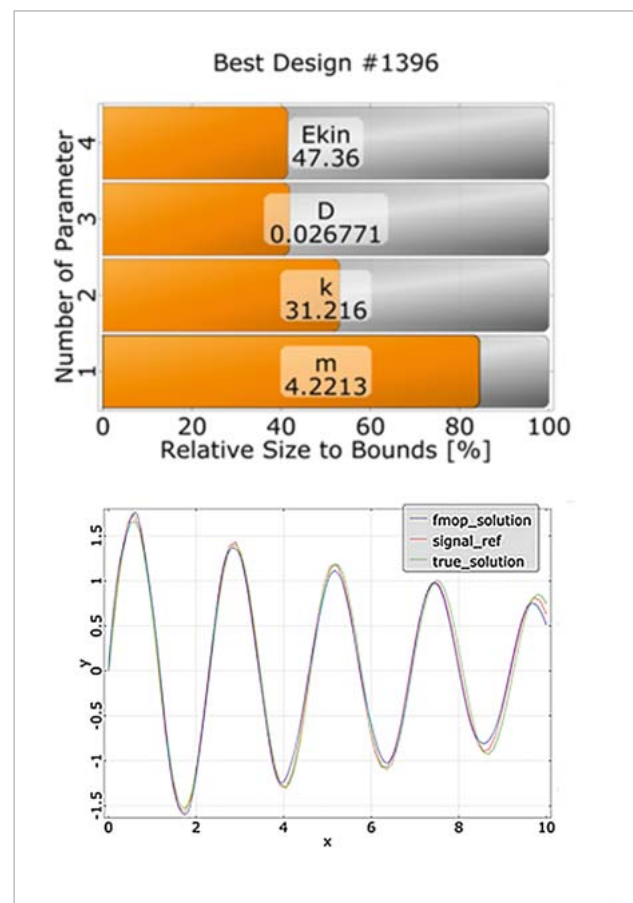


Fig 10: Solution of a pre-optimization of a model calibration

Correlation analysis in space

The methodology and work flows for modeling of signal variations can also be applied to spatial variations in 3D. Typical quantities are geometric variations (e.g. random imperfections due to manufacturing) like boundary coordinates or shell thickness, state variables (e.g. stresses, displacements) used to evaluate structural performance, damage (e.g. distribution of plastic strains), material properties (e.g. surface friction properties, fiber angles) etc.

Case 1: Parameterization of geometric imperfections based on measurements

Nowadays, detailed laser scans of manufactured products are often done in order to ensure the dimensional accuracy at critical locations. The same information can be reused, for example, to create a realistic statistical model of the geometric imperfections in order to virtually create random geometries, e.g. for a robustness analysis.

The following example is presented by Nunes et al [2]. Therein, the robustness of an automotive brake system regarding brake squeal noise was analyzed. The squeal noise frequencies predicted by the numerical model did not match the observed frequencies in the hardware experiments. Engineers suspected the geometric imperfections of the brake pad surfaces. To model these variations, laser scans of brake pad sur-

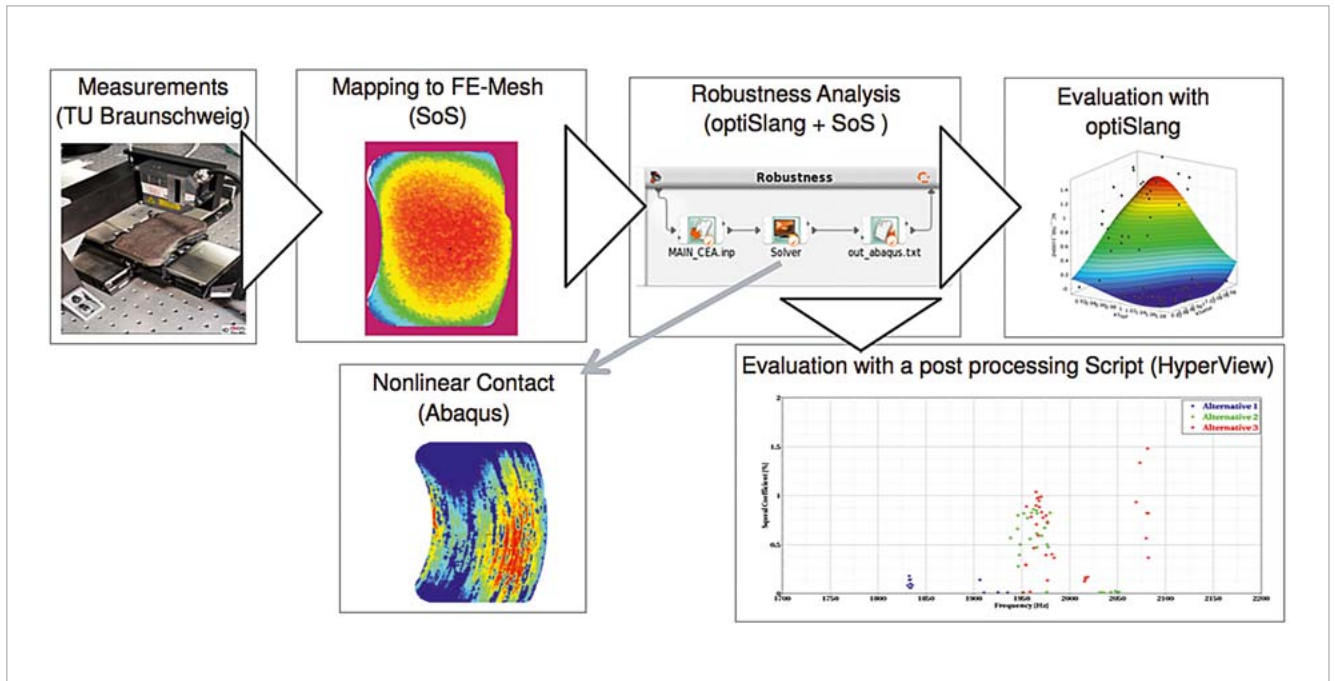


Fig. 11: Consideration workflow of measured geometries in a numerical robustness analysis

faces were done. The results were mapped onto a FEM mesh. Finally, a random field model was created which was capable of changing the FEM nodes on the surface according to the identified distribution parameters. The schematic workflow is illustrated in Figure 11. The results are illustrated in Figure 12. Therein one compares the numerically predicted noise frequencies obtained from a DoE with random scalar parameters (red) with predicted noise frequencies obtained from a DoE with additionally consideration of geometric variation patterns (blue). Obviously, the results obtained from varying the surfaces are much closer to the hardware observations.

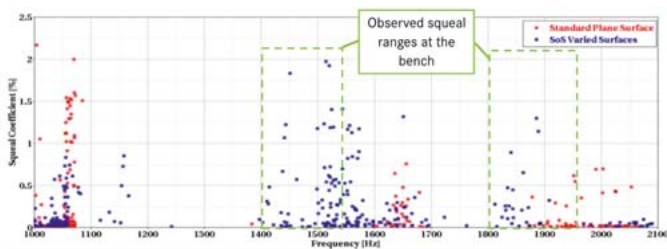


Fig. 12: Results of a robustness evaluation comparing a DoE without (red) and with (blue) varied geometry

Case 2: Modeling ad-hoc variations of geometric variations

In this example from automotive, the influence of geometric imperfections of a knuckle onto the brake squeal noise frequency was analyzed, see Nunes et al [3]. Only a single measurement of the true geometry was available. It was used to estimate the principal magnitude of variation of the true geometry from the CAD model. A synthetic random field model was employed to virtually create random knuckle geometries. A schematic workflow is illustrated in Figure 13. First a random field is created after determining

the geometric deviation between a FEM mesh (based on a CAD geometry) and a measurement (STL), Figure 13 top left. Then the model is used to generate new random designs (Figure 13 top right). In the concluding sensitivity analysis, one identified that a material parameter, but not the geometric imperfections of the knuckle, was of significant influence onto the squeal noise, see [3] for more details.

Case 3: Sensitivity analysis of 3D field variations

This is an example how the field meta models can be applied to sensitivity analysis of 3D distributed data. The example was presented by Konrad et al [4] wherein a metal forming production process was simulated. After deep drawing of a metal sheet, the resulting sheets are typically joined (joining and spring back simulation). In the considered case, the joining process is defined by the position and size of 6 clamps linking two metal sheet, see Figure 14. The main target of the analysis is a calibration of the joining parameters with the objective of minimizing the geometric deviation of the final geometry after joining with a CAD geometry created by a designer. Since the final deviation error is a different value at each spatial location, one performs a sensitivity analysis to identify the joining parameters that influence each respective position at most. The result of such a sensitivity analysis are illustrated in Figures 15 and 16: First one checks the accuracy (F-CoP) of the meta model and relates it to the magnitude of variation (e.g. standard deviation) of the geometric deviation. Locations with very small standard deviation are typically not well explained by a field meta model, while location with large variation should have a large CoP. Here the F-CoP are well distributed with an average value of 94%. After that one can identify the individual sensitivities of the input parameters (Figure 16).

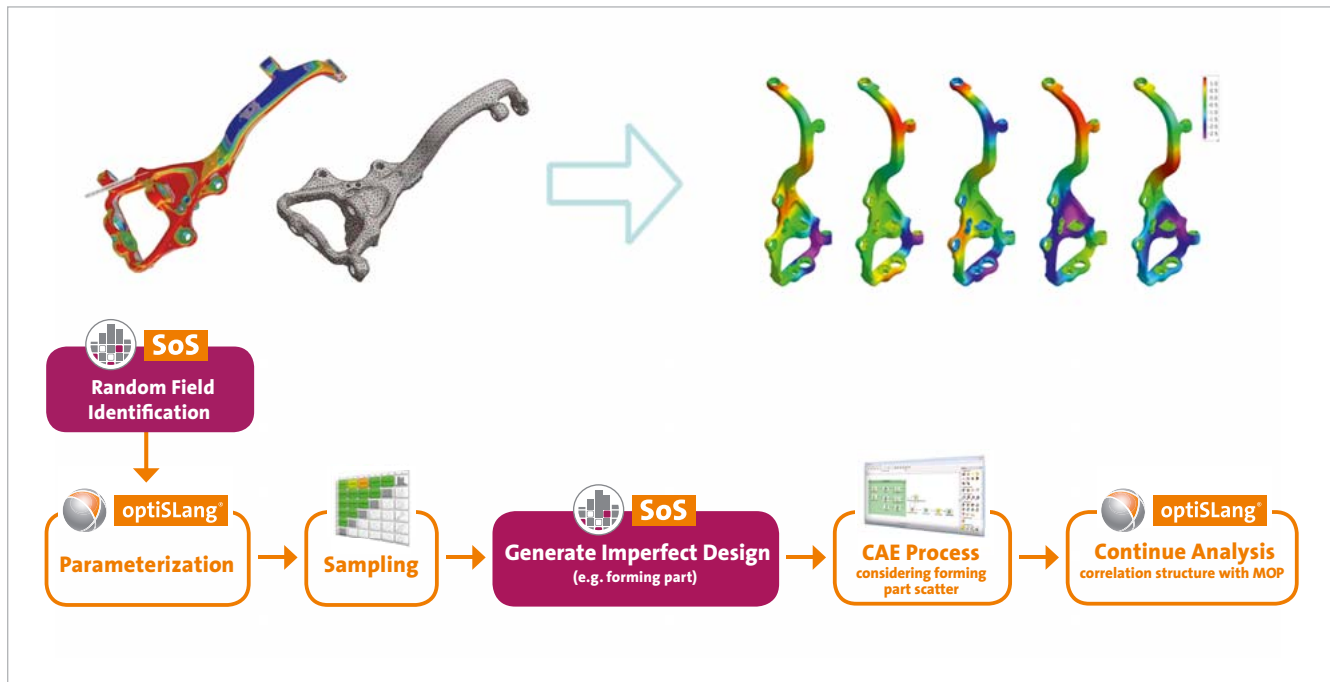


Fig. 13: Workflow of a synthetic random field model for the geometric imperfections of a knuckle

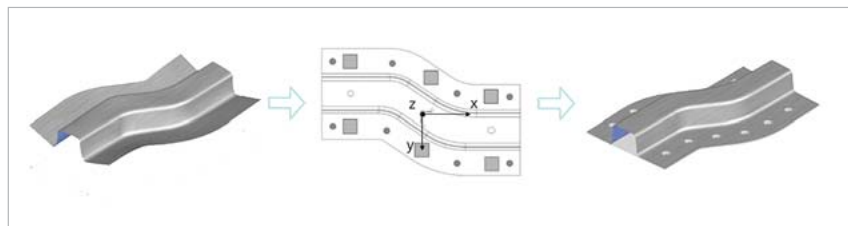


Fig. 14: A joining process after a deep drawing step using 6 clamps

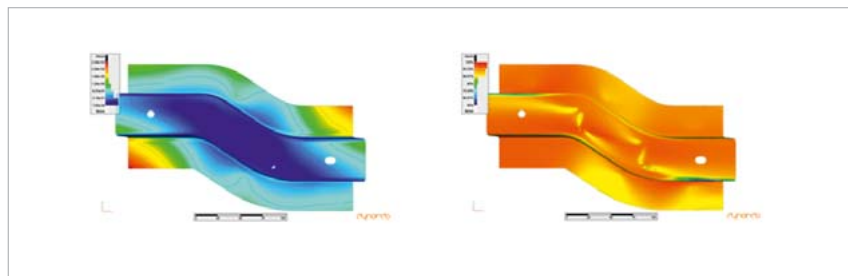


Fig. 15: Field meta model of a geometric deviation. Left: Standard deviation of the geometric deviation in vertical direction for each location on the FEM mesh (blue: small; red: large). Right: Explainable variation (F-CoP) by the field meta model

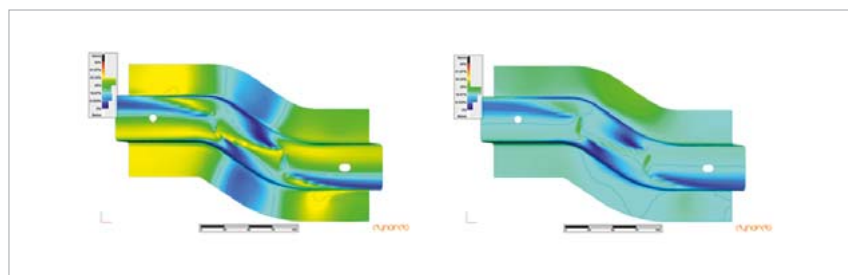


Fig. 16: Field meta model of a geometric deviation in vertical direction. Left: Distribution of the influence (F-CoP) of the position of the left-bottom clamp. Right: Distribution of the influence (F-CoP) of the position of the center-top clamp (yellow: large influence, blue: small influence)

Case 4: Pre-optimization on a 3D field meta model

Using field meta models in space, one can pre-optimize a design utilizing distributed quantities. This example was presented by Kellermeyer [5]. Therein, the draping process of a composite, as illustrated in Figure 17, is simulated. After draping the composite material onto the desired shape, a spatially varying distribution of fiber angles can be observed. Additionally, the task was to calibrate the process parameters of a draping simulation with ANSYS™ such that it matches the observed fiber angle distribution (see Figure 18). This was solved using a field meta model in SoS. First a sensitivity analysis of the draping simulation model was employed analyzing the field of fiber angles. Second, the spatial distribution of the fiber angles was measured and associated with the FEM nodes in the numerical model. The optimization objective was to minimize the average squared error between the fiber angle predicted by the numerical model and the measured fiber angle. As a result, the average deviation of the fiber direction between numerical model and measurement was reduced from initially 7.3° to 5.2°. The field meta model

was verified by a reference solution of the original numerical model, obtaining an average error of 5% between field meta model and CAE process.

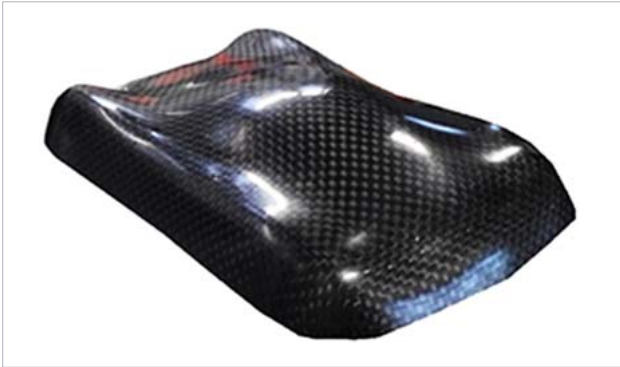


Fig. 17: A composite structure

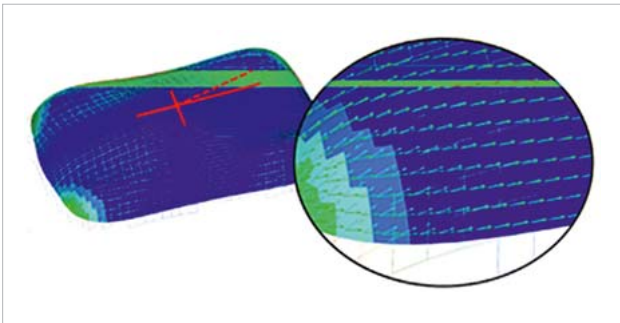


Fig. 18: Fiber directions of a composite structure after draping, comparing the result of a draping simulation and a measured direction field

Summary

This article presented some applications of random fields and field meta models in time and space. The main properties and applications of such models are

- Field statistics can be used to identify hot spots (locations of large variation, of large failure probability, etc.).
- Random fields automatically find a parameterization for parameter-free variations in time or space.
- Field meta models can be used to perform a sensitivity analysis of distributed data, i.e. if the hot spot is not yet known, if the hot spot is varying its location, if the quantity is of distributed nature, if the scalar MOP has a low CoP or if the user wants to increase understanding of the numerical model
- Random fields can be used to generate random designs. Empirical random fields are based on the evaluation of measurements (or virtual experiments) and can represent the field statistics very accurate (distribution type, statistical moments, anisotropy, inhomogeneity). If no measurements are available, one can create a synthetic random field model based on assumptions of the mean standard deviation and correlation in time or space. If a few measurements are available, one can estimate mean and standard deviation and assume only the correlation.

- Field meta models can further approximate the whole field response of a CAE/FEM model. This is particularly useful in pre-optimization whenever distributed or location-varying quantities are considered, e.g. in model calibration.
- Further applications are robustness and tolerance analysis or shape optimization.

