IMPORTANT ASPECTS IN PARAMETRIC SHAPE OPTIMIZATION

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ABSTRACT –

An essential mission in virtual product development is to identify an optimal design with minimal weight that meets multiple and often conflicting requirements.

Beside the variation of material and physical properties, the challenge is to realize geometric modifications in an automated process with commercial software tools. This paper gives an introduction to important aspects in parametric shape optimization. It presents a realistic application example on efficient shape optimization methods based on finite element morphing.

In this paper the entire process chain ranging from choosing parameters and integrating the simulation in the optimization process to analyzing the results of a global optimization strategy are shown. As the requirements for each component constantly increase the use of advanced optimization strategies in combination with response surface models becomes more and more important. This process also includes a consideration of small perturbations in the geometrical shape and distributed parameters to evaluate the robustness and reliability of a given design or the determined optimum.

TECHNICAL PAPER –

1. PARAMETERIZATION TECHNIQUES

Structural optimization can be integrated as a general tool in the design process of complex structures already during the early phase. Efficient methods to create innovative design concepts require the possibility of a completely automated shape variation. In parametric shape optimization the shape of a body is changed by parameters to determine the optimal shape for achieving certain standards. Result values and constraints of complex models are often highly nonlinear dependent on the design variables, which requires the use of sophisticated and advanced optimization algorithms. The management and the control of the parameters is taken by the optimization software OPTIMUS, which is characterized by a high flexibility and direct interfaces to most commercial software tools. The next section gives an overview of different possibilities to parameterize the geometry of a body including the respective advantages and disadvantages of each method.

CAD based Parameterization

The basis of a CAD based parameterization method is a parameterized CAD model, whose parameters can be directly linked with the design variables of the optimization process. The general sequence of such an optimization is shown in Figure 1. The management of the process and the variation of design variables is administrated by an external optimization tool, in this case OPTIMUS. The optimization tool substitutes the contemporary parameter values directly in the model file and generates a modified file using an update command. Subsequent to this step the new model is automatically meshed and a solver is called to obtain the responses, which are used by the optimization tool to assess the quality of the parameter combination.

One advantage of this procedure is that the final result of the optimization process is an optimized CAD model, which can be returned back to the development process. Precondition for that procedure is a CAD model with integrated parameters, i.e. a parameterized CAD model. In this case all included parameters can be used as design variables during the optimization process. On the other hand, have no parameters been considered during construction, there is no possibility to introduce parameters a posteriori in the model file. Another aspect is the possibility of automated batch meshing and ensuring a good quality of the mesh, as the model has to be completely remeshed in every iteration. In many cases automated meshing without any user intervention can not be used as the complexity of the model is too difficult to guarantee a good mesh quality.

Mesh based Parameterization – Morphing Technology

Morphing is called a technology in ANSA that is not based on the CAD description of the geometry but only on the finite element mesh. This approach requires an already meshed model. It varies the shape of the model according to the position inside predefined boxes (Box-Morphing) or directly moves certain nodes (Direct Morphing). As the parameterization is done on the FE model it also only affects the mesh and not the underlying CAD geometry. Therefore the model does not have to be completely remeshed each time. However severe distortions of some elements may arise when boxes are stretched significantly and thus the mesh quality can be substantially deteriorated. To avoid this problem or to be able to react in case of bad quality criteria the possibility of an automated remesh of the modified model has to be given, e.g. using ANSA Scripting.

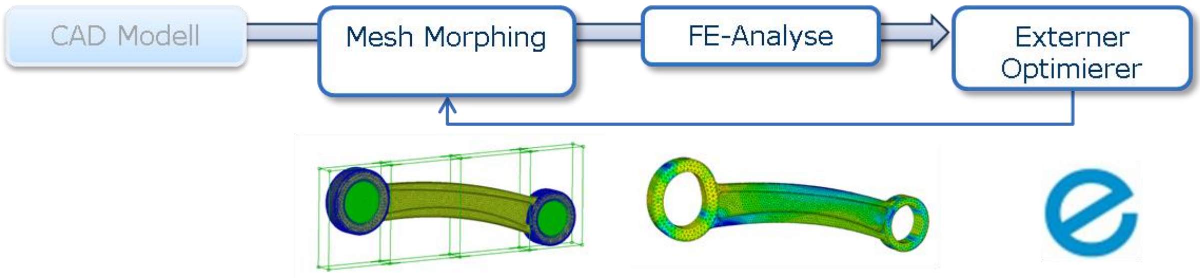

Figure 1 – Automated loop using ANSA for morphing and OPTIMUS as optimization tool

In this approach not parameterized CAD models can also be used as initial geometry. As an already meshed model is used as basis for the optimization process a complete and often complex remesh procedure after each modification is not mandatory. In case of bad mesh quality criteria some additional functionality to create a new mesh can be included. An additional advantage of modifying geometry using the morphing technology is the easy parameterization and the high flexibility of possible shape variations [3]. The depicted application example from the chassis area has been realized in the ANSA software, which has a direct interface to OPTIMUS.