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Images //

CADFEM

Fig. 6/7/17/18 With Courtesy of CADFEM GmbH

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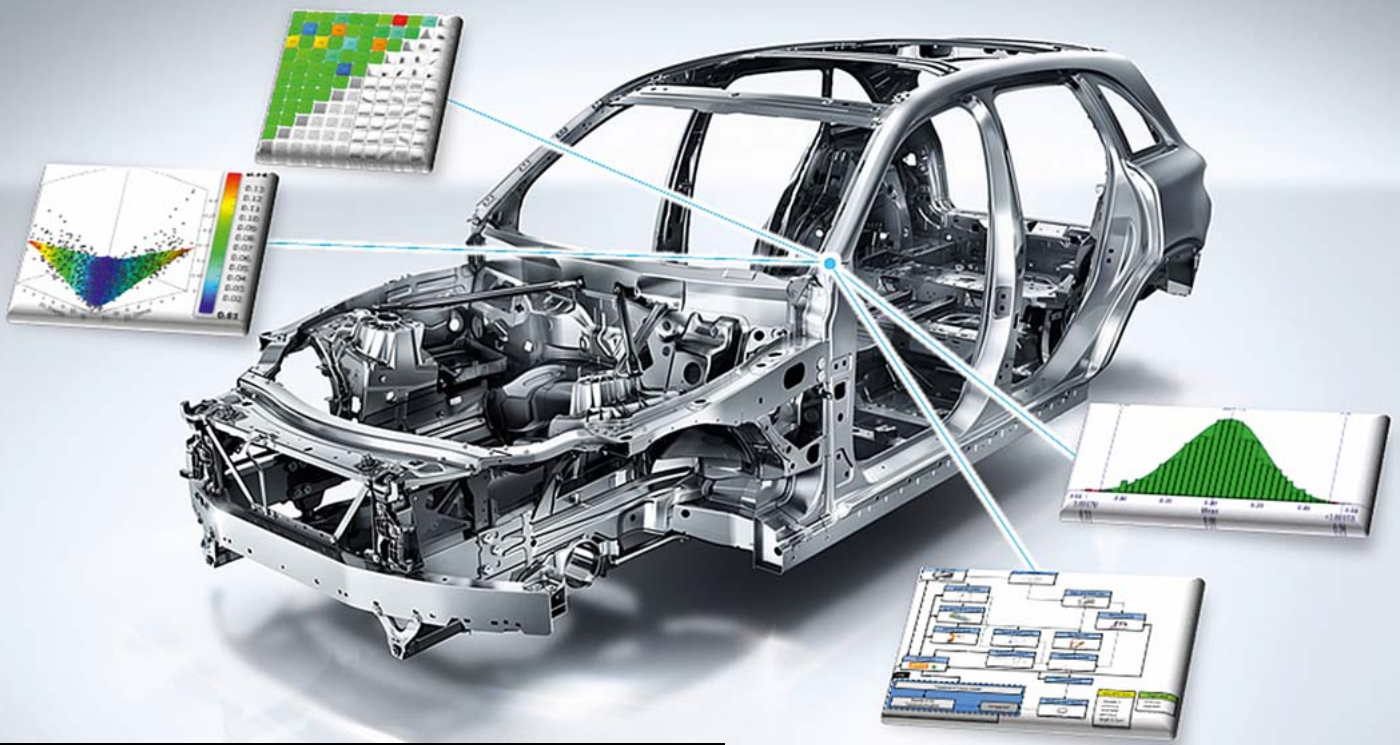
Fig. 11/12/13/14/15/16 With courtesy of DAIMLER AG

KTM TECHNOLOGIES

Fig. 17/18 With courtesy of KTM Technologies GmbH

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CUSTOMER STORY // AUTOMOTIVE INDUSTRY

SENSITIVITY ANALYSIS OF SEVERAL BODY-IN-WHITE PARAMETERS USING TOLERANCE ANALYSIS

In order to ensure the manufacturability of assemblies to the Body-in-White structure in car series production, optiSLang supports engineers at Daimler AG in the planning and developing of adequate tolerance concepts.

Introduction

Today's mass production environment requires assemblies to be built up with a specific dimensional accuracy, ensuring the fulfillment of functional requirements and their processability to a higher-level of assembly. The manufacturing of single parts always produces some deviations. The assembling process itself also causes inconsistency, for example, due to inaccuracies in the positioning of the parts at the manufacturing plant or in the joining process as well as due to elastic deformation.

Tolerance analysis generally provides ranges, in which single parts are allowed to deviate, thus, the functionality of the assembly is still guaranteed. It needs certain information to build up such a tolerance analysis model properly. A distinction can be drawn here between product data, such as part geometry and tolerance information, as well as process data, for instance the assembly graph, jig and fixture concept, joining locations or measurement points. This information is necessary to define contact conditions, ranges and measurements with the help of tolerance simulation software. In the automotive industry, the build-up process of these tolerance simulation models is time consuming and, due to human interaction, fault-prone. Today, more than one hundred assemblies are attached to

a sophisticated Body-in-White (BiW) structure, which itself already consists of several hundred parts. In order to ensure a manufacturability of the assemblies to the BiW structure in series production, experienced engineers are required for planning and developing adequate tolerance concepts. Regarding the multidimensional orientation of the tolerance chains in a BiW structure, it is a challenge to find an optimal concept for attaching certain parts. Beside long-term experience, the usage of IT-tools is indispensable for helping the engineer in making the right decision. This article will explain an approach how to interlink optimization software, product and production development data as well as CAT-simulation tools in order to conduct a sensitivity analysis on simulation input parameters. Furthermore, it will be shown how this approach can be integrated in the process of the automotive BiW sector. The concept was firstly implemented by using the software optiSLang for the sensitivity analysis and 3DCS for the tolerance analysis.

State of the art

Fig. 1 shows how the different kinds of information are used to build up a tolerance analysis model. First of all, a CAD-ge-

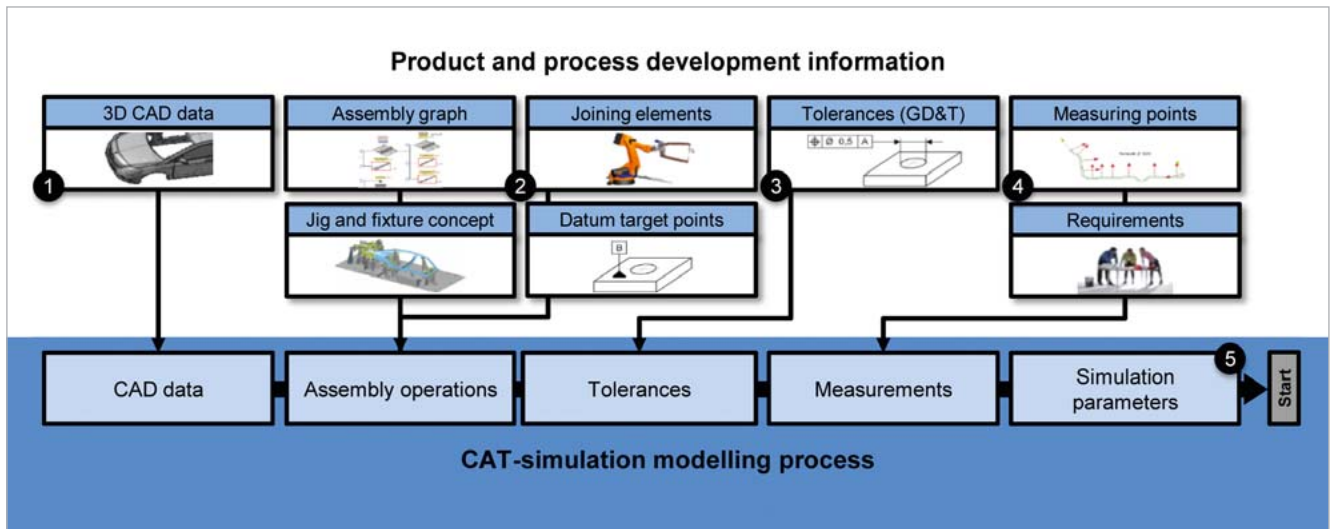


Fig. 1: Dependencies of product and process information with regard to the CAT simulation model

ometry is needed to display the deviations of and between the parts (refer to 1 in Fig. 1). Furthermore, different kinds of information are used to map the manufacturing process in the simulation model (refer to 2 in Fig.1). The assembly graph sets up the model tree in the simulation environment. It additionally provides the logical order of part assembling and, thereof, the engineer can derive the number of assembly operations. In order to assign points to the assembly operations, joining elements, jig layouts, fixture layout and datum target points are used. The tolerance information of the single parts, which is created during the product development process, is directly transferred to the simulation model (refer to 3 in Fig.1). Also, additional tolerances caused by the manufacturing process, such as inaccuracies in the positioning process of the parts, will be considered in the simulation model. Measurement points are furthermore used to define the quality features in the tolerance simulation environment as a closing dimension of the tolerance chain (refer to 4 in Fig.1). The last step is to define several simulation parameters (refer to 5 in Fig.1). Afterwards, the simulation model is ready for application.

Several quality features have to be fulfilled in the BiW manufacturing process to ensure a robust manufacturing of the assembly. They can be divided into dimensional technical specifications and quality features at the outer skin of a vehicle. Examples of the first type are all technical connections to the BiW, for example the whole pattern for connecting the chassis. If these specifications do not violate the required tolerance ranges, a correct assembling process of the additional mounted parts to the BiW will be guaranteed. Examples for the second type of quality features are the gap and flushness measurements. Fulfilling these requirements ensures an aesthetical high quality product, as well as a faultless function of the external parts, e.g., recesses for a correct door opening. The number of both types of quality features sum up to several hundred measurements. Fig.2 shows sample drawings of the two different categories.

In order to reach a high level of automation during the build-up process of tolerance simulation and the import of the required information to the CAT environment, a neutral exchange format like XML is needed. In this project, 3DCS

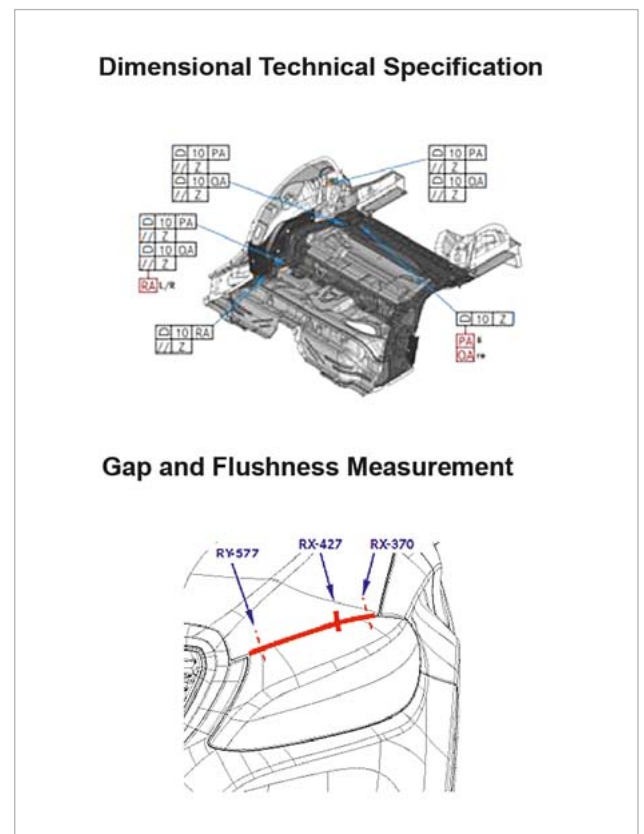


Fig. 2: Different kinds of quality features in the automotive industry

software was chosen to fulfill this precondition. The tool also provides basic functionality for an optimization. There are two optimization possibilities available for the procedure. On the one hand, a tolerance cost optimization is possible

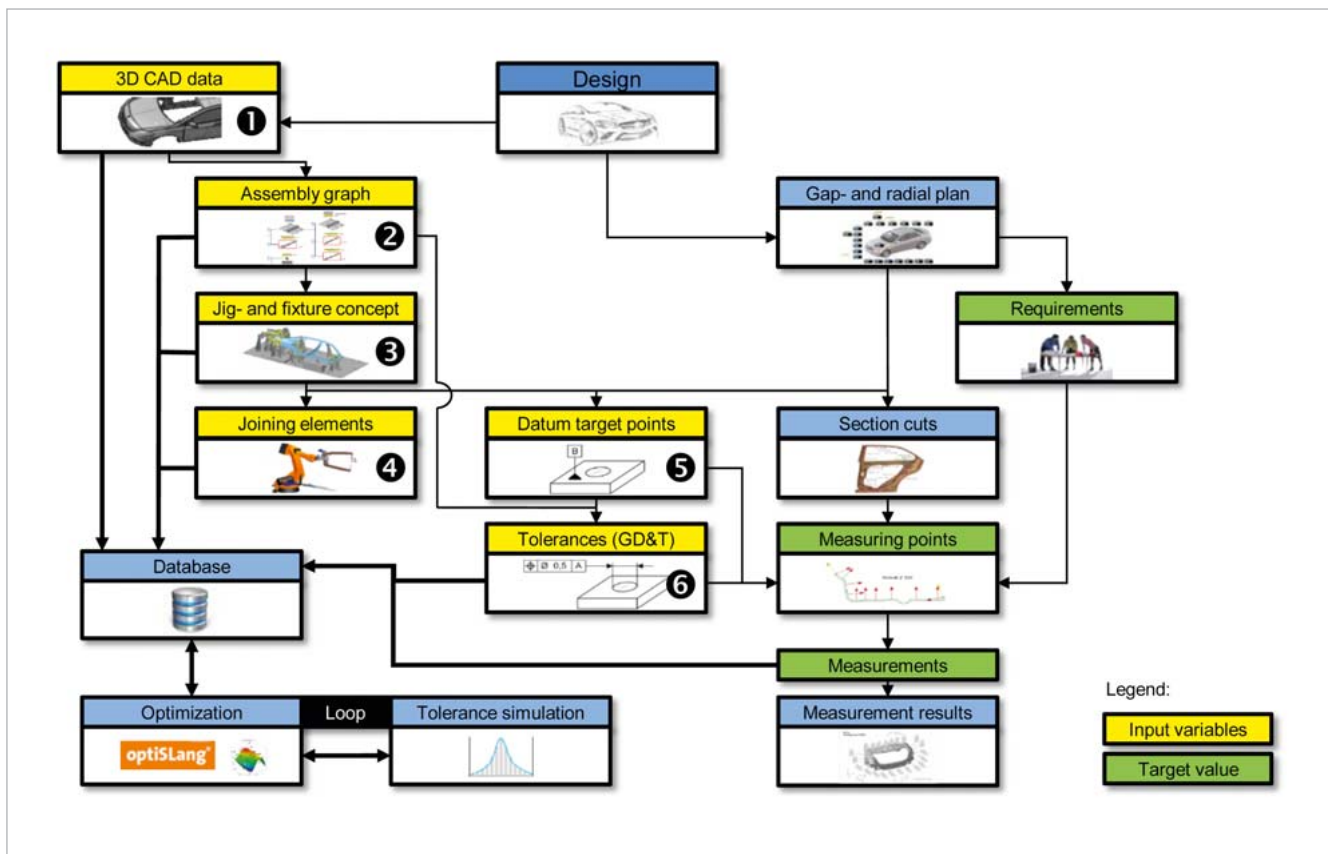


Fig. 3: General approach for a sensitivity analysis of product and process information using tolerance simulations

to achieve best quality at a minimum of costs. The user can allocate the largest possible tolerance while still meeting dimensional objectives. On the other hand, a tolerance quality optimization could be performed where the quality would be optimized for a given fixed budget.

Hence the development of adequate tolerance concepts for BiW can furthermore be supported by the usage of optimization tools. The software platforms LS-OPT, optiSLang and AutoForm-Sigma were compared with regard to the optimization task. Thereby, the degree of openness of the program code was a major focus. Regarding the import of several input parameters, the software LS-OPT offers an easy implementation of LS-DYNA projects and can also be extended to the inclusion of other simple ASCII files. The software solutions ModeFrontier and optiSLang, on the contrary, offer some script nodes which enable a customized integration of the optimization tool towards other disciplines based on their specific Application-Programming-Interface (API). Here, the software optiSLang was chosen for application.

For the interlinkage of the product and process development information (input data), as well as the tolerance simulation model to the optimization tool, a standardized exchange format is required. Since the main exchange format is based on an XML database, the optimization tool has to provide absolute readability of this format to secure a con-

sistent exchange between all the disciplines. Thus, handing over the input parameters of the sensitivity analysis and the target features of the optimization task makes it necessary to create an input deck in the used software optiSLang. Being a part of a more complex script, this deck is able to read the provided tolerance simulation XML, build an optiSLang project for the execution of a sensitivity analysis and, finally, perform an optimization using the results obtained from the sensitivity analysis. This script will be described in detail later in this article.

What the approaches in literature have in common are to focus only on a single input parameter used for optimization. Consequently, a main research question is to find a possibility for the optimization of several input parameters. There is also a need for a basic database capable of processing all these input parameters. Thus, the main focus of this project is a principal concept of linking the database towards an optimization tool. An application example will be given here to clarify these functionalities.

Proposed Approach

General Approach

Fig. 3 shows the general approach of linking product and process data with the optimization software. A basic distinction between the parameters of an optimization prob-

lem is whether they are continuous or discrete. Continuous design parameters can take nominal values in a certain range ($\mathbf{p}_{inf}, \mathbf{p}_{sup}$) and may carry deviations from this nominal value ($\mathbf{p} - \Delta\mathbf{p}_{lower}; \mathbf{p} - \Delta\mathbf{p}_{upper}$). Discrete design parameters, on the other hand, can only adopt specific values taken from a closed, finite set. The multi-objective optimization problem can be mathematically formulated as follows:

$$\min_{\mathbf{p} \in P} f(\mathbf{p}) \quad (1a)$$

$$\text{over: } \mathbf{P} = \{\mathbf{p}_{st}, \mathbf{p}_{dev}\} \quad (1b)$$

$$\text{subjected to: } g_i(\mathbf{p}) \leq 0, \quad i = 1, 2, \dots, n$$

The definition of continuous design variables can be found in formula 1.c:

$$\mathbf{P}_{st} = \{\mathbf{p}_{st} \in \mathbb{R}^m | \mathbf{p}_{inf} \leq \mathbf{p} \leq \mathbf{p}_{sup}\} \quad (1c)$$

Parameters carrying certain deviations are defined as follows:

$$\mathbf{P}_{dev} = \{\mathbf{p}_{dev} \in \mathbb{R}^m | \mathbf{p} - \Delta\mathbf{p}_{lower} \leq \mathbf{p} \leq \mathbf{p} + \Delta\mathbf{p}_{upper}\} \quad (1d)$$

where \mathbf{p} are the design parameters carrying upper and lower bounds ($\mathbf{p}_{inf}, \mathbf{p}_{sup}$) and m characterizes the dimension of the design space. g_i represents the i^{th} inequality constrain function. To find the Pareto optimal solutions of the equation means searching for a feasible point $\mathbf{p}^* \in \mathbb{R}^m$ ensuring there is no other feasible point $\mathbf{p} \in \mathbb{R}^m$ so that $\forall i, j; f_i(\mathbf{p}) \leq f_i(\mathbf{p}^*)$ with strict inequality in at least one condition, $f_j(\mathbf{p}) \leq f_j(\mathbf{p}^*)$. Single objective optimization problems ($m=1$) have to satisfy the Karush-Kuhn-Tucker condition for the solution \mathbf{p}^* of the Pareto optimum.

When considering a Robust Design Optimization (RDO), the goal is to obtain a solution which is robust against uncertainties on the design variables. The multi-objective optimization extends to stochastic variables (X) and is formulated as follows:

$$\min_{\mathbf{p} \in P} f(\mathbf{p}; X) \quad (1e)$$

$$\min_{\mathbf{p} \in P} \Delta f(\mathbf{p}; X) \quad (1f)$$

$$\Delta f = \max f(\mathbf{p}; X) - \min f(\mathbf{p}; X) \quad (1g)$$

$$\mathbf{p}_k \in \mathbf{S}, \quad \mathbf{S}^k = \{\mathbf{p}_k, j = 1 \dots J^{(k)}\}; \quad (1h)$$

$$\mathbf{X}_l \in \mathbf{S}, \quad \mathbf{S}^l = \{\mathbf{X}_l, j = 1 \dots J^{(l)}\}$$

subjected to:

$$g_a(\mathbf{p}; X) + \Delta g_a(\mathbf{p}; X) \leq 0, \quad a = 1, 2, \dots, m \quad (1i)$$

where X is the stochastic variable, \mathbf{S} represents the Set of sampling points \mathbf{p}_k . g_a represents the a^{th} inequality constrain function.

The stochastic variables can be expressed with

$$\mathbf{X} \sim N(\boldsymbol{\mu}_X, \mathbf{Cov}_X) \quad (1j)$$

where $\boldsymbol{\mu}_X$ characterizes the mean value and \mathbf{Cov}_X the covariance matrix of normal distributed uncertainties (N).

In the particular case of the BiW during an automobile body manufacturing process, the input parameters for a tolerance simulation and further optimization can be classified as shown in Fig. 3. The variation of the CAD-geometry, e.g. flange angle and dimension (see 1 in Fig.3), is represented by a continuous design variable without deviation equal to formula 1c, e.g. $P_{CAD_{flange\ angle}}, P_{CAD_{flange\ size}}$. The assembly graph (see 2 in Fig.3) represents a discrete design variable having a finite number of characteristics $p_{ASM} = [p_{ASM_1}, p_{ASM_2}, \dots, p_{ASM_l}]$, $l \in \mathbb{N}^+$. Additionally, the design variables (see 3,4,5 in Fig. 3) jig and fixture concept, joining elements as well as datum target points are continuous and, in this case, without uncertain deviation ($p_{Jig}, p_{Join}, p_{Datum}$). For the tolerances (see 6 in Fig. 3), on the other hand, a deviation has to be considered (P_{Tol}) equal to formula 1d.

Additional uncertainties, such as inaccuracies in the manufacturing process, can be considered by including stochastic variables (X) in the system. Stochastic deviations in the jig and fixture, e.g. positioning inaccuracies of the parts, are represented by X_{JigPos} . Deviations of the joining process, for instance deviations of the weld gun accuracy due to the clearance in the welding robot guidance, are characterized by $X_{JoinPos}$. Uncertainties of the alignment, e.g. wear of the manufacturing station, are represented by $X_{DatumPos}$. Different distribution types have to be considered regarding each specific stochastic variable, for example, the influence of wear follows a trapezoidal distribution.

Nowadays, solving an optimization task entails the performance of an initial sampling on the design variables in their set range. The first step is the creation of a predefined number of sample designs (\mathbf{r}_k). The sampling method can basically be divided in two different approaches: deterministic Design of Experiments (DoE) and stochastic sampling. In cases where a high number of input variables are involved causing an unjustifiable amount of processing times, an Advanced Latin Hypercube Sampling (ALHS) should be employed. Moreover, there is also a single-switch-method available to reduce correlation errors. After the calculation of the selected samples, the results are used as nodes to calculate a response surface covering the entire design space. The program optiSLang offers a response surface approach named Metamodel of Optimal Prognosis (MOP), which automatically searches for the best response surface technique according to the selected validation method. Other available techniques are Polynomial Least Squares Regression (PLSR), Moving Least Squares (MLS) and ordinary Kriging. The resulting response surface is then used in the optimization problem.

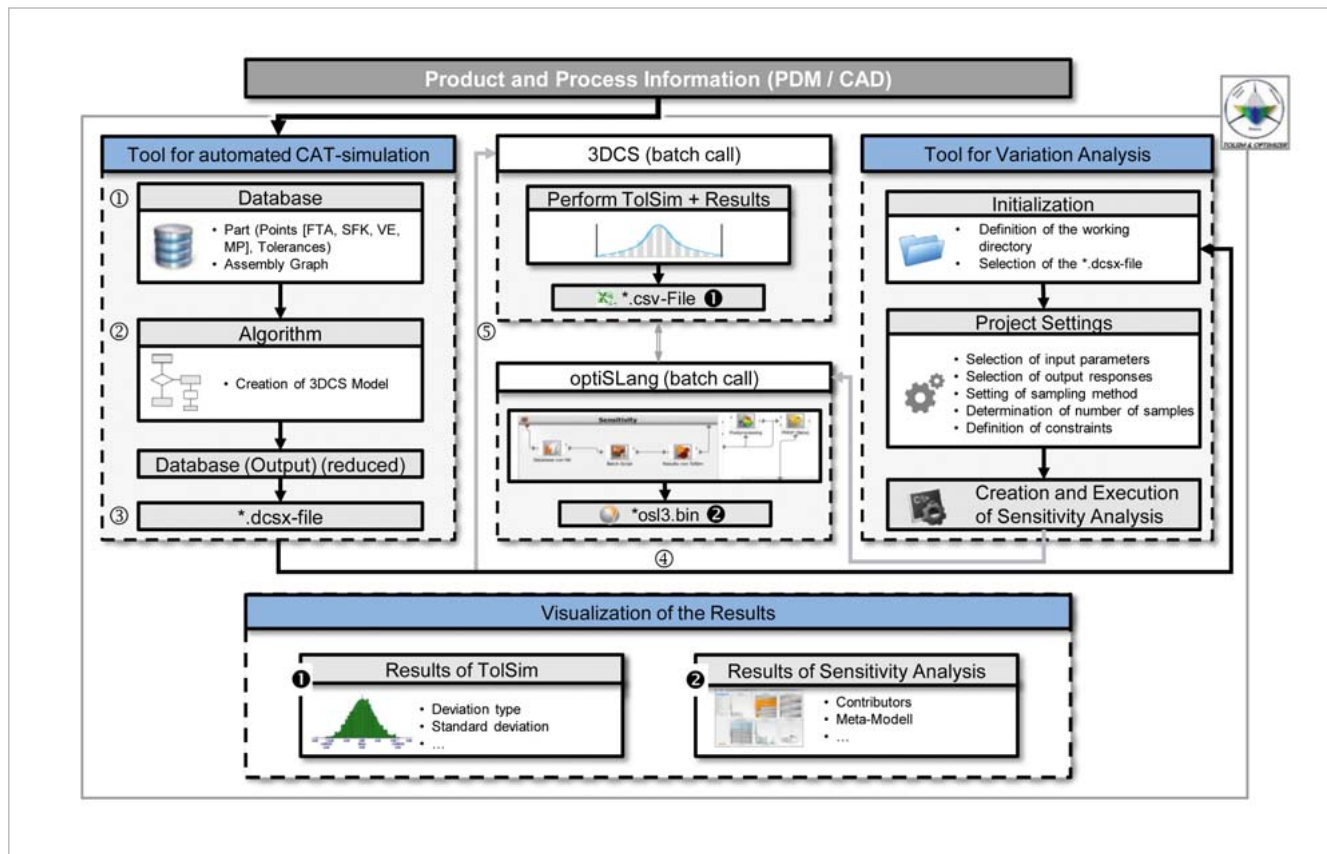


Fig.4: Implementation of the general approach in the automotive Body-in-White environment

The variation of the values of some design variables may have an effect on other design variables of the tolerance simulation model. In this case, variables such as CAD data, the assembly graph or the jig and fixture concept (see 1,2,3 in Fig. 3), have a significant influence on the values of other variables. For example, a change in the assembling order of different parts or the redesign of joining elements, datum target points and tolerances would lead to different layout concepts. The repercussions of a changed assembly graph would also influence, among others, the crash and welding gun simulations. On the other hand, other design variables do not have such great consequences on other variables (see 4,5,6 in Fig.3). For instance, modifying datum target points or tolerances would only have an effect on the upper and lower measuring point specification limits (USL and LSL). In order to maintain the calculation effort at a manageable state, these design variables having a low impact on other variables were firstly classified as modifiable. The usage of a common database was proposed in order to hand over the information to the optimization tool and to the tolerance simulation tool. The implementation of this general approach will be clarified in more detailed in the following chapter.

Process integration

First of all, the product and process information to build up a tolerance simulation model is exported from the PDM/CAD system to an external tool (see 1 in Fig.4), which represents the database and ensures further processing of the data.

The regarded CAD system, Siemens NX, provides an API called NX Open. Using this API enables an access to specific information stored in the CAD model. Thereby, the API provides a standardized communication code where the user can select the preferred programming language. Fig. 5 shows an example of the data access using NX Open and the GUI for a derived database.

In the next step, the information of the database is used to create a tolerance simulation model. For this reason, the data is reduced and appropriately structured with the help of a specially developed algorithm (see 2 in Fig.4). As a result, the restructured information can be exported to the tolerance simulation model. In this application, an XML based DCSX format was used for export (see 3 in Fig.4). This format can be imported directly in the tolerance simulation environment to run a tolerance analysis.

In this project, the reduced XML format is used for a sensitivity analysis being performed based on the input parameters of the tolerance simulation. The external tool shown in Fig.6 hands over the XML information to the variation analysis section (see 4 in Fig.4). In this example, a variation of the datum target system of the parts is conducted. Thereby, the objective is to Figure out which is the alignment concept leading to a minimum deviation in a gap and flushness measurement. To register the datum target points as an input parameter, the reduced XML is parsed. The different datum target points of the parts are listed and the user is then able

to select the parameters which are allowed to be modified in the sensitivity analysis (see Fig.6). Furthermore, the reduced XML format is used to perform a first tolerance analysis on the “start design” of the variation analysis project. The tolerance analysis software 3DCS is therefore batch called (see 5 in Fig.4). Afterwards, the resulting file of this analysis, carrying the required gap and flushness measurements, is imported by the external tool. This enables the user to select the response parameters, e.g. standard deviation, for the sensitivity analysis. Additionally, the tool offers the possibility to edit several parameters of the sensitivity analysis project, e.g. sampling method, number of samples, etc..

Once the user has defined the settings for the sensitivity analysis through the GUI, the script can be run to solve the optimization task. By starting the analysis, the user calls for the execution of a *.cmd batch-script which is responsible for the control and coordination of all other sub-scripts and routines (see 1 in Fig.7).

Taking that into consideration, several folders are firstly created in the selected working directory. To enable a smooth interlinkage of the predefined user-input parameters towards the optimization tool, the specific information, for example, datum target point coordinates and direction, is stored in a text file. With the help of a simple macro, a text file containing the simulation results is also created. The last step of the *.cmd is an optiSlang batch-call which then reads a python script for the creation of the sensitivity analysis project (see 2 in Fig.7 on previous page).

Summarizing the tasks performed by the Python script, the parameters for the DoE are selected first, like sampling method, samples, range for the upper and lower bounds for the allowed deviation of the select-

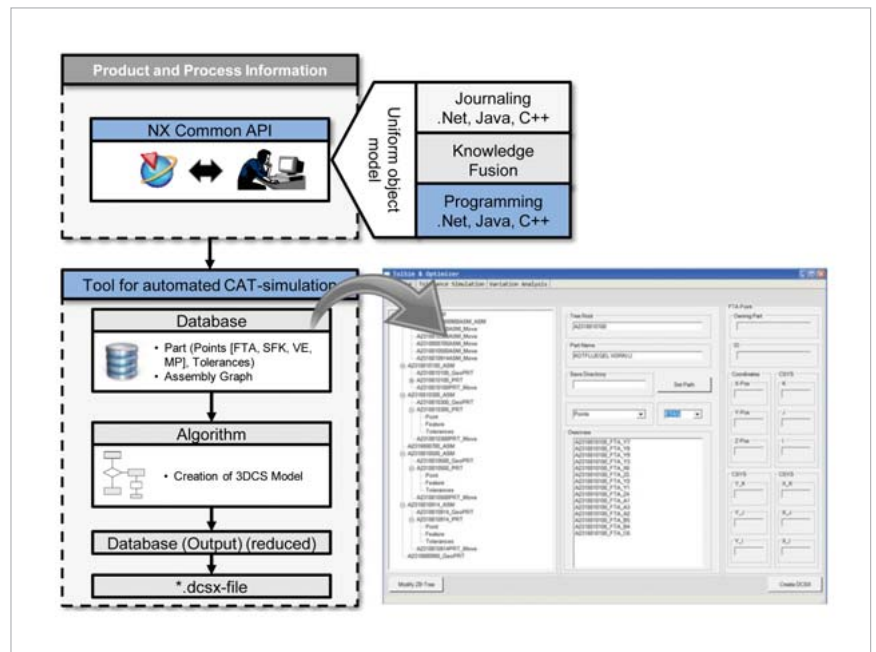


Fig. 5: Product and production data access using NX-Open and storage of the data using an external tool

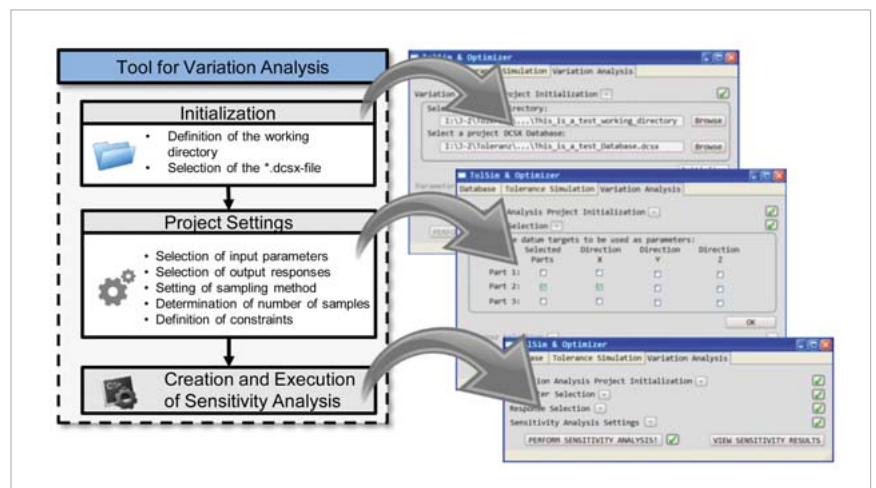


Fig.6: Required user settings to perform a sensitivity analysis

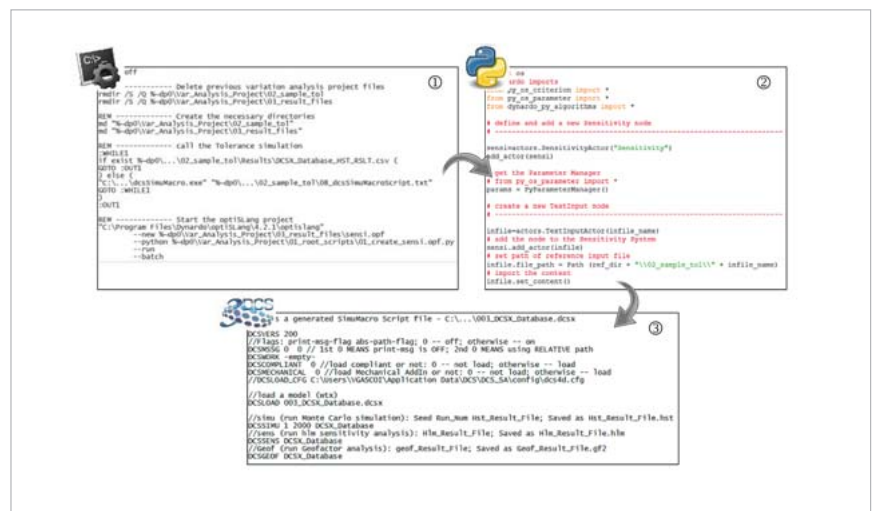


Fig.7 *.cmd call, the Python script creates optiSlang project, the tolerance simulation in batch call

ed datum target points, etc.. Then, the parametric system is created, which includes the input node (input.txt), the solver node (solver.bat) and the output node (output.txt). Afterwards, these nodes are completed: the input node is filled with the information of the input text file created in the first step (see 1 in Fig.7 on previous page), the output node is handed the information of an example result text file and the solver node is assigned the commands in an external prepared batch file. Finally, the Post-Processor and MOP nodes are created and all the necessary connections are completed. The first step in the solver script (see 3 in Fig.7 on previous page) enables the usage of the input.txt file in the tolerance simulation environment. This file will later carry the modified coordinates for the datum target points for the DoE. Therefore, the information is included in the *.dcsx file. Thus, it is possible to perform a tolerance analysis with a slightly modified datum target system. For this matter, the tolerance analysis is batch-called. The resulting file of the specific design is stored afterwards in the specific design folder and subsequently translated to a text file to ensure usability in the output node of the optimization tool. Solving all the required designs makes it possible to create an MOP and study the sensitivity results.

Conclusion and Outlook

The considered approach to perform sensitivity analyses in several BiW single parts and assembly parameters with the help of tolerance analysis opens several opportunities. It is, for example, possible to perform an HLM-analysis to Figure out the main affecting contributors in a tolerance chain. Therefore, the tolerance range has to be set as an input parameter. The existing tools on the market already offer this functionality. The essential part and the unique feature of this approach is an easy way of considering more than one input variable in a tolerance sensitivity analysis, for example, tolerances, joining information, jig and fixture concept, etc.. A common database achieves this by processing the required information in a system independent format (XML). With this customized tool, engineers can run tolerance analysis and optimization on a selected system (database) without deeper knowledge of the multidisciplinary system or the involved software. Once the user has defined the relevant input parameters for a sensitivity analysis and its maximum allowed deviation, the simulation model is simply handed over to the optimization software using the XML related format. In that respect, the set-up of the required sensitivity analysis is performed in batch mode using specifically developed scripts. The results of the sensitivity analysis are then transferred back into the customized tool. Thus, a study of options can be conducted in a very short amount of time. Different alignment concepts of parts are considered to find the most robust solution regarding the quality features on a given set of parameters. The deviation of the quality features will be minimized in BiW (gap and flushness measurements, dimensional technical specifica-

tions). Future research might prove the feasibility of the methodical approach using a demonstrator which carries different kinds of input data.

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MODEL-BASED ANALYSIS AND OPTIMIZATION OF VERTICAL AXIS WIND TURBINES

Wind turbines are highly complex devices. They are very sensitive to poor design and faulty operation. optiSlang helps to mitigate such potential problems and to develop effective optimization strategies.

Introduction

In Germany the energy transition is already well underway and it is only a question of time before this scenario is adopted by other nations. The energy transition is revolutionizing the production of electricity in favour of renewable energy sources. In the future, solar and wind energy are likely to become the most important sources of energy. In this context, it is hardly surprising that small, decentralized wind turbines are becoming increasingly important.

Wind turbines are highly complex devices. They are very sensitive to poor design and faulty operation. To mitigate such potential problems requires an effective optimization strategy.

Large wind turbines invariably consist of a single design type: they operate with a horizontal axis. In contrast, smaller wind turbines may use one of two very different design concepts: those that operate with a horizontal axis, and those that use a vertical axis. The latter have a number of advantages compared to the horizontal axis variant: they are generally simpler in design, cost less, and manifest greater efficiencies at low wind speeds.

The last point indicates why this design is preferred for small wind turbines, as they operate closer to the ground where wind velocity is predominantly lower.



Fig. 1: Left - horizontal axis wind turbine; right - vertical axis wind turbine

Figure 1 shows the different types of construction. The left-hand frame shows a large, horizontal axis wind turbine. The right-hand frame shows a typical small vertical axis wind turbine. Vertical axis turbines require thoughtful in-

stallation as the blade profiles are subject to airflow from different directions during rotation. The following sections describe a workflow developed by the Computer Simulation in Mechanical Engineering Research Centre which makes it possible not only to define the complete geometry of such turbines for given wind velocities and determine power output at optimal efficiency, but also to characterize the operational behaviour of an existing wind turbine at different wind velocities.

The workflow

The development of the workflow was based on decades of experience working on the optimization of turbomachines. Figure 2 shows a comparative compilation of the major projects undertaken by the research group. As can be seen in Fig. 2, the optimization of wind turbines is a category of project that calls for a relatively high degree of numerical complexity, with only the geometric optimization of turbo compressor deemed more demanding.

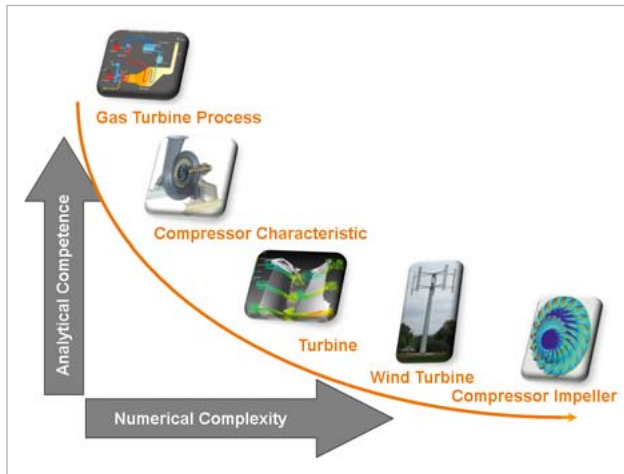


Fig.2: Optimization projects from turbomachine construction sector

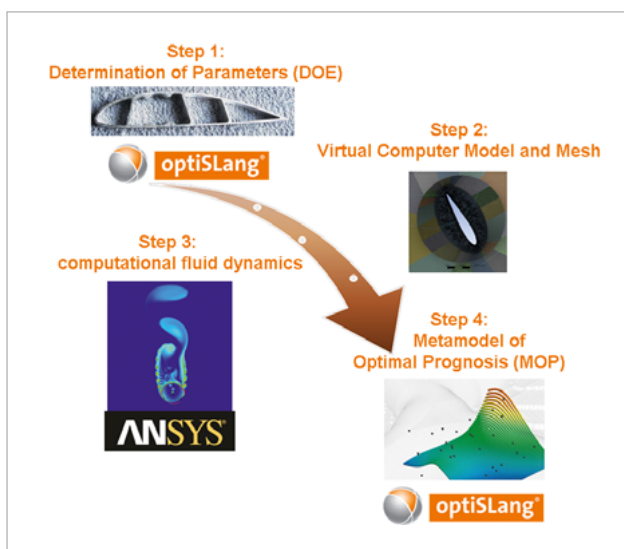


Fig. 3: The main workflow steps

The four important steps and accompanying software used in the workflow are illustrated in Figure 3. The first step entails geometric definition and parametrization. This step is vital for success of the project and typically the most time-consuming. Steps 2 and 3 call for considerable experience to ensure complete integrity of the final results. Each of these work phases presents its own challenges, described in detail in the following sections.