2. PROBLEM SETUP

In this paper the entire process chain ranging from parameter selection and integrating the simulation in the optimization process to analyzing the results of a global optimization strategy is shown. To illustrate the concept of optimization strategies and robust design analysis a simplified application example was chosen, that was derived from a realistic problem setup.

The aim is to reduce the weight of a control arm while not deteriorating the initial values for maximum buckling force and for the torsion angle. Transferred into an optimization problem this means, that the mass of the control arm is used as the objective function and two constraints are taken into consideration, namely an upper bound for the torsion angle and a lower limit for the maximum buckling force. Figure 2 illustrates the workflow setup in OPTIMUS showing the 3 responses *Torsion_Angle*, *Max_Buckling_Force* and *Mass_in_kg* at the bottom of the graph. To derive the output values two finite-element analyses are run using the Abaqus software, one analysis for torsion and one for buckling. The mass of the arm model is computed using an ANSA script command and exported to the file *Mass.txt* from which the optimization software extracts the value in the workflow. Next to the morphing parameters, which are explained in more detail in the next section, some constants are also integrated in the workflow. They keep the workflow as flexible as possible and display some additional information on model characteristics without having to read the input deck separately. The constant parameters for example include material parameters like Young's modulus, density or Poisson's ratio.

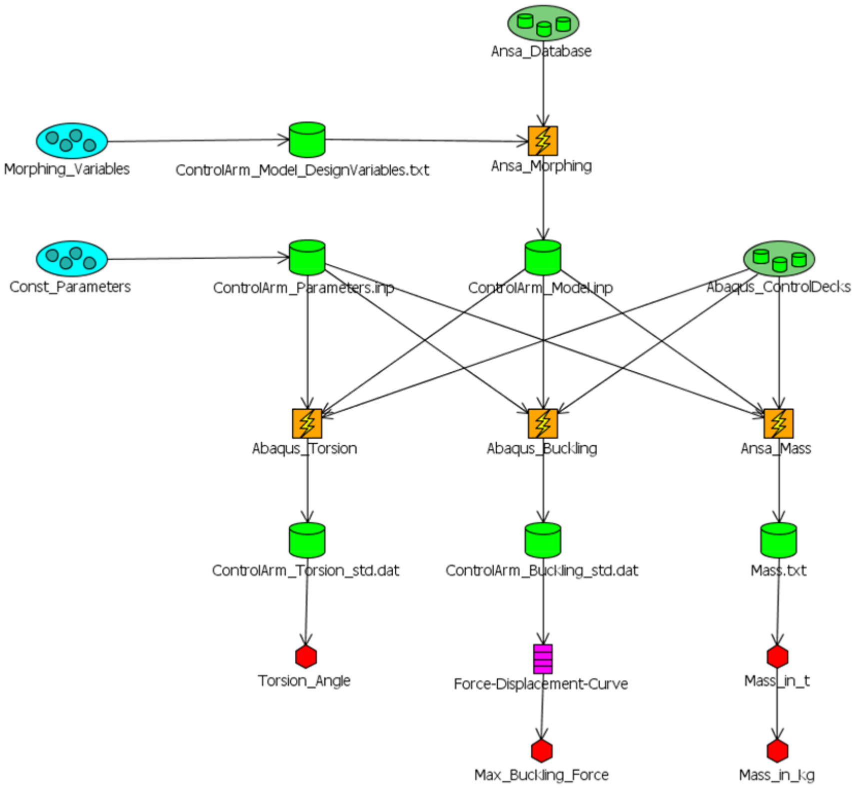

Figure 2 – Illustration of the simulation sequence giving an overview of the flow of data

2. SELECTION OF PARAMETERS

At any stage of the design process the challenge is to choose suitable parameters for shape variation in the optimization task from an often large design space. One possibility to automatically support the parameter selection is to use knowledge from sensitivity analysis based on intelligent design tables. The aim of this process is to determine the most significant design variables with the highest influence on the responses. The software OPTIMUS supplies the user with different statistical measures to compute the correlation values between the variables of the system. As a result the most significant factors can be determined and less important parameters can be excluded from the further process. That leads to a reduction of dimensionality of the design space and therefore also to the reduction of the problem complexity.