The functional principle of a vertical axis wind turbine

In contrast to 'conventional' wind turbines, those with a vertical axis require further explanation as the direction of airflow relative to the blade profile varies (Fig. 4) during rotation. The left frame of Fig. 4 shows a wind turbine profile with three arms. The turbine rotates anti-clockwise in the plane shown, with the wind blowing from the left-hand side with velocity c (see Fig. 4).

The velocity triangle at the leading edge of the blade reveals that it receives a relative wind velocity, w . The direction and velocity is determined when the wind velocity, c , and the rotational velocity of the turbine, u , are given. This is generally the case for each blade position. The relative incident wind velocity, w , determines the lift, F_a and the resistance, F_w . The subsequent angle and also the resultant blade force, R , are explicitly defined. Figure 4, shows force R as torque which develops in the same direction as rotation of the turbine. This ensures that blades in the opposing direction to the wind develop a positive driving torque.

The distribution of pressure around the rotating blades shown in the right-hand frame of Fig. 4 provides further information about functionality of the turbine. The pressure distribution clearly shows suction on the inner side of the blade.

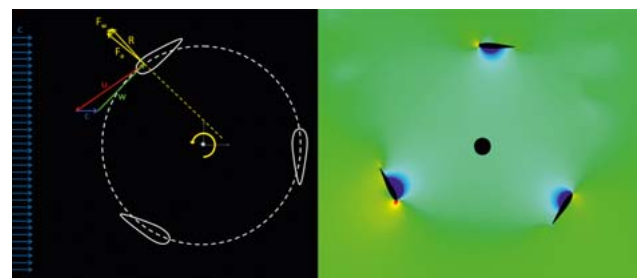


Fig.4: The working principle of a vertical axis wind turbine (left) velocity vectors and pressure distribution on blades (right)

Parametrization

Optimizing wind turbine geometry requires a set of parameters that can provide a meaningful and workable description of such geometry. The parameters listed in Figure 5 were initially of interest: they are organized into parameters associated with main dimensions of the turbine, and those associated with its operational status.

- | | |
|---------------------|----------------------------------|
| 1. Diameter | 5. Wind velocity |
| 2. Height | 6. r.p.m. or rotational velocity |
| 3. Blade length | |
| 4. Number of blades | |

Fig. 5: Left - main parameters for the turbine and right - parameters for operational status of the turbine

The blades themselves also require an equally demanding parametrization. Parameterization of the blade has a decisive influence on the veracity of the entire metamodel. Figure 6 shows a typical profile geometry of a blade. This is created using data points. It is not unusual to describe blade cross section with more than 100 data points. However, this type of geometry should be rejected as the basis of blade profile parameterization: the use of large numbers of independent data points poses a multitude of problems for stability of any later modeling.

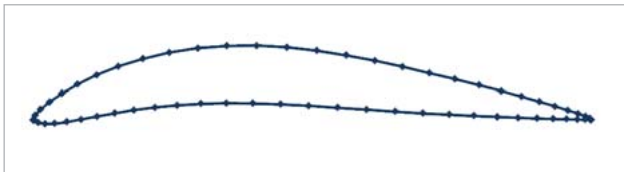


Fig. 6: Definition of blade profile geometry using data points

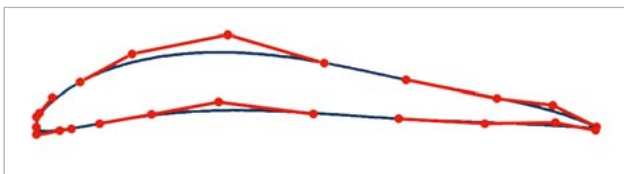


Fig. 7: The definition of blade profile geometry (blue) using control points (red)

An alternative is the use of splines. Figure 7 shows modeling with Bezier splines using the same blade cross section shown in Fig. 6.

Although at first glance this method may appear better, it is not recommended for several reasons. Although the use of control points, which can be considerably fewer than when using data points, can reproduce smooth surfaces, they are not suitable for parameterization. It has been shown that Latin Hypercube sampling for definition of DOE's produces profile geometries that are almost always unsuitable for flow mechanics. This type of parameterizations is far too arbitrary to be reproducible. To ensure that only useful profiles are generated requires a more complex strategy. Using a complex morphing algorithm, it is possible to create geometries that are able to be used in flow mechanics studies.

To describe geometries, simple arithmetic values are not used but rather parameter values categorized by descriptive nomenclature (see Fig. 8).

A total of 15 parametric values are used to describe the geometry of the wind turbine and its operational status. These are listed in detail in Figs. 5 & 8.

- | | |
|------------------------|----------------------------|
| 7. Thickness ratio | 12. Trailing edge radius |
| 8. x-max thickness | 13. Reflex (trailing edge) |
| 9. Camber ratio | 14. Wetted aspect ratio |
| 10. x-max camber | 15. Angle of attack |
| 11. Nose circle radius | |

Fig. 8: Parameterization of the profile model

Figure 9 shows a selection of cross sectional profiles modelled using the parameters outlined in Fig. 8. The outline of the profiles demonstrate the quality and range of flow mechanics profiles that can be created.

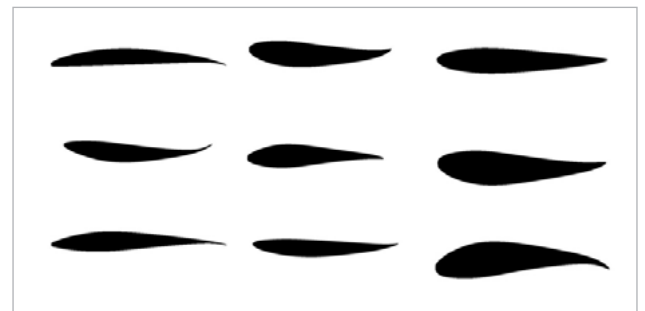


Fig. 9: A selection of parameter-based profiles

Meshing

High quality meshing is extremely important because the greatest deviation due to numerical error is manifest in the mesh. This is, in turn, also extremely important for the reliability of a metamodel.

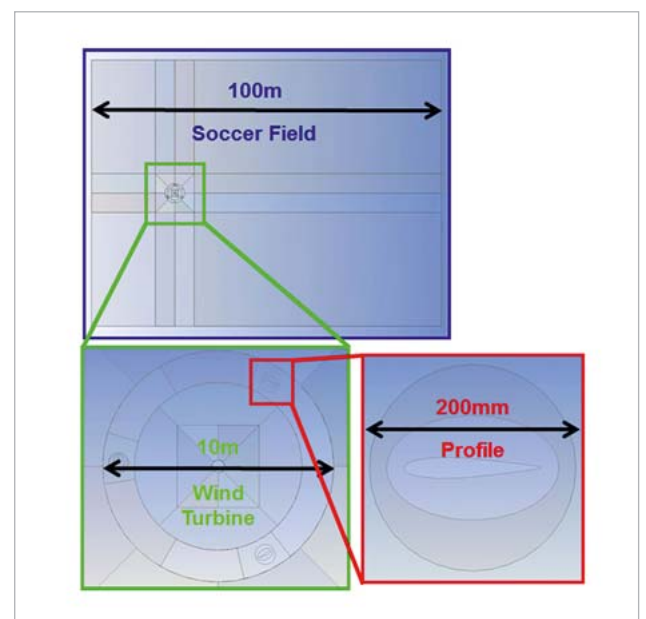
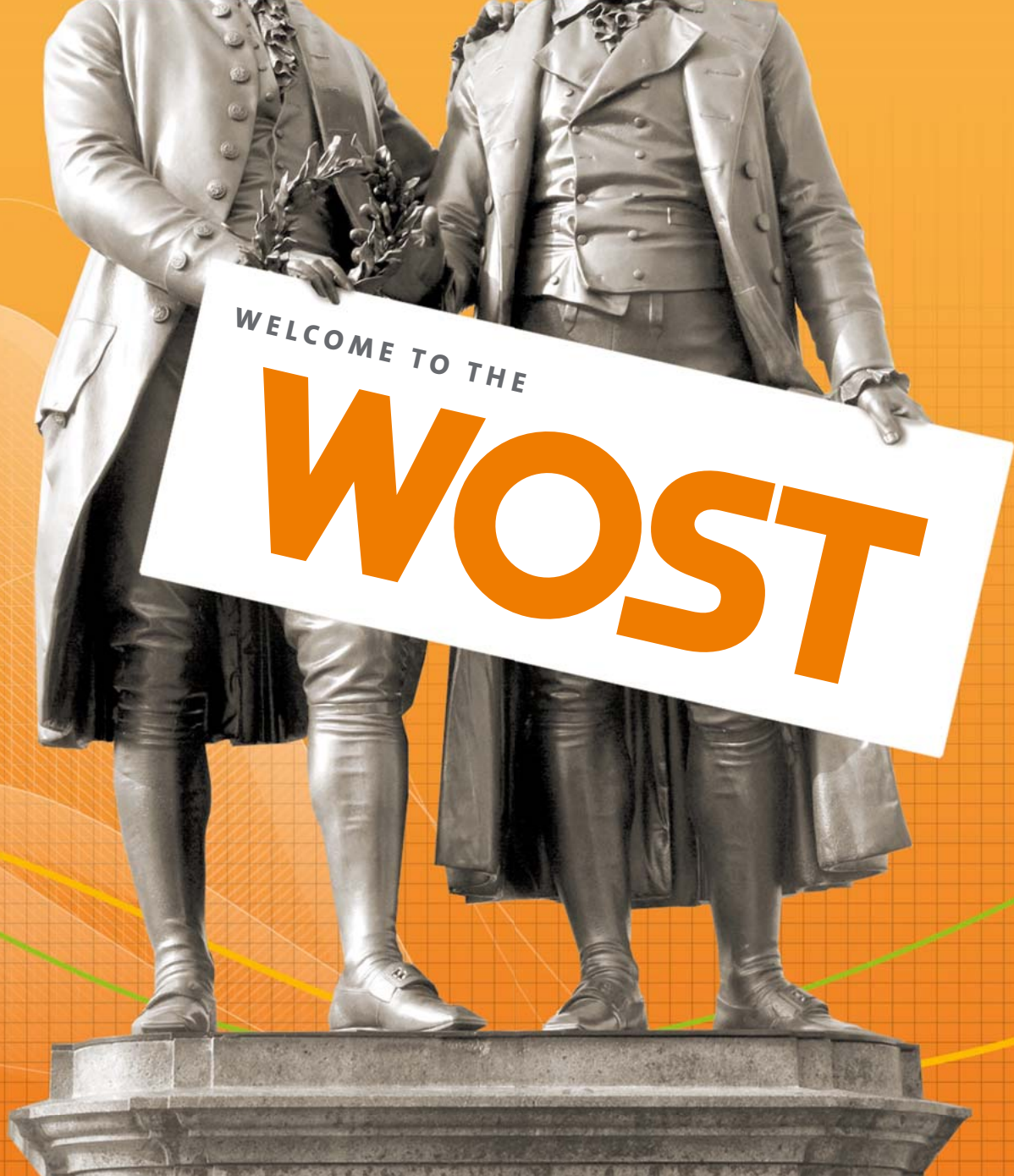


Fig. 10: Comparison of size relationships (scales)



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The large difference in scales presents one of the greatest challenges for flow simulations. To maximize mesh quality, it was set to use only hexahedral elements.

Figure 10 (see previous page) illustrates the differences in scale. A wind turbine with a rotor diameter of approx. 10 m and a typical blade profile length of 0.2 m requires a simulation area the size of a football field to include the necessary up- and down-stream air flow trails.

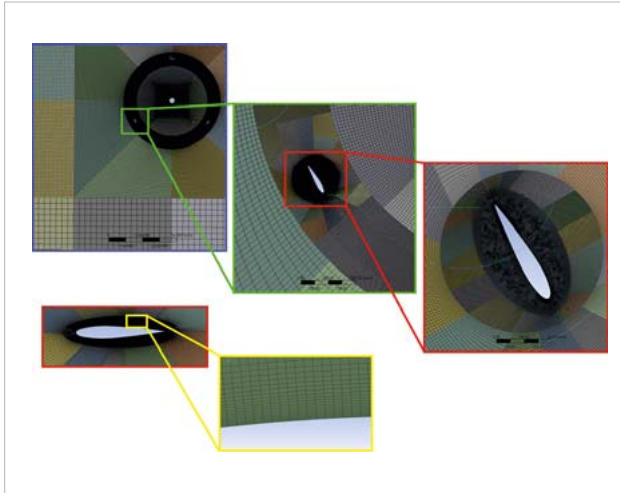


Fig. 11: Meshing of different scale sizes

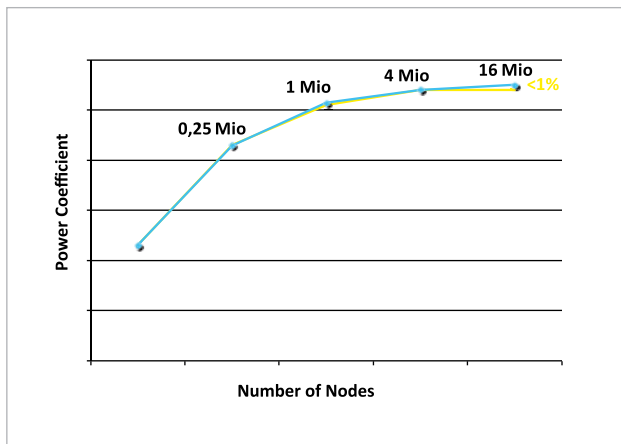


Fig. 12: Study of mesh dependency

The appropriate mesh, including all the extreme differences in element measurements, is shown in Figure 11. These differences become particularly apparent when comparing the mesh density in the area surrounding the turbine and the area close to the blade profile. Since boundary layer thickness is virtually uninfluenced by the dimensions of the turbine, and that 15 nodes vertical to the wall are assigned to achieve the appropriate mesh resolution, this region has mesh with smallest dimensions.

As a matter of routine, such projects always include a check of mesh independency: decades of experiences has shown

that the integration of such studies is indispensable for the development of a robust workflow. The result of such a study is shown in Figure 12. This study was based on 2D simulation. A factor of 4 was selected for mesh refinement.

Meshes of more than 16 million nodes ensure reliable simulation results and are therefore suitable for generating a metamodel.

Flow simulation

All flow simulations need to be done transiently since the rotation axes of these wind turbines, in contrast to horizontal axes turbines, is vertical to the air flow. This dramatically increases the computational effort required since only after at least 10 revolutions of the rotor is it possible to determine whether the simulation is stable.

Furthermore, convergence cannot be established by conventional means, since the derived solution is not characterized by constant velocity or pressure, but rather by values that oscillate as a function of turbine revolutions multiplied by the number turbine arms.

The result of such a simulation is shown in Figure 13 (see next page) as a snap shot of a rotating wind turbine and the downstream air flow trails. This clearly indicates the relatively large area that needs to be included the simulation relative to blade area. The airflow trail clearly extends some considerable distance downstream from the turbine.

Evaluation proved to be more demanding than usual because analysis of turbine power output or calculation of efficiency requires integration of the moment and loss per period. The power delivered to a generator fluctuates dramatically for each rotor arm during each rotation.

The Metamodel

The parameterization used for the metamodel has already been described in section 4. A DOE consisting of 200 Latin Hypercube Samples was used to generate the metamodel. Particularly worthy of note, is the contribution made by meshing to the painstaking construction of the geometry, such that only one of 200 samples needed to be discarded. Equally satisfying was the careful processing of parameter sets that benefitted from definitions based on flow mechanical interactions which resulted in the detection of no redundant parameters. In other words, the sensitivity analysis vindicated the selection of all the parameters defined at the start of the development work.

The metamodel shown in Fig. 14 describes the turbine power output dependent on the wetted aspect surface and the specific rpm. A Moving Least Squares (MLS) algorithm has been shown to be the best predictor of variation in turbine

power output. Somewhat (pleasantly) surprising was that for all the turbine-relevant parameters which determine the effective power output in a specific operational range, the predictive accuracy of the metamodel with respect to their variation was greater than 91%. This value was calculated as the Coefficient of Prognosis (CoP) using optiSLang.

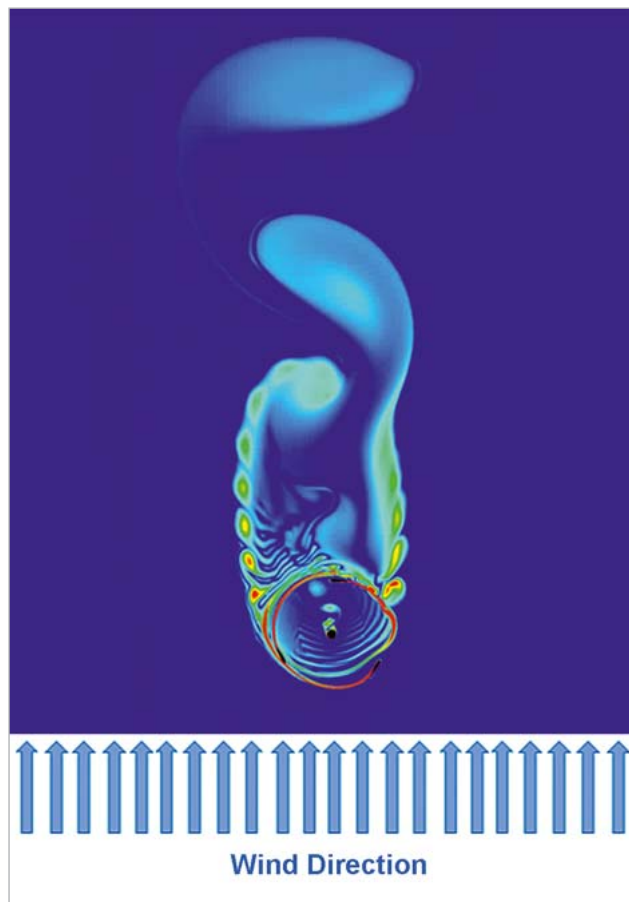


Fig. 13: Visualization of flow simulation

The reason for this high value, which exceeds the determined value of similar turbomachine projects, was the scrupulously careful definition of the parameters (see section 4.)

However, this ability represents only a fraction of the information a metamodel can deliver. It is normal practice to configure turbomachinery for a specific operational point or some optimal parameter. In reality, however, operational conditions occur that deviate considerably from the original configuration. These deviations are then usually plotted graphically as characteristic operational curves over a range of conditions.

The quality of the metamodel is shown in Figure 15 which shows a derived curve and four computed operational points, which show good congruence of the four evaluation points.

As a conclusion, the following can be stated:

It is possible with a metamodel to predict turbine power output and efficiency not only for a single operational point

but also for the operational behaviour with a given wind velocity. Whereby, of course, the turbine rpm is optimally calculated for a given wind speed.

The obverse is also true: For a desired power output from the wind turbine it is possible using the metamodel to compute the turbine size or blade geometry. That the optimal turbine rpm can also be analysed is almost a matter of course if the minimum loss is defined as a target value.

Evaluation of results

Although the validation, as shown in Fig 15, provides highly significant information because of the high reliability of the simulation results, it nevertheless, made sense to compare the model with an existing wind turbine.

The University of Uppsala have made recordings from a test turbine (Figure 16a) which provided suitable data. In the right-hand frame is a plot of power output against wind velocity for the turbine as predicted by the model.

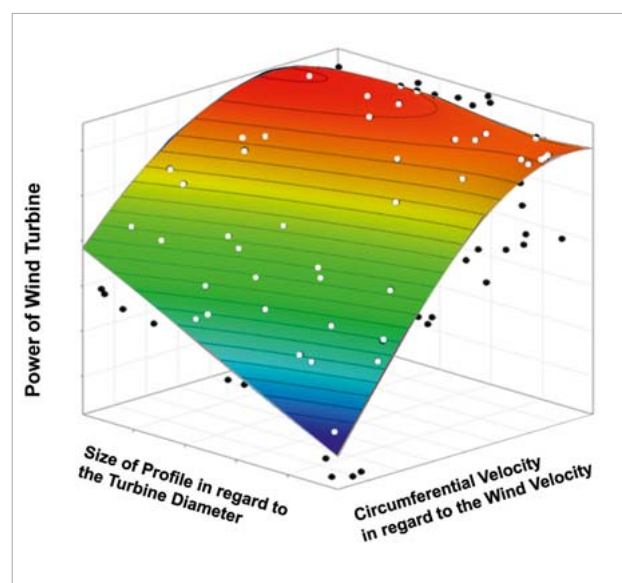


Fig. 14: The metamodel for a wind turbine as target value

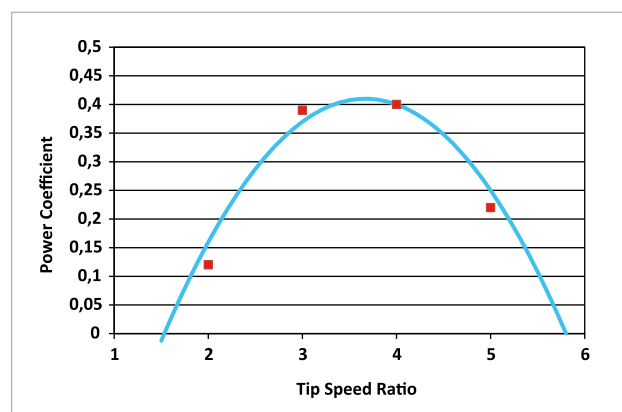


Fig. 15: Validation of parameters computed operational points

In addition, an operating point (red square in Fig. 16b) from measured data has been superimposed; deviation from the model was less than 5%. This vindicates the value of the approach described in this work. It should be said that no flow simulation has been computed for this turbine but rather the curve was derived from the metamodel.

Comparison of the metamodel with conventional methods

A model for semi-analytical computation of vertical axis wind turbines has existed for decades. The computations principle is based on the concept that the turbine rotor consists of a mesh comprised of a finite number of streamtubes, and that the flow size is calculated for each streamtube.

The Double Multiple Streamtube Model developed by Paraschivoiu is the most commonly used model. This model makes it possible to consider the rotor in both the downwind and upwind areas and the interaction of each rotor blade with the air flow.

As streamtubes are created separately in an upwind and downwind area, it is possible to recreate more realistically the effect of the upwind rotor blade on the downwind rotor blade. In this case it is assumed the trail from the upwind blade is fully developed and velocity is fully developed before interaction with the downwind blade.



Fig. 16a: Turbine near Uppsala, Sweden (image source: see last paragraph)

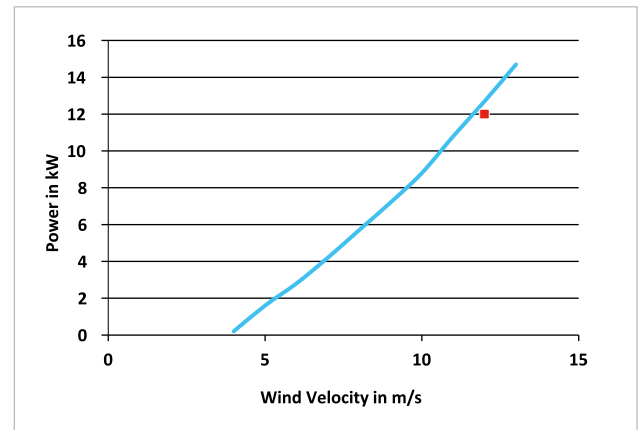


Fig. 16b: Validation of plot by comparison with measured data from an existing turbine near Uppsala, Sweden

Figure 17 shows plots derived from the metamodel (blue) and Double Multiple Streamtube models (yellow). In addition, CFD calculated operational points (red) have also been added for comparison. Greater congruence between the operational points and the metamodel curve strongly suggest it is the more accurate predictor.

Metamodel-based prognosis for three different sites

It is well-known that the effectiveness of wind turbines is strongly influenced by its location. Equally important is the influence of local factors and factors determined by given global boundary conditions. Both can be rapidly calculated using the metamodel, including the influence of local fluctuations in wind velocity, since the metamodel is capable of predicting power output for any given turbine geometry at any given wind velocity.

Figure 18 shows the power output of the turbine as a dimensionless power coefficient plotted against wind velocity as a function of rotational velocity. This graphic clearly indicates at which rpm for a given wind speed the turbine functions optimally.

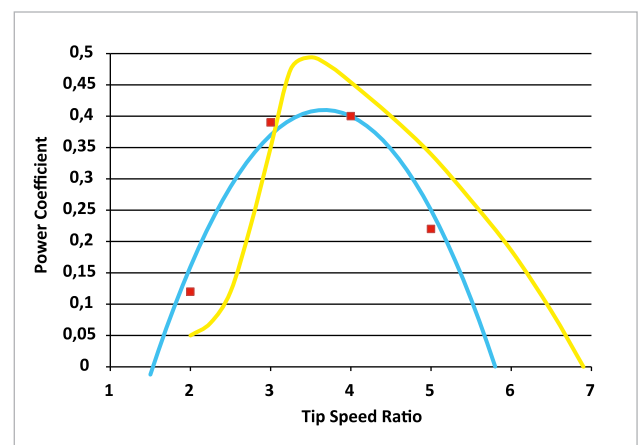


Fig. 17: Comparisons between the Metamodel (blue line), an analytical model (yellow line) and a CFD simulation (red squares)

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Fig. 16a taken from the article: Evaluation of a Blade Force Measurement System for a Vertical Axis Wind Turbine Using Load Cells by Morgan Rossander, Eduard Dyachuk, Senad Apelfröjd, Kristian Trolin, Anders Goude, Hans Bernhoff and Sandra Eriksson (Energies 2015, 8(6), 5973-5996; doi:10.3390/en8065973)

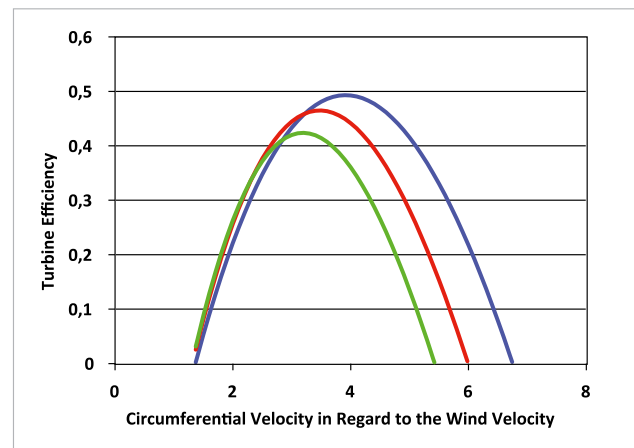
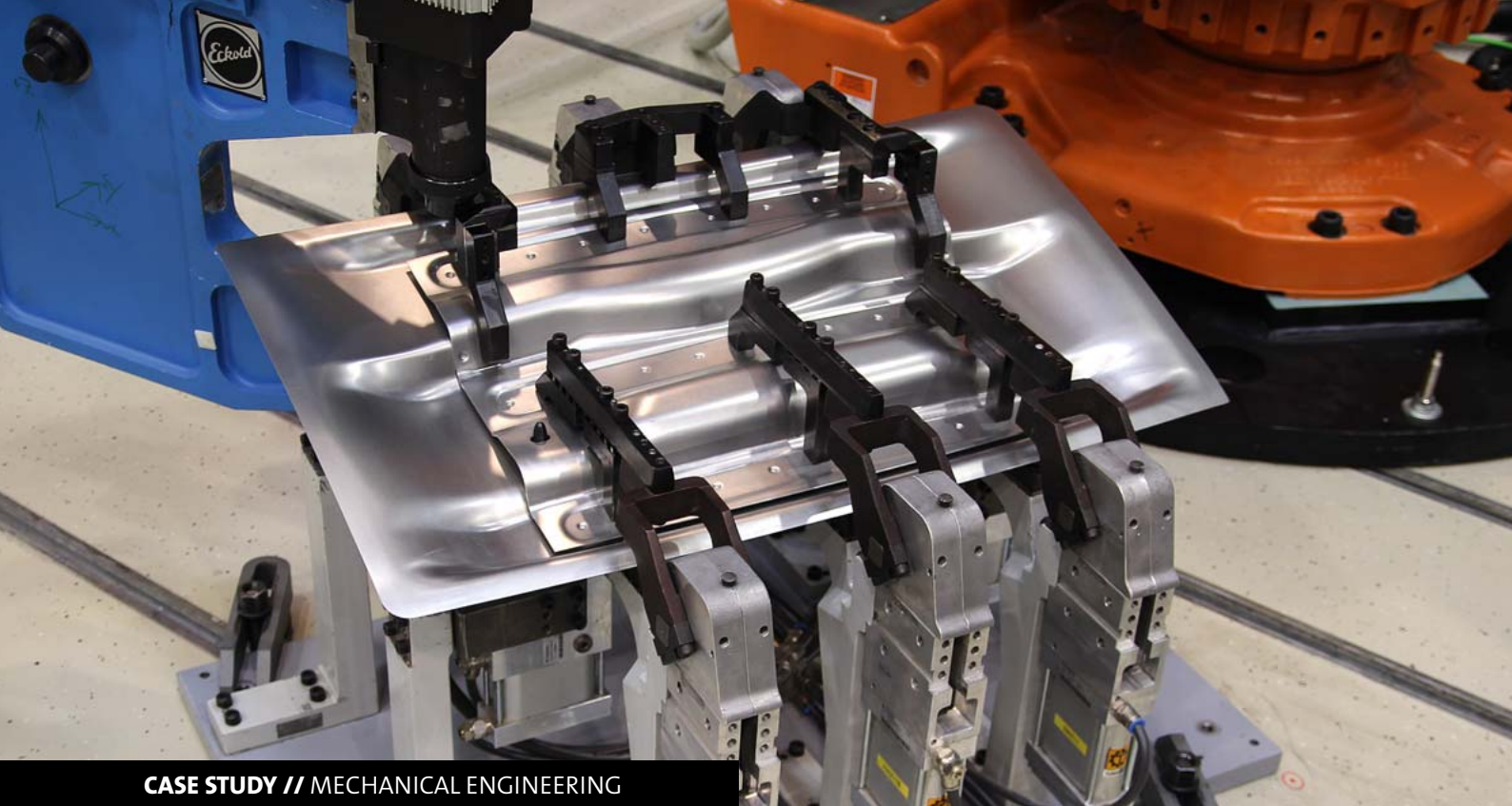


Fig. 18: Curves for different types of turbine location; blue-city; red-island; green-mountain

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CASE STUDY // MECHANICAL ENGINEERING

AUTOMATIC CALIBRATION OF SUBSTITUTE LOADS TO ESTIMATE THE IMPACT OF JOINING DISTORTION

optiSlang optimizes the process of model calibration by automatic identification of suitable input and output parameters for a realistic impact prognosis of joining distortion on the deformation of parts in the assembly.

Introduction

Due to the rising possibilities of the Finite Element Method (FEM) regarding virtual tolerance prognosis, it is also increasingly used in Car-Body-Production. Among others, one application is to simulate the distortion caused by the up to 6,000 joining operations during car manufacturing. However, the calculation of deformations related to joining procedures, as well as the integration of detailed FE-models for joints into full car models would result in prohibitive simulation time. As a solution, simplified model approaches for joints are necessary. The idea behind these simplified approaches is to use mechanical loads to estimate the deformation brought about by joining processes in the FEM. At present, adequate surrogate loads for mapping joining distortion are often still derived in a manual calibration process which consumes a lot of time and effort.

One approach is using the optimization software optiSlang for the automatic calibration of surrogate mechanical loads. The article will show how the tool can be applied to properly derive suitable input and output parameters, to generate a target function and to develop methods of optimization with the help of a real-life joining situation.

Customer's requirements regarding the quality of the car's impression cause a constant reduction of gap dimensions and tolerances. At the same time, using more and more lightweight materials, such as higher-strength steel, makes the manufacturing process for component parts and assemblies increasingly complex. The automotive industry uses more and more simulation tools based upon the FE method to meet these challenges. Thus, for example, the joining of car bodies can be simulated in an early phase of the manufacturing process.

Here, the potential of FE based simulation will particularly be shown in using a surrogate mechanical model to numerically predict the impact of the joining process on the deformation of parts in the assembly. The basic idea is to simulate the geometrical deformations resulting from the joining process with the help of locally induced mechanical loads. These loads have to be calibrated in advance using simplified experimental reference setups. During this process, the following steps for substitute modeling of joining distortion have to be considered (see Fig.1):

1. Derive a simplified reference assembly from a car body structure
2. Join the reference assembly and determine the deformation experimentally
3. Calibrate the substitute mechanical loads for a substitute model build on a local level using the experimental data
4. Transfer the resulting substitute loads of the substitute model to the joint model of the complex car body structure
5. Use an elastic FE calculation to determine the global component part distortion

The aim here is to replicate the distortion shapes of the simplified process model. Thus, the calibrated substitute mechanical loads transferred to the global component part structure result in approximately the same state of deformation as seen in reality. The quality of model calibration (i.e. the capability of the simulation model to map the experimental reference) is crucial for the quality of the substitute mechanical model. Using a manual process, a high level of personal effort is necessary to produce a reasonable mapping quality. With complex calibration models, this iterative analytical process can take several days. In the future, the calibration process can be supported by methods of CAE-based optimization to automatically generate a high quality level of responding substitute mechanical loads for mapping. As Fig. 2 (see next page) shows, the software optiSLang was integrated in the calibration process with the objective to decrease time and effort needed for calibrating substitute mechanical models. Here, a reduction from several days to a maximum of four hours could be achieved.

Simulation method

The FE program PAM-STAMP 2G (ESI group) was used for simulative mapping of the joining process. As the schematic example of a spot-welded joint shows (Fig. 3, see next page), the modeling of the joining process can be reduced to the following simulation steps:

1. Positioning and clamping of the specific components
2. Connecting the joining components with rigid girder elements at the position of the electrodes
3. Use of mapping to implement substitute mechanical loads in the form of tensions (stress) in the area of the joining point
4. Calculating the balance where a change in the geometry has a result on the component parts

Parameter identification

Input parameters

2-D shell elements are used to make the parts to be joined discrete in the FE model, reaching a conformity with the Belytschko-Tsay element formulation. These shell elements are mostly used in the sheet metal forming simulation and describe the behavior up to five integration levels above the virtual sheet thickness. The specific integration levels of the shell elements are mapped with the stress deposited in the mapping file during the mapping procedure as depicted in Fig. 3 (see next page, refer to Step 3). Thus, the distortion measured in Point 2 in Fig.1 was reached. This enables the