<u>Design of Experiments</u>

Intelligent design tables or Design of Experiments (DOE) are statistical methods to systematically plan experiments and analyze technical systems. The purpose is to maximize the gain of information while keeping the number of evaluations at a minimum. In the context of simulation processes different DOE methods are used for screening as there are often many design variables that do not have to be considered in a first step.

In many use cases a so-called Latin-Hypercube sampling is chosen to achieve a complete and equally distributed covering of the design range for each variable. An additional advantage is that the number N of requested experiments can be chosen independently from the number of variables. This sampling method separates the range of each factor into a chosen number of equidistant intervals. Next it randomly choses a point inside one of the intervals, while each of the intervals is only picked once.

Sensitivity Analysis

Sensitivity analyses are often used to support the decision making process and to support the identification process of important parameters. To determine the main factors with the greatest impact on the responses linear correlation factors can be considered as important measurement factors. This value varies in a range of -1 to 1, while a correlation factor of 1 represents a direct linear influence on the considered response. Analyzing the correlation matrix reveals some design variables without any or only with minor influence on any of the responses. These parameters can consequently be excluded from further computations and can be set to constant values which were predefined as nominal values or can be chosen arbitrarily.

In this case the selection of parameters was determined by engineering experience and possible variations in the model without prior sensitivity analysis. Figure 3 gives an overview of the used morphing parameters to determine the optimal shape of a control arm with minimal weight while meeting predefined target specifications.

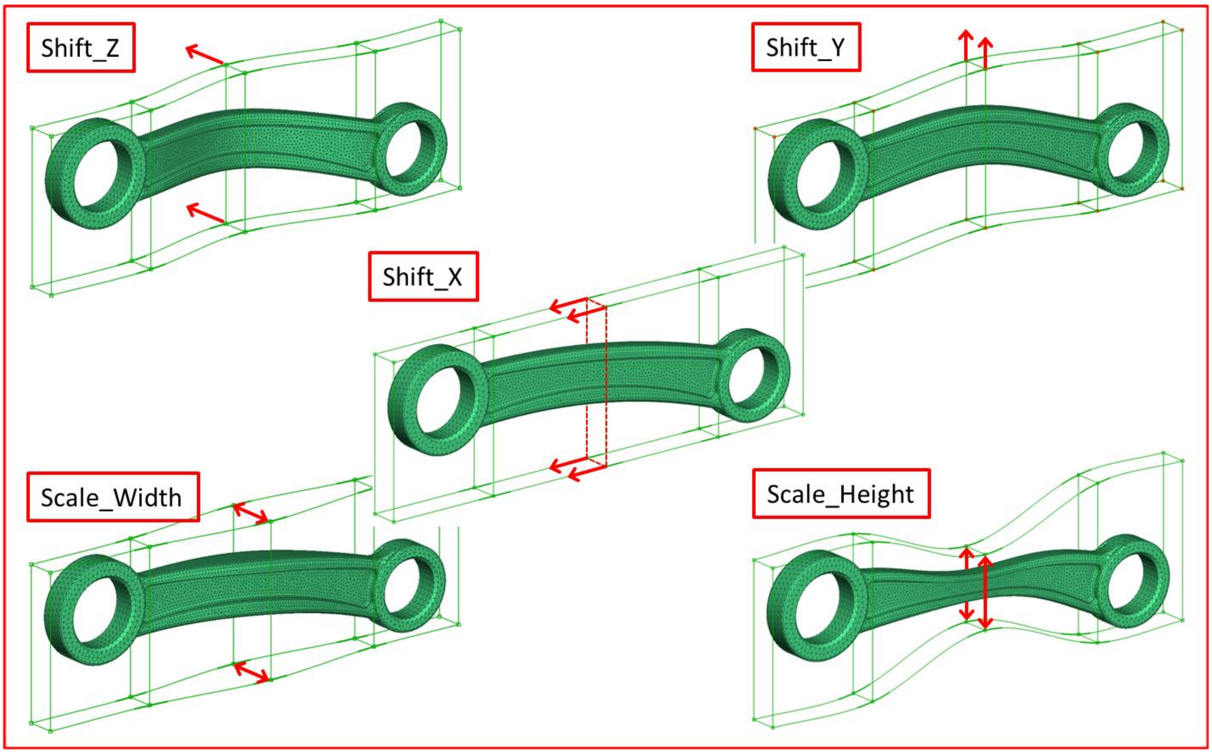

Figure 3 – Used design parameters in ANSA Morphing to vary the shape of a control arm