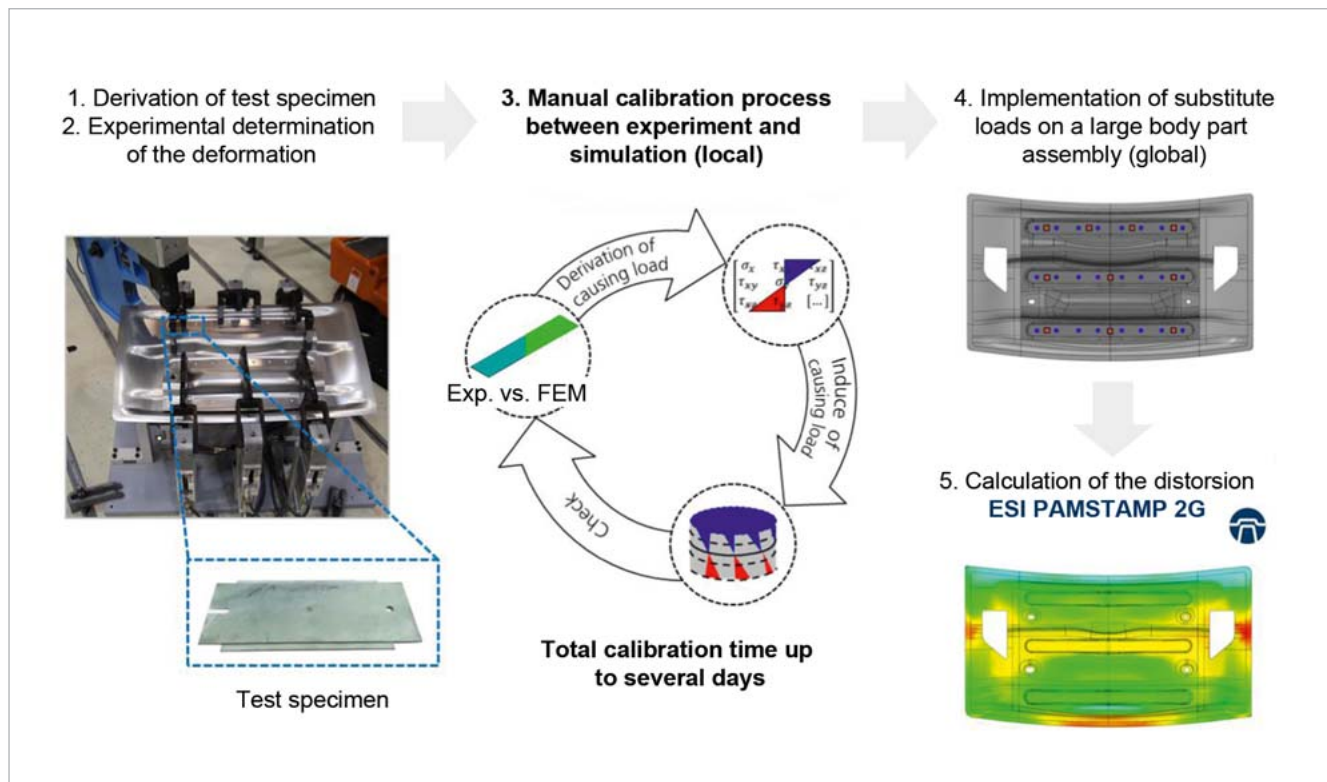


Fig. 1: Manual calibration process for substitute mechanical models

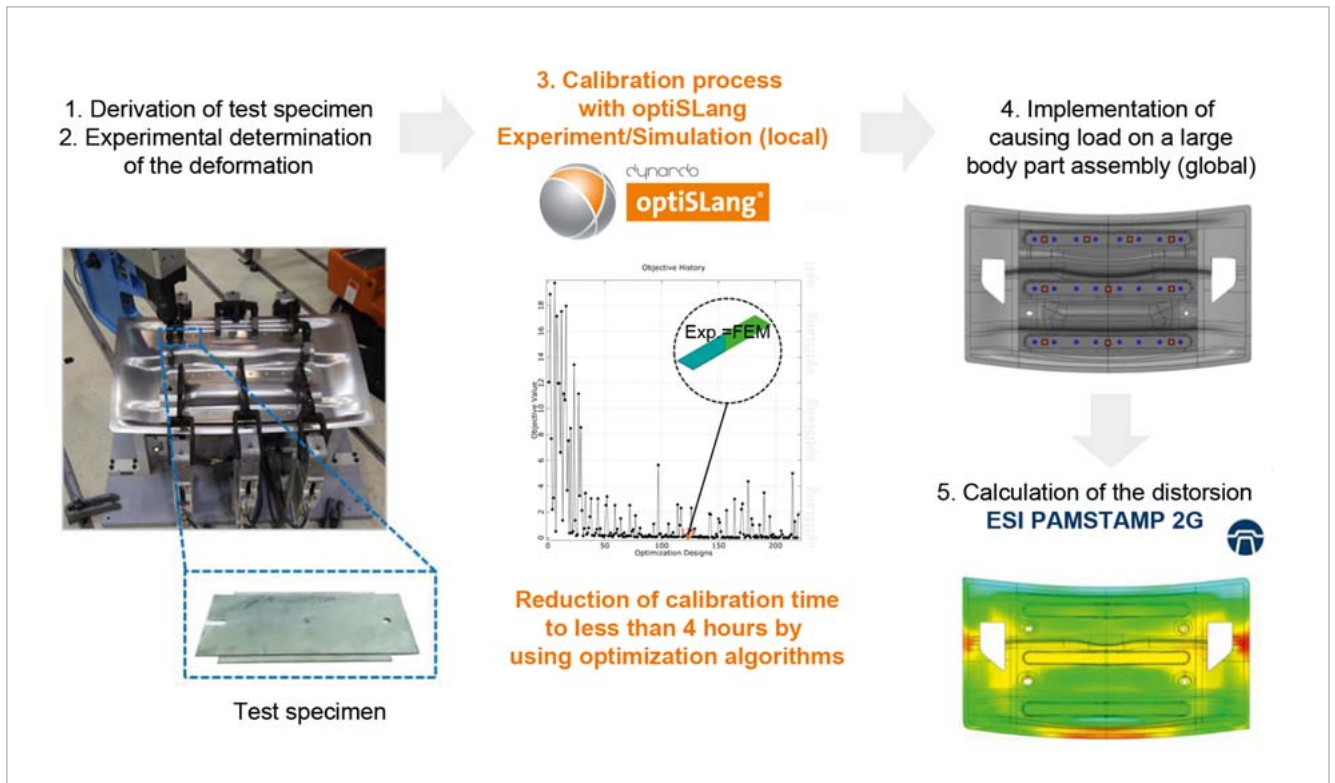


Fig. 2: Integration of optiSLang into the calibration process

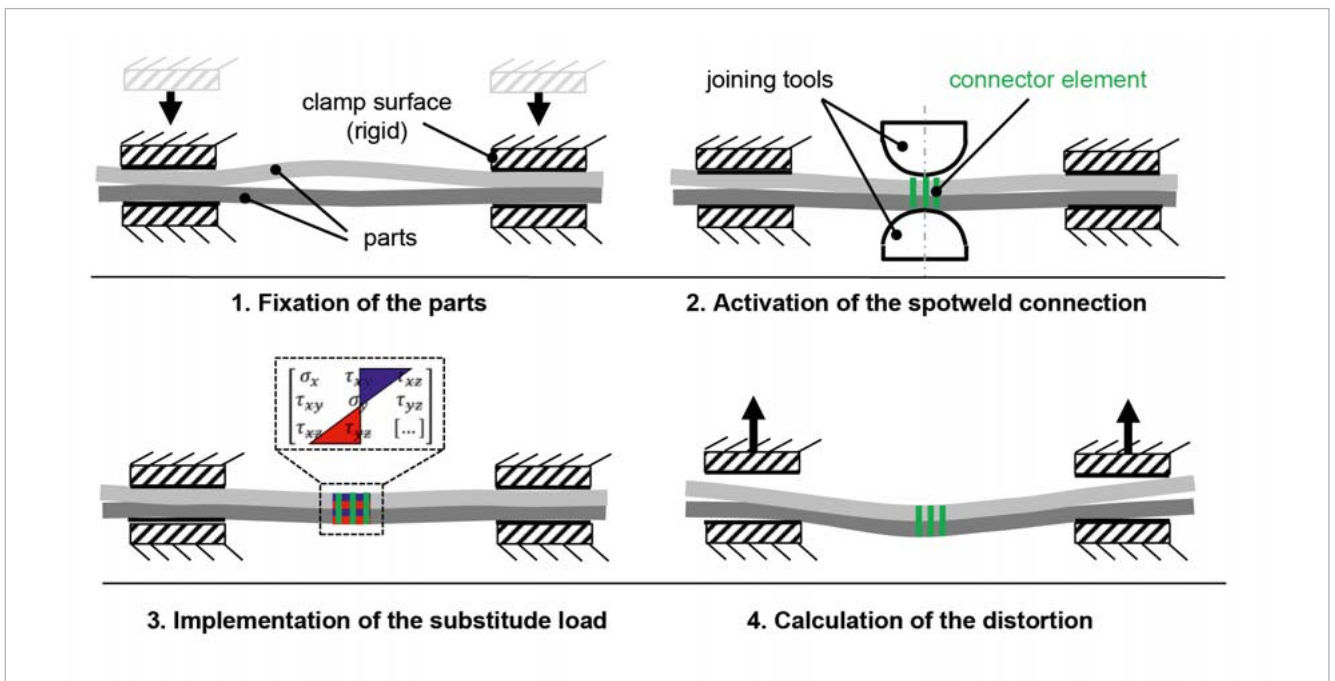


Fig. 3: simulation steps to compute the joining process

user to have control over the intensity of distortion in regard to the simulation model. Therefore, the fundamental idea is using optiSLang to access needed stress defined in the mapping file and to use an optimizing algorithm to systematically modify them. So, the simulation model comes closest to the experimental reference during the calibration processes.

Because both the upper and lower blanks were independently mapped with substitute mechanical loads, a total of ten input parameters for optimization (see Table 1) were produced. The derived input quantities that were supposed to describe the behavior of the shell's cross-section mathematically are shown in Fig. 4. Furthermore, the parametrized stress from the optimization algorithm could be continuously varied for

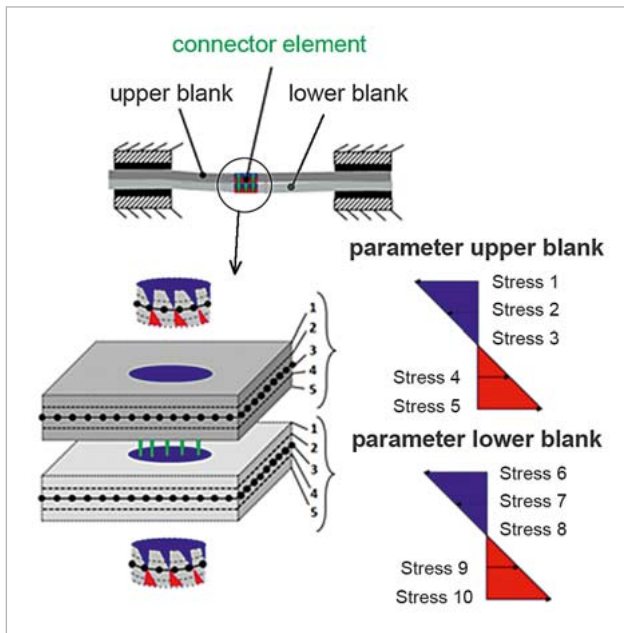


Fig. 4: Identification of the parameters on the 2-D shell element

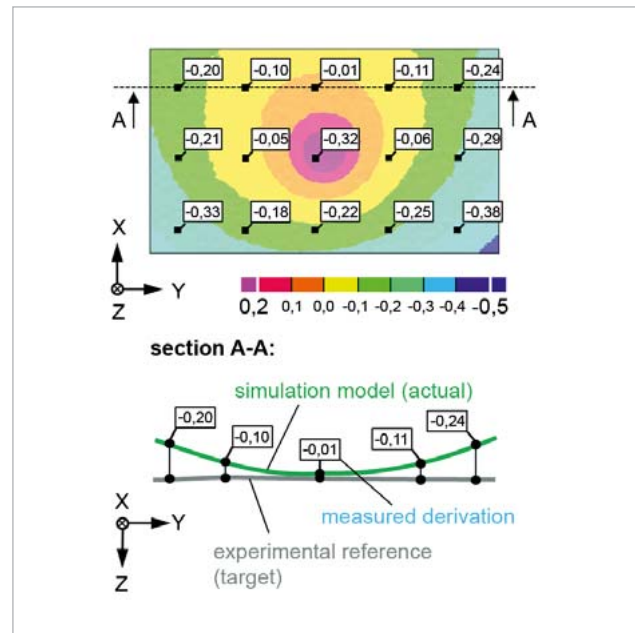


Fig. 5: Definition of objective

No	Parameters	Lower Bound	Upper Bound	No	Parameters	Lower Bound	Upper Bound
1	Stress1_Oberblech	-10 MPa	10 MPa	6	Stress1_Unterblech	-10 MPa	10 MPa
2	Stress2_Oberblech	-10 MPa	10 MPa	7	Stress2_Unterblech	-10 MPa	10 MPa
3	Stress3_Oberblech	-10 MPa	10 MPa	8	Stress3_Unterblech	-10 MPa	10 MPa
4	Stress4_Oberblech	-10 MPa	10 MPa	9	Stress4_Unterblech	-10 MPa	10 MPa
5	Stress5_Oberblech	-10 MPa	10 MPa	10	Stress5_Unterblech	-10 MPa	10 MPa

Table 1: selected parameters and their variation limits

the upper and lower blank to search for the optimum design configuration where the pressure and tensile stresses can be assigned to the shell elements in the joining zone.

Objective criterion

Discrete measuring points were defined as targets on the entire surface of the assembly of the calibration model. This created the space in the Z-direction of the simulation model (ACTUAL) in regard to the experimental reference (TARGET) at the end of a simulation run-through. Fig. 5 shows the definition of the targets on the calibration model.

To be able to consider all of the measuring points, it is necessary to use a target function to combine the effective interrelationships discovered in an optimization model. The value of the target function was calculated from the total of the squared spaces between the experiment and simulation at the specific measuring points. The objective of optimization is to keep this function value as minimal as possible or, in other words, to minimize the amount of which the simulation model and the experimental reference differ from one another at all measuring points.

Case study

A real-life example of car body engineering was used for examining the functionality of the calibration procedure. It is described here by deriving two specimens from one complex car body structure: specimen no. 1, consisting of three joining points and specimen no. 2, consisting of five joining points (see next page, refer to Fig. 6). Specimen no. 1 was used to automatically calibrate the model with optiSlang while specimen no. 2 was used to check the quality of the calibrated substitute model for the second situation. Finally, any divergences between the experiment and simulation were calculated.

Calibration model: specimen no.1

Because of the small number of just ten parameters to be calibrated, the optimization was based on an adaptive response surface method (ARSM) implemented in optiSlang. The ARSM algorithm generates a support point pattern consisting of ten samples in every iteration step and shifts it until the algorithm reaches a user-defined termination criterion. In the case of this example, the termination criterion is met when either the optimizer reaches a maximum of 90 simulation runs, i.e. nine iterations, or the objective function shows

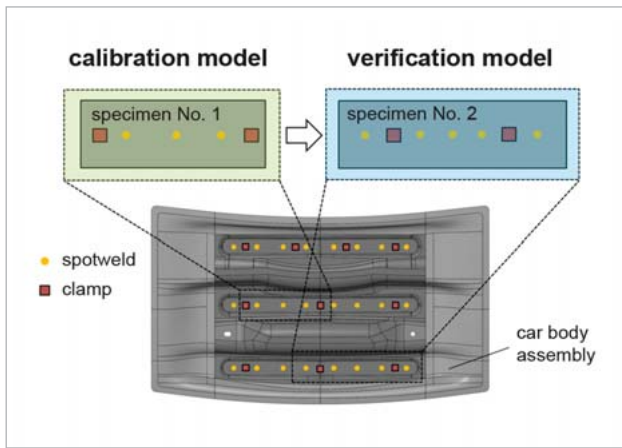


Fig. 6: Test specimens used during the test

a value smaller than 0,01. The convergence procedure of the ARSM could be derived from the objective history diagram shown in Fig. 7 (top) and the parameter history diagram for the parameter Unterblech_Stress5 in Fig. 7 (bottom). In this connection, the optimizer reliably converges after a total of nine iterations (90 simulations) and reduces the functional value of the target function to 1.2 in the first iteration loop and to the user defined stop criterion of approximately 0.033 in the final iteration step. Altogether, the optimization of the substitute loads required approximately three hours running four simulations simultaneously. Thus, the target of reducing the simulation time for the calibration process to less than four hours was reached without any problems.

The resulting deformation from both the experimental reference (blue) and the simulation (red) were referenced to the design state (CAD-0) for evaluating the quality of calibration. The welding distortion was evaluated along the cutting plane designated on the upper and lower blank in the sheet's normal direction (refer to Fig. 8).

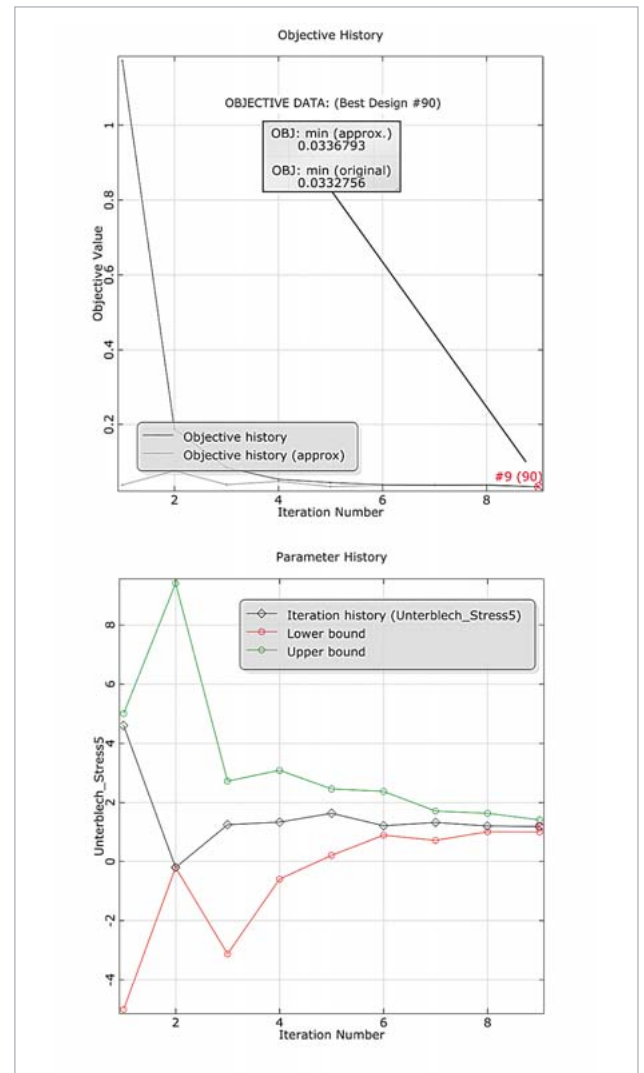


Fig. 7: The objective history diagram of the ARSM algorithm (left) and the parameter history diagram of the Parameter Unterblech_Stress5 (right)

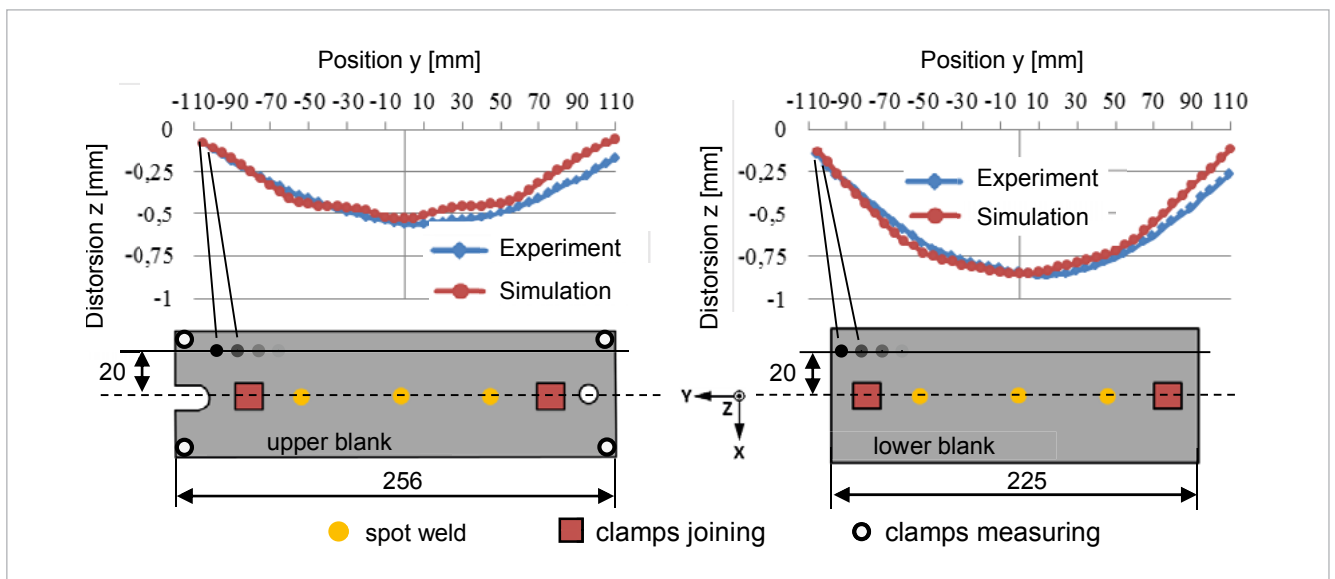


Fig. 8: Calibration results (Simulation vs. Experiment) for specimen no. 1

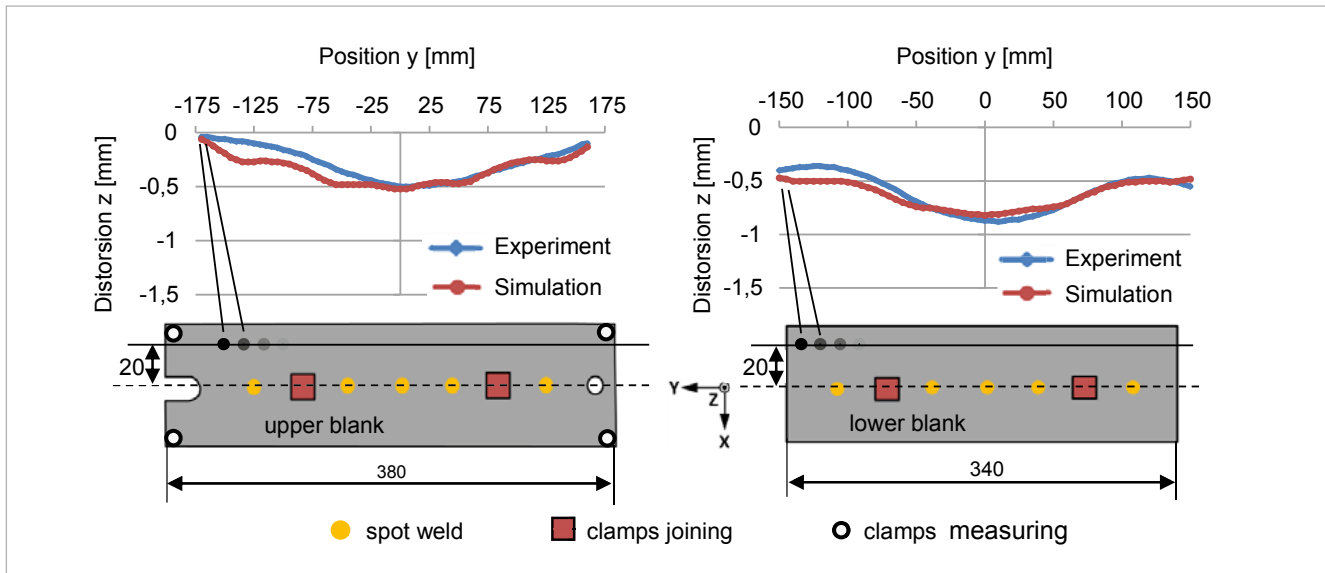


Fig. 9: Comparison of measured and simulated distortions of specimen No. 2 (Calibration model: specimen No. 1)

The prognosis of deviations in the simulation showed excellent agreement with the experimental data. Furthermore, the maximum difference of the distortion values from the simulation and experiment are less than 0.07 mm on both the upper and lower blank. From the calibration process of specimen no. 1, it can be concluded that the ARSM algorithm finds the matching configuration within a few iterations. Thus, the time and effort for identifying suitable substitute loads could be substantially reduced. The achieved calibrating quality was high in this example which indicates a proper suitability for further transferring of the substitute mechanical loads to more complex applications.

Verification model: specimen no.2

To verify the quality of results, the substitute loads calculated by the optimizer were transferred to specimen no.2 (five joining points) without any alteration. Fig. 9 shows the appropriate divergences between experiment and simulation.

The maximum deviation between the experiment and simulation is 0.05mm on the upper blank and 0.1mm on the lower blank. These matches indicate the high level of calibration quality of specimen no.1 making the substitute mechanical model capable of predicting reasonable distortions while being transferred to more complex applications.

Conclusion

An experience-based analytical process could be set up to exclusively calibrated substitute mechanical models. Without this procedure, surrogate mechanical loads, needed for matching the distortion, have to be manually calibrated. They were based on experimental iterations to the point where the joining distortion from experiment and simulation agreed. This requires not only a high level of user ex-

pertise, but also especially time-consuming change loops. Here, the potential of optimization-based model calibration could be demonstrated. The optimization algorithms decisively reduced time and effort for calibrating the substitute parameter to a couple of hours while maintaining a high level of calibration quality.