3. OPTIMIZATION STRATEGY

To achieve optimal model characteristics the objective functions have to be defined, i.e. the responses that have to be minimized or maximized. Additionally the possibility is given to respect certain output variables as constraints during the optimization process. The selection of a suitable optimization strategy and algorithm is influenced by many factors. Long simulation times of a single experiment, parallelization possibilities and available solver licenses, number of design variables and behavior of the system have great influence on which strategy should be chosen. In many cases the number of experiments that can be computed in a reasonable timeframe and the efficient use of resources determines the selection of a strategy.

A common approach is to create response surface models on a widely spread series of experiments that describe the systems behavior as good as possible. Based on this meta-model the actual optimization method can be run without having to execute any further expensive simulations. The found optimal design then has to be validated on the actual simulation sequence to check for correctness of the result values on the models.

Response Surface Modeling

A Response Surface Model is an abstract representation of the system and it is computed based on simulation data from DOEs or testing data. To achieve a good global quality for the model the sampling points have to be spread uniformly in the design space. This is why a Latin-Hypercube sampling is used in many cases with an arbitrary number of evaluations.

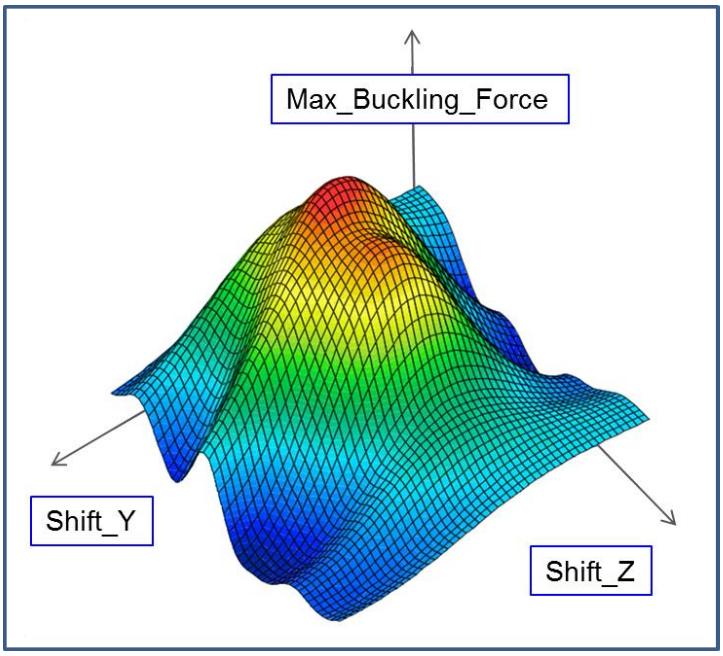

Figure 4 – Response Surface Model for maximum buckling force displayed for parameters *Shift_Y* and *Shift_Z* with all other parameters fixed

The used optimization tool provides two different techniques to create meta-models. The user can either choose manually from a list of different methods or make use of the automated computation of the best fitting model on the data for each response. Dependent on the systems behavior and the purpose of the model a certain method can be chosen directly. In case of high nonlinearities a Kriging model is often a good choice to create a continuous representation of the functions behavior. The model in Figure 4 shows a Kriging model that approximates the behavior of the maximum buckling force based on parameters *Shift_Y* and *Shift_Z*. Once a mathematical model is created it can be used for running the selected algorithms on the analytic model, given a sufficient model quality.

Quality Check

The quality of the analytical models can be assessed with different available criteria that are computed automatically during model creation. One method to determine the quality of the response surface is based on cross validation. The procedure is to exclude subsets of the results from creating the meta-model and compare the results in the left out set with the predicted values on the model. The cumulated and normalized error between actual values and approximated values can then be used as criteria for the model quality.

Is the quality of the chosen model sufficient, the optimization algorithm can perform the evaluations on the model definition. In this case no additional simulation run is needed and even several hundred or thousands of evaluations can be executed in a few seconds. Especially for algorithms like evolution strategies or multi-objective optimizations that require many functional evaluations this is a significant advantage.