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COSTUMER STORY // PROCESS ENGINEERING

OPTIMIZATION OF FIBER COMPOSITE COMPONENTS IN YACHT RACING

Apart from ANSYS Composite PrepPost, ar engineers used optiSLang in the design phase for an advanced optimization of the boom of a sailing race dinghy.

For decades, fiber composites have been successfully applied in yacht racing. The knowledge of application has reached an incredibly advanced level. Especially for construction parts with just a few requirements regarding the boat design, the technical development supported by simulation software is an important factor for success.

Sailing and construction teams consider further technical optimization as an economic challenge, especially in the highly developed boat classes. Low production quantities even increase the cost pressure on development asking for special approaches of design.

Less weight, but the same strength and rigidity

The boom of a racing dinghy serves for hoisting and trimming the main sail. It takes up a significant part of the sailing force. Thus, strength and rigidity properties of the boom are of crucial importance for the sailing performance. At the same time, the boom needs to be as light as possible to meet the requirements of competitive racing. As boundary conditions for the optimization, the load cases and the design space of the boom were predefined. In addition, the

solution should ensure the reutilization of existing molding tools. This eventually restricted the focus of optimization potential to the multi-layer laminate. The aim was a significant weight reduction of the boom while keeping its properties regarding strength and stiffness unchanged. Eventually, the team focused on four key parameters to improve the properties of the fiber composite laminate: the layer angle, the layer number and arrangement, as well as the selection of materials. The reduction of theoretically possible parameter combinations to the practically meaningful ones regarding manufacturability and material availability accelerated the actual optimization process.

Simulation tools for composite structures

The construction team of ar engineers designed the fiber composite components with the assistance of the software ANSYS Composite PrepPost, which is fully integrated in the simulation environment ANSYS Workbench. The tool is especially capable for design development and considers the modeling of structures and the draping. In addition, the software provides a compact display of results based on combined failure criteria. With the software optiSLang in-

side ANSYS, the optimization procedure can be conducted without leaving ANSYS Workbench. This guarantees a data transfer without connecting problems. The uniform and user-friendly interface also resulted in an overall shorter processing time. A parameterized FEM model functioned as a basis for optimization with the parameter set generated by optiSLang and controlled by ANSYS Workbench.

The application of optiSLang was performed in three steps:

- Sensitivity analysis
- Optimization
- Robustness evaluation

In the first step, the sensitivity analysis, the design or input parameters and the result values or output parameters were defined and classified within a value range (10% standard). Based on these parameters, optiSLang then generated a design of experiment including various combinations of parameter values. After simulating the individual design variants, optiSLang created a surrogate model for the result visualization of the sensitivity analysis using different types of graphical post processing. The evaluation of the results illustrated the correlations between the individual parameters as a significant contribution to the understanding of the function and component behavior. This represented the basis for a target-oriented optimization.

Optimization with subsequent validation

In the following step, the procedure of optimization differed depending on the significance of the surrogate model. A high prognosis coefficient indicates the possibility to conduct an optimization just by using the surrogate model and a subsequent validation through the FEM model. This time saving procedure is therefore preferable. In the case of having a surrogate model with low prognosis quality, possible causing effects should firstly be investigated. The recalculation of certain design points or changing input parameters can already help to improve the coefficient of prognosis.

A minimization of weight as the main goal of the boom optimization was configured in optiSLang. The team of ar engineers considered safety limits at various points of the boom as constraints. In addition, the deflection was not allowed to exceed the limit. Due to the carefully prepared optimization, the surrogate model showed a high accuracy capable of running a direct simulation. The procedure of optimization, the validation with the FEM model as well as further parameter adjustments finally achieved a weight reduction of 18%. At the same time, the mechanical properties of the boom remained unchanged or were even improved in several cases.

Since some design input parameters, like layer angles, have typically been subjected to production-related scatter, the consideration of this influence by conducting a robustness analysis is also of great importance. Combined with the

knowledge of the underlying stochastic process, optiSLang allows a classification of distribution and, thus, the determination of the reliability of the individual design values.

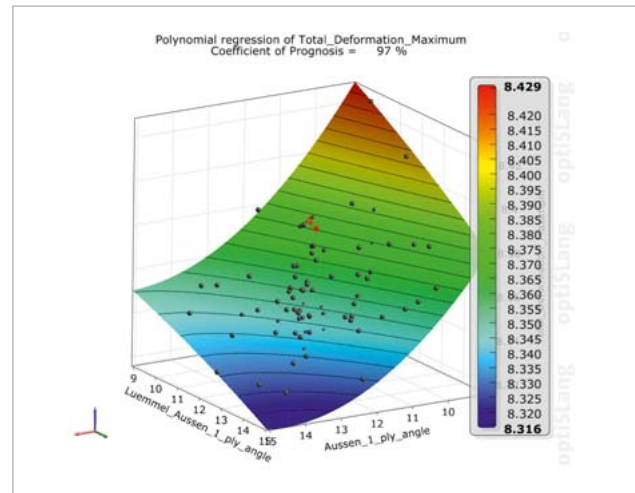


Illustration of evaluation results in optiSLang

Especially while exploring the performance limits of a component, as it is often the case in yacht racing, the results of a robustness analysis provide several advantages. A proven robust design guarantees an increased safety against random scatter of input parameters. Thus, the individual components can already be optimized during the design phase according to the extreme demands in later use.

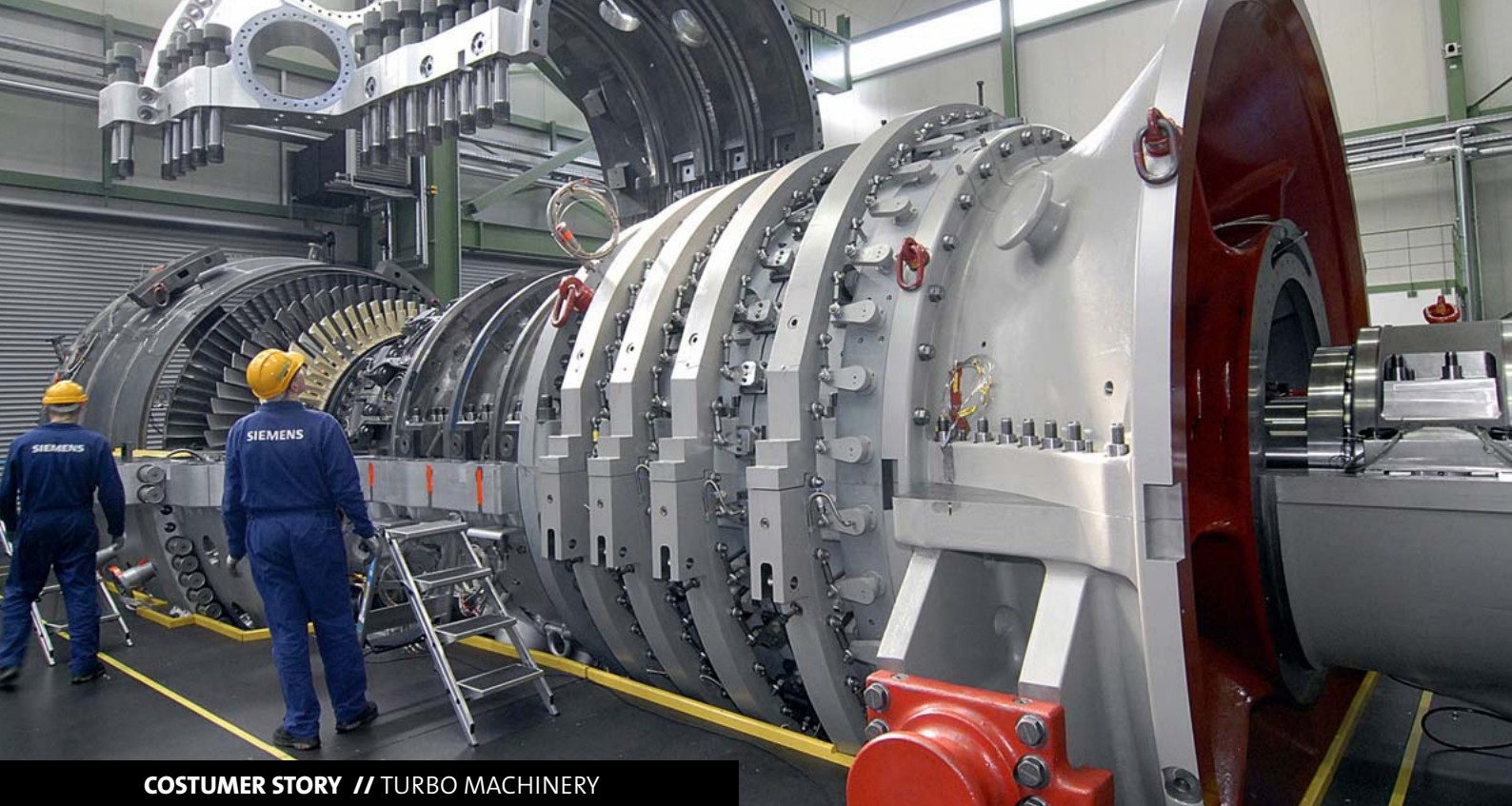


Puck failure criteria

ar engineers has performed an optimization that resulted in a boom that is lighter and even more rigid than the previous model while also fulfilling the predefined safety margins for the material. A better utilization of the safety margins in all fields could further improve the weight reduction potential of the component. At the same time, an effective product development process could be determined by combining the optimization software optiSLang inside ANSYS with the practical know how in the design of components made of fiber composite materials. The results of this application will also serve as a basis for future component optimizations and feasibility studies.

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COSTUMER STORY // TURBO MACHINERY

FEASIBILITY STUDY OF LARGE GAS TURBINE OUTER CASING BOLTS

Potential improvements are identified with the help of optiSlang for optimizing outer casing bolts of large gas turbines regarding life and cost requirements.

Introduction

The bolted connections at the outer casing of large gas turbines are critical regarding life and cost. One critical feature is the difference in temperature between bolt and flange during transient start-up and shut-down. This can cause, in combination with a hydraulic tensioning pretension close to the yield strength, an overstretching of the bolts. An overstretching causes a loss of pretension and reduces the clamping force at the flanges. Reduced clamping force can cause leakage and requires an expensive seal.

This feasibility study shows the development of a heat transfer model. The heat transfer values are fitted from different site measurement on actual casings in operation. Further, the influence of the manufacturing, tolerances as well as the variation of the heat transfer value caused by different bolt positions or bolt-flange geometries, are studied regarding the robustness of the result and temperature difference.

Finally, the hurdles and potential improvements are identified with the help of the software optiSlang for further use on gas turbine projects.

In order to produce work shaft output, a gas turbine compresses air and adds fuel, which expands after ignition and drives the turbine.

These steps come along with a high temperature gradient of the working gas and all the components involved. These gradients again are the main reason for stresses and thereby crucial for the lifetime of the whole assembly.

During transient start-up and shut-down, temperature gradients also occur in radial direction, especially in the split plane where the rather thin top and bottom housing are bolted together through thick flanges. The small contact area between bolt head and flange causes a slow conduction of the heat into the bolt and an even higher temperature difference between those two parts. This temperature difference is directly proportional to the low cycle fatigue of the bolt. Even an overstretching of the bolts is possible in combination with a bolt pretension close to the yield strength. Overstretched bolts lead to a reduced clamping force which can result in leakage. To prevent this leakage, a relatively expensive seal is placed between the flanges.

The long-term aim is to minimize fatigue, reduce maintenance costs, and maybe even completely remove the necessity for the seal.

This feasibility study shows the development of an appropriate model fulfilling these requirements. The parameters of the heat transfer were fitted from different site measurements on actual casings in operation. Finally, the influence of the manufacturing, tolerances as well as heat transfer value variation caused by different bolt positions or bolt-flange geometries, were studied regarding robustness of the result and temperature difference (Fig. 1).

Numerical Model

An FE-model was developed to study the general behavior of the bolted connection. Taking advantage of symmetries, only the upper housing and half a bolt were modeled (Fig. 2), while the bolt was fully parametric (Fig. 3, see next page).

The heat transfer coefficients (HTC) at the contacts between bolt, washer, nut and flange are essential for the resulting temperatures. Since there is no easy way to obtain exact values these parameter have been just estimated usually. In order to consider this uncertainty, the HTC was also parameterized for each contact (Fig. 4, see next page).

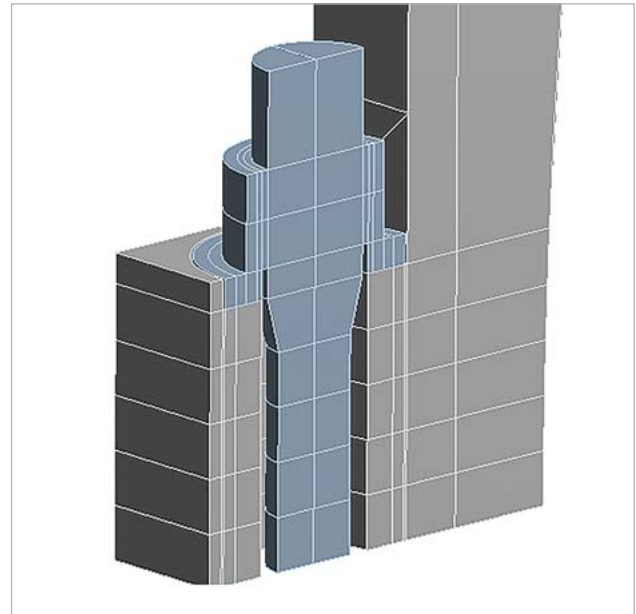


Fig. 2: Overview of the geometry

In general, parameterization of all input data of the model is possible. However, different effort is necessary. Accessing some of the parameters was made possible by using scripts utilizing the Ansys Parametric Design Language (APDL) which allows in-depth access to every detail of the setup (Fig. 5, see next page).

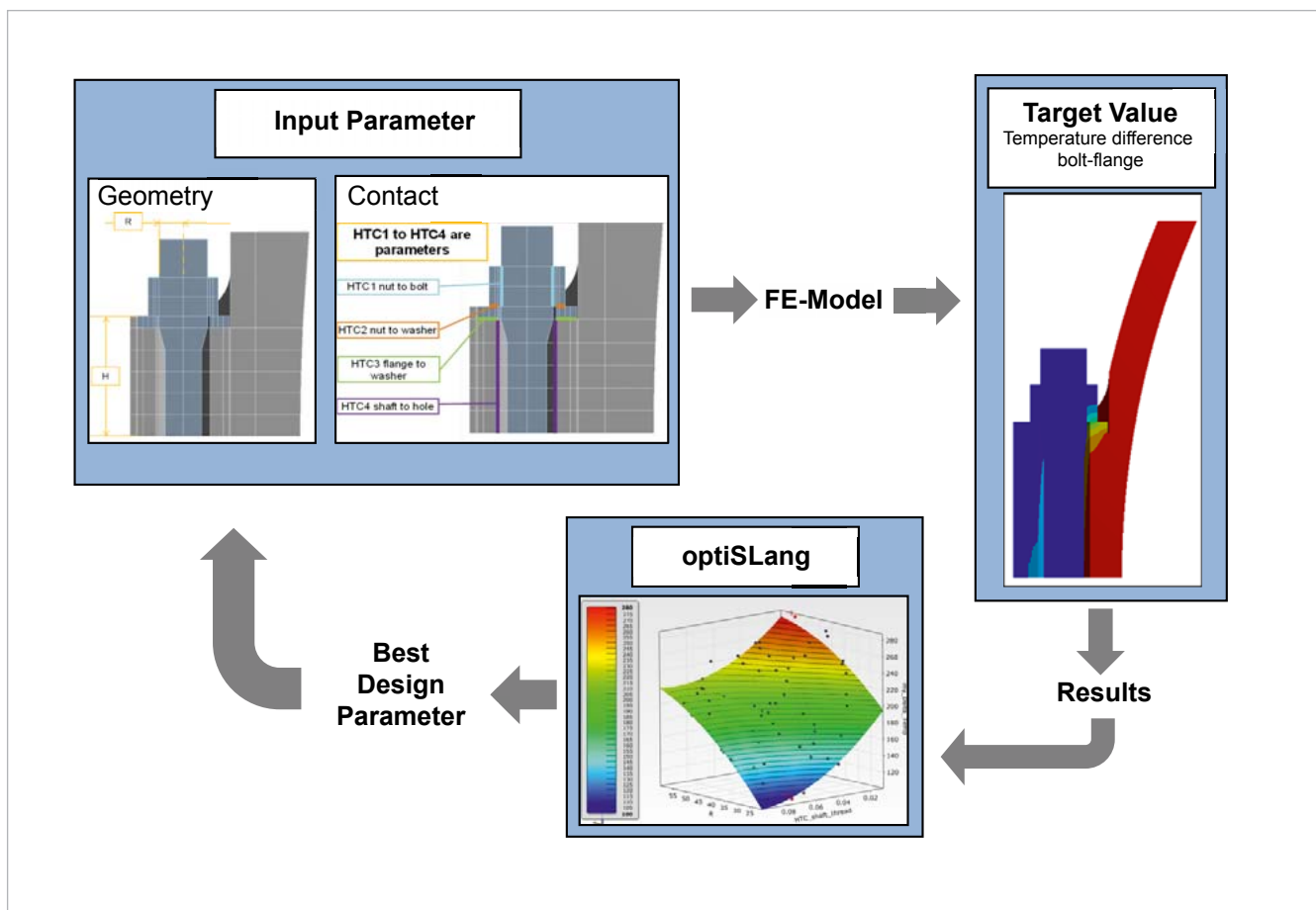


Fig. 1: Workflow

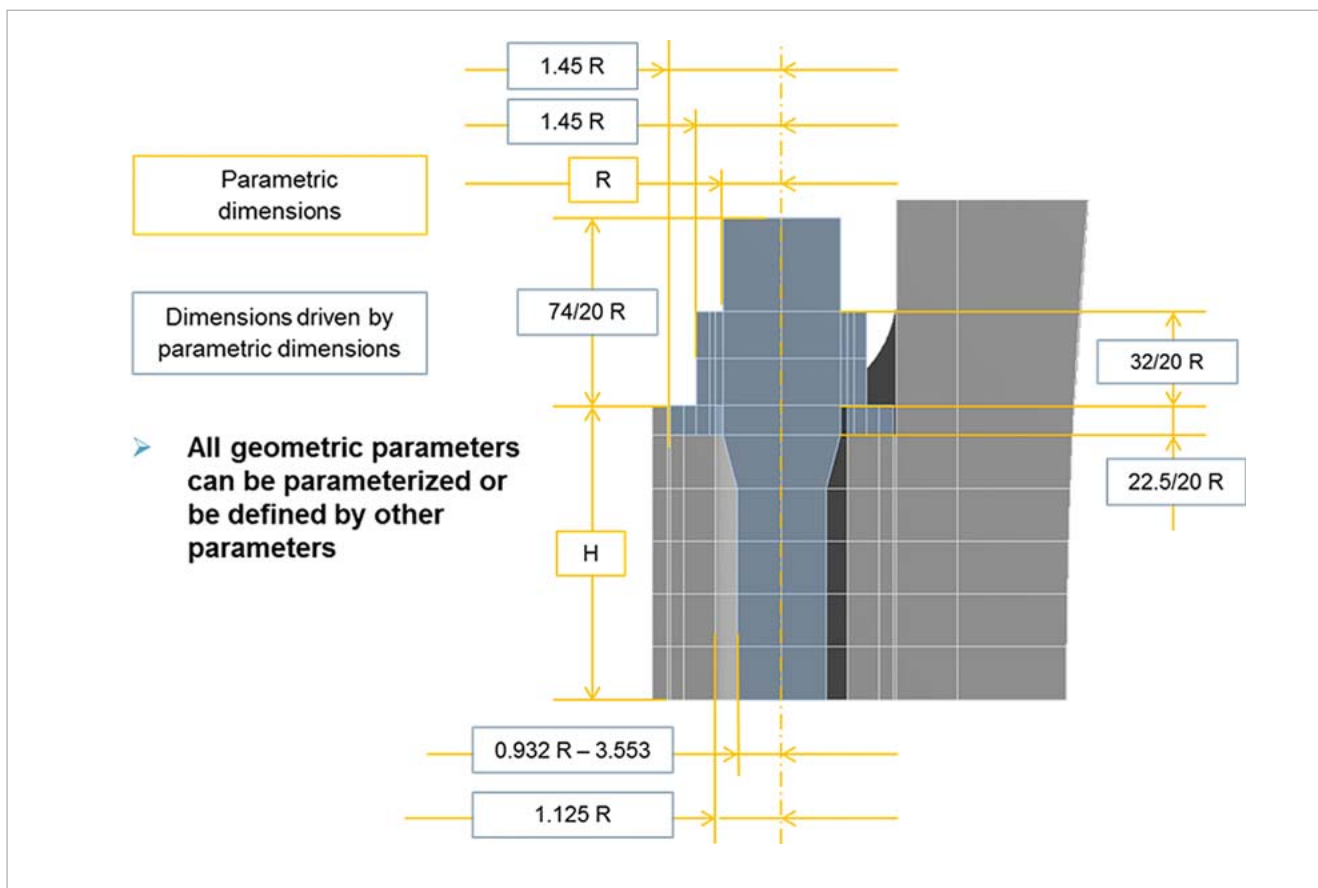


Fig. 3: Parameterization of the geometry

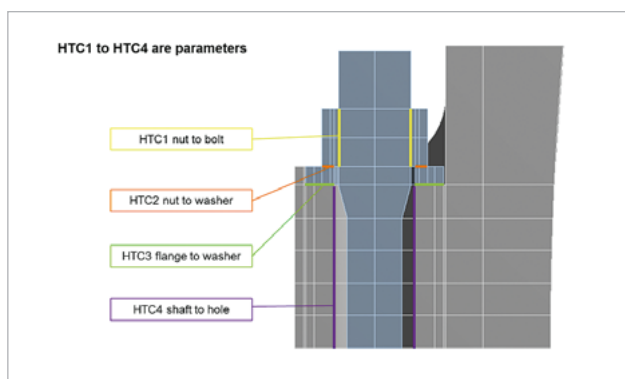


Fig. 4: Definition of heat transfer coefficients

Action	Geometry	Contact Properties	Boundary conditions	Material properties
Values Constant	●	●	●	●
Values to depend on temperature	-	●	-	●
Values to depend on time	-	●	●	●

Fig. 5: Effort for parameterization of certain properties | ● Workbench function, low effort | ● Small APDL commands, low effort | ● APDL commands, high effort

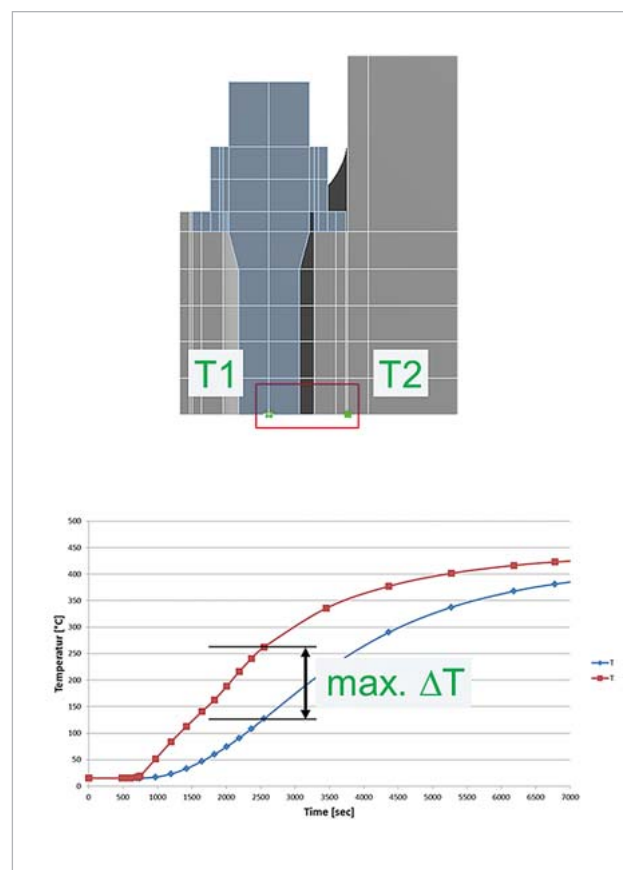


Fig. 7: Definition of the temperature difference

No.	Description	Variable	Range Minimum	Range Maximum	Unit
1	radius	R	20	60	mm
2	flange-height	H	100	400	mm
3	HTC bolt to nut	HTC_bolt_nut	1 000	50 000	W/m ² C
4	HTC nut to flange	HTC_nut_flange	1 000	50 000	W/m ² C
5	HTC washer to flange	HTC_washer_flange	1 000	50 000	W/m ² C
6	HTC shaft to hole	HTC_shaft_thread	10	50 000	W/m ² C
7	thermal conductivity bolt material	lambda_bolt	25	40	W/mK
8	thermal conductivity flange material	lambda_flange	28	35	W/mK
9	specific heat bolt / flange material	sp_heat_flange	500	600	J/kgK

Fig. 6: Example for parameter ranges for the optimization

All resulting input parameters are shown in Fig. 6. While there are only two geometric variables (bolt radius R and flange height H), the majority of the variables includes the material properties of the parts (thermal conductivity and specific heat) and only roughly known boundary conditions (HTC between parts). Especially the HTC values are usually taken from literature and are often a point of discussion.

Output parameter

Due to similar thermal expansion factors of bolt and flange material, the overall best behavior is expected when there is no temperature difference between these parts. This leads to the target of the optimization to minimize the temperature difference. The difference is simply calculated by subtracting two temperature probes at the bolt and flange (Fig. 7). Since the simulation is transient, at each probe the temperature varies over time resulting in a time dependent temperature difference where the maximum Tmax over all time steps has to be identified. This can be done by utilizing an ANSYS APDL macro or using Dynardo's Extraction Tool Kit (ETK).

Results

For this model, a DOE was created and a sensitivity analysis was performed. As a matter of fact, a Latin Hypercube Sampling (LHS) of 100 samples was already sufficient to achieve a Coefficient of Prognosis (CoP) of 99% for the most important response value. The three parameters with the highest impact on the temperature difference are the bolt radius, the HTC between the bolt's shaft and the bore hole as well as the height of the flange (Fig. 8). The other parameters have a negligible influence on the variation of the results and were automatically filtered by optiSLang MOP algorithm. The correlations turned out to be rather trivial, which is obvious and was expected before. With a small bolt radius R and a high HTC between bolt shaft and bore hole, the temperature difference (my_Delta_Temp) between both parts is small and vice versa (Fig. 9, next page).

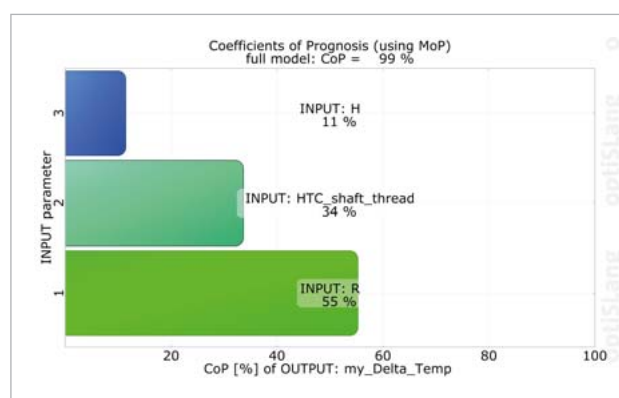


Fig. 8: Coefficient of Prognosis

Calibration of the HTC Value

While the height of the flange and the bolt radius are geometric constants which can easily be measured, fitting the HTC4 shaft-thread (Fig. 10, see next page) value was a challenge.

In this case, the input parameter HTC4 shaft-thread is actually the heat conductivity of a contact without any stiffness, connecting the bore hole through the air to the bolt's shaft. This single parametric conductivity is supposed to replace the whole system of the two HTC, i.e. from the flange to air respectively from the bolt to air as well as the thermal conductivity of the air itself. This problem would usually require a full fluid simulation. To find an appropriate value within the thermal transient environment, the model was fitted to actual measurements of the bolt temperature.

Therefore, the start-up time, where the highest temperature gradients are expected to occur, was divided into several sections, each with its own parametric HTC (Fig. 11, see next page). These values were then fitted by matching the resulting temperatures at the bolt with the corresponding measured temperatures.

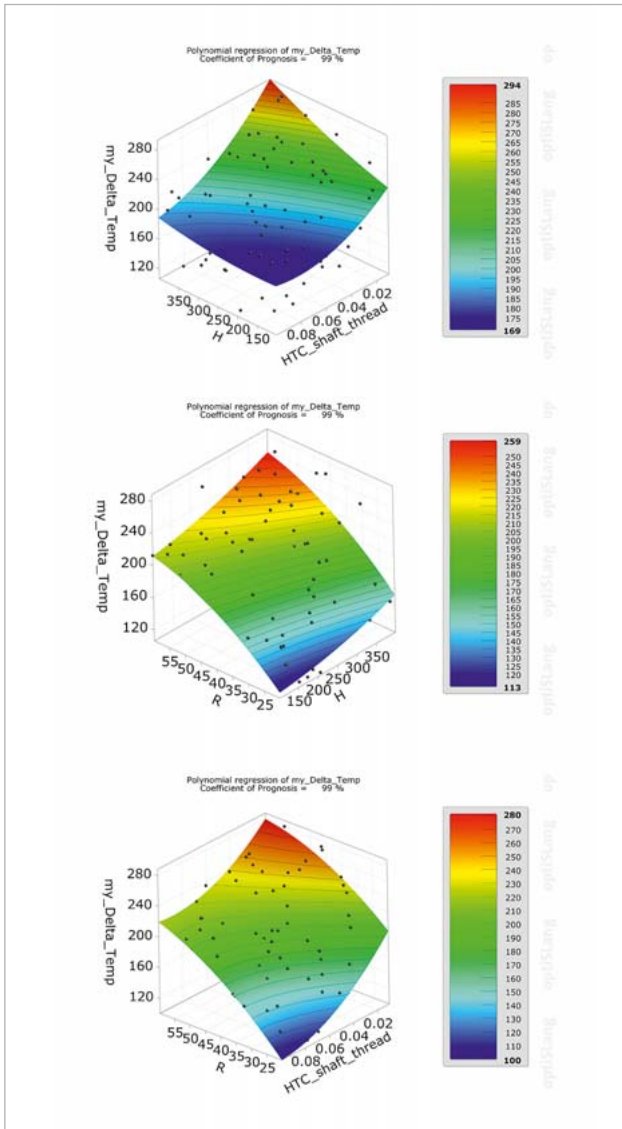


Fig. 9: Response surfaces

This fitting resulted in three different HTCs, one for every time section, all better matching the actual measured temperatures compared to a constant estimation. Thus, discussions about which HTC should be assumed were ended. With these fitted parameters, the temperature difference between flange and bolt was calculated to improve the original target of the optimization.

In Fig. 11, the temperature differences between bolt and flange are shown. The three graphs compare the measured temperature difference between bolt and flange, the difference resulting from the simulation with a constant HTC and the difference from the simulation with the time depending fitted HTC.

While the fitted HTC values already provide a better match to the measurements, there is still a gap between those two. This was expected, because the second component of the temperature difference – the temperature of the flange - is not yet fitted. This can be done using the same technique as before.

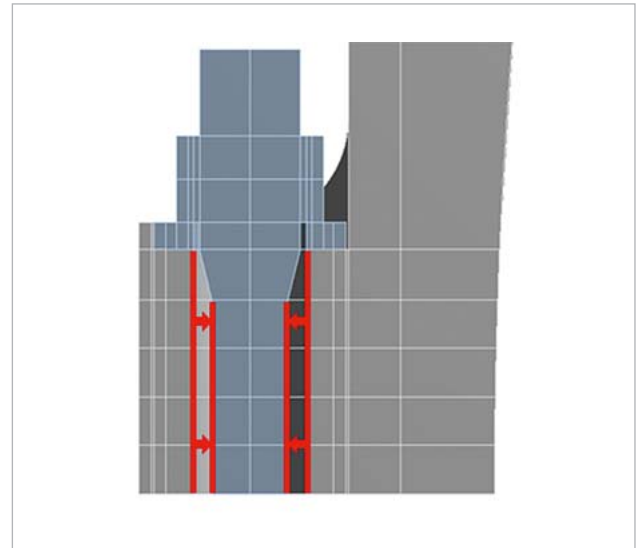


Fig. 10: HTC4 shaft-thread

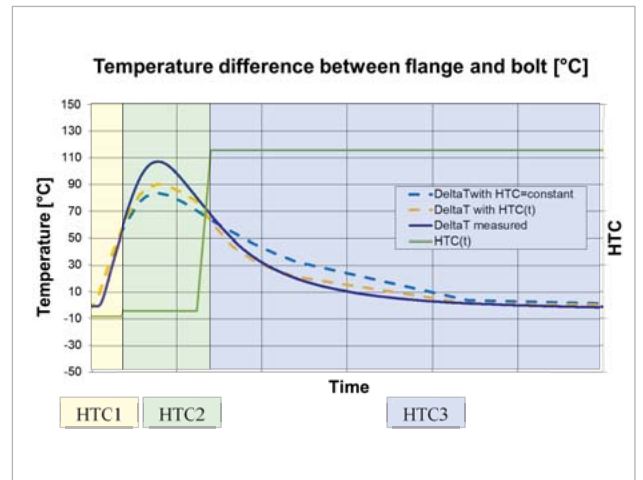


Fig. 11: Temperature difference between flange and bolt

Robust Design Study

For the feasibility, it is of higher interest to take a look at the influences of manufacturing and material tolerances on the model in a Robust Design Study.

For robustness evaluation the metamodel from the sensitivity study was used. Using the metamodel is feasible if all important scattering parameter are part of the sensitivity analysis and the variation range of the sensitivity analysis covers the scatter range. Using distribution functions of the three most influencing parameters, a latin hypercube sampling of 100 designs was generated on the metamodel to see the influence of deviations on the resulting temperature difference (Fig. 12).

Fig. 13 shows the deviations impact on the temperature difference. Obviously, scatter of the parameter HTC_shaft_thread has a major influence on the variation of temperature, while the parameters H's and R's scatter are insignificant, adding even more value to the previously performed fitting of the parameter.

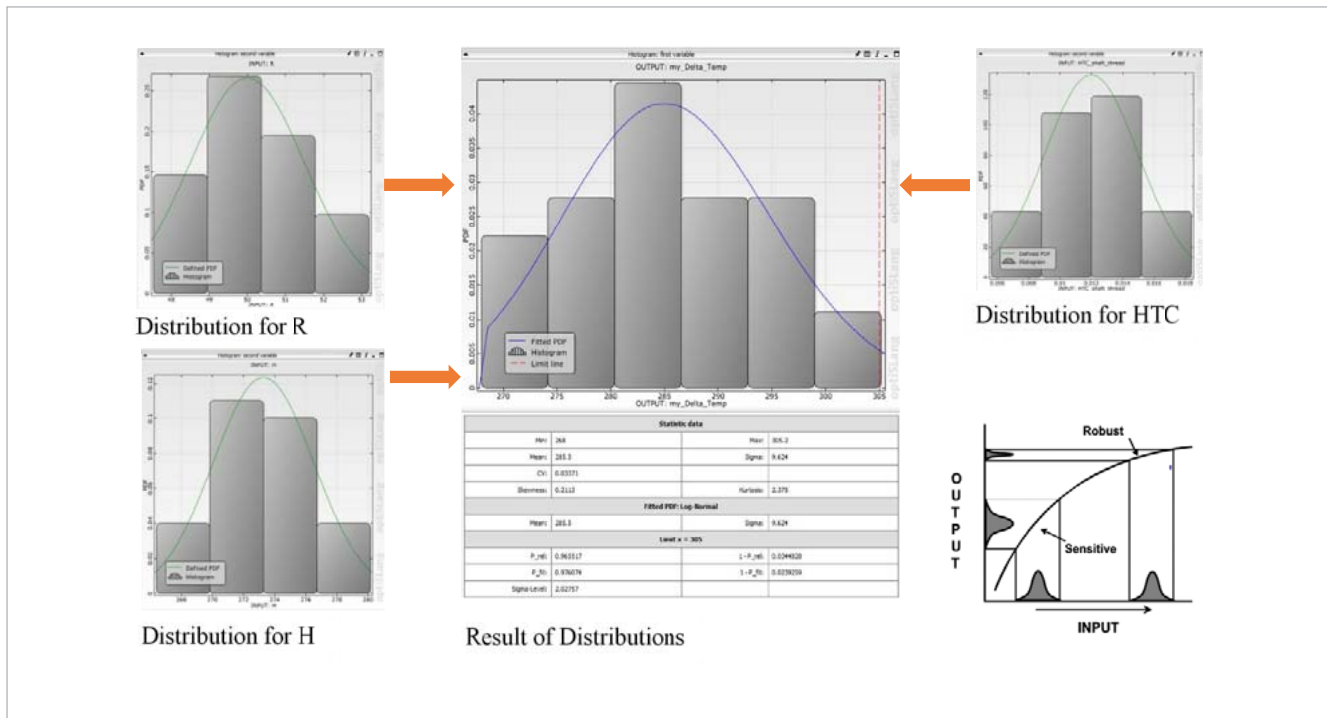


Fig. 12: Impact on the temperature difference - parameter

Conclusion

This feasibility study showed a fast way to optimize the model. Especially the possibility to easily fit the model to measurements and thereby eliminate estimated parameters from the simulation was very useful and increased the overall accuracy of the model tremendously.

The Robust Design Study showed a very small influence of the flanges height deviation on the resulting temperature difference. This is interesting, since the height is still an important parameter for the resulting temperature difference, but the deviations are far less influential than the HTC's deviations. This indicates that loosening the tolerances on the flange height is feasible without increasing the temperature difference and thereby decreasing the parts lifetime, while manufacturing time and costs can be reduced.

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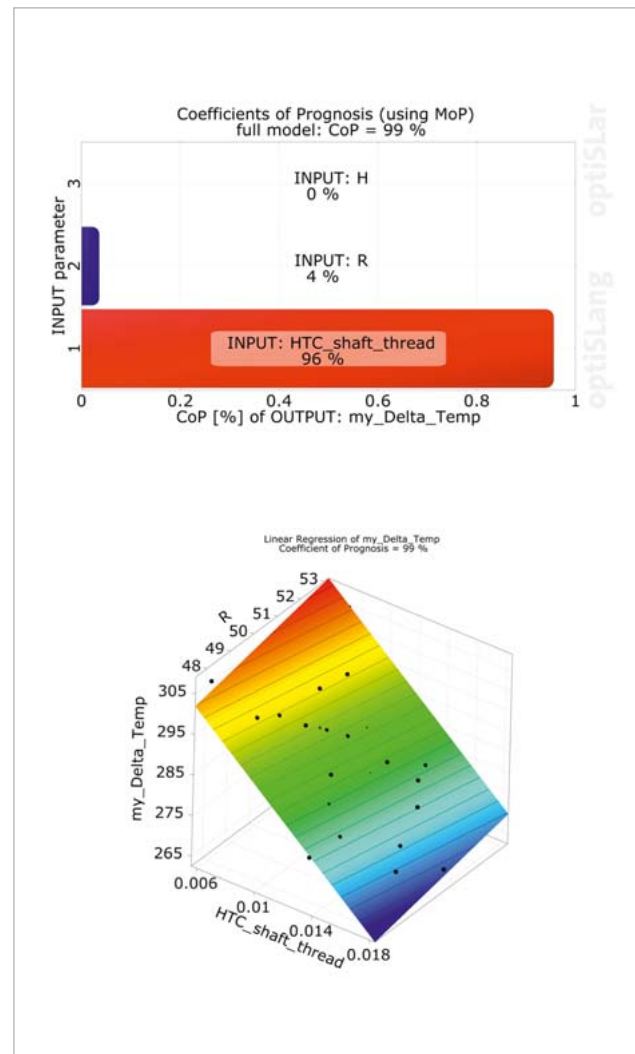


Fig. 13: Impact on the temperature difference - results

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