4. ROBUSTNESS AND RELIABILITY OF OPTIMUM

To ensure the computed product properties and behavior in the optimal point, its reliability and safety in a working environment under real life conditions must also be retained. Uncertainties for variables such as manufacturing precisions, material characteristics or environmental effects are introduced to measure the variability in system performance. To assess the stability of the point that has been found using optimization algorithms different techniques for robustness and reliability analysis can be used. The goal is to derive the probability of failure or to derive the distribution of the responses given a specific distribution of the input variables. Evaluating the robustness and performing reliability analyses allows the user to derive a better predictive quality of the results.

Distributed Input Parameters – Robustness Analysis

Investigating systems with highly nonlinear behavior small perturbations around the found optimal point on the input side might lead to large variations on the output side. To predict this behavior the robustness of the optimum has to be computed respecting a given distribution for the independent input parameters. Also for ensuring the functionality and fulfilling certain constraints small perturbations that derive from reality are taken into account. To measure the robustness of certain responses the sigma value of the resulting distribution is used. Employing stochastic sampling methods experiments are generated around the interesting points to measure and characterize the variability of the system performance.

The aim in statistical robustness analysis is to optimize products such that the final design is minimally sensitive to various sources of variation and thus resulting in high quality products. Therefore next to optimizing the actual objective function also the variability due to variation should be minimal. Using sensitivities and design search methods parameters with the largest potential impact for improving a design or disturbing the predictive quality can be identified and influenced.

Fulfilling Constraints – Reliability Analysis

The goal in reliability analysis and uncertainty qualification is to investigate and improve the transgression of limits or constraints, so that the functionality of products can be guaranteed and possible failure can be prevented. As in robustness analysis distributed design variables and additional noise factors that cannot be controlled are considered to simulate realistic conditions in a working environment. Especially the investigation of small failure probabilities requires advanced computational techniques using statistical reliability methods (FORM, FORM + Importance Sampling, SORM) [2]. In the used optimization software several probabilistic methods for reliability analysis are provided in order to determine the probability of failure or a reliability index at a certain point in a given system [4]. The probability of output values that cannot meet the predefined targets is called failure probability

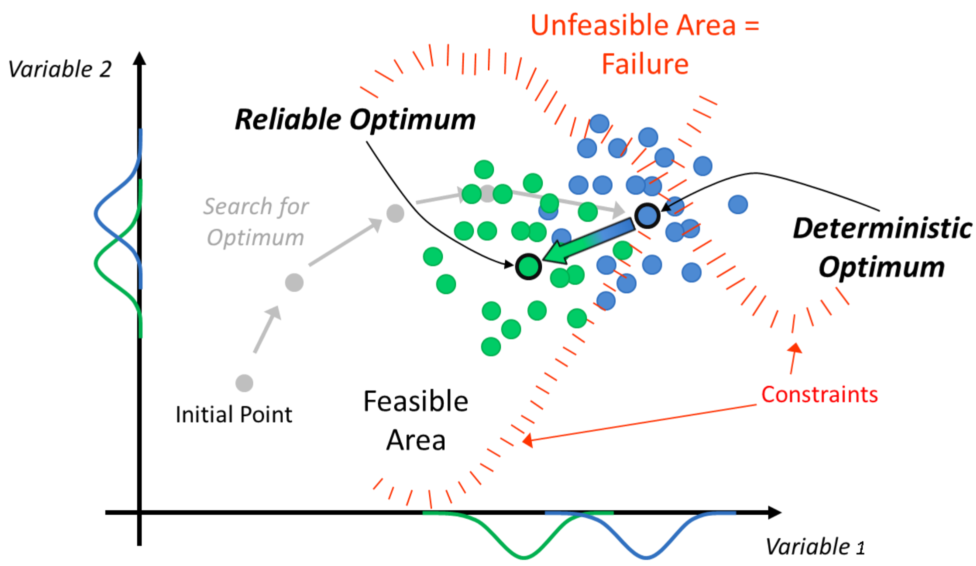

Figure 5 – Optimization process to derive a reliable design given distributed parameters

Developing robust design through optimization methods becomes more and more accepted in the virtual product development process as the requirements to product characteristics constantly increase. To achieve those demands the optimized model characteristics are often close to the given constraints and therefore close to the unfeasible area [1]. Small variations of the inputs to the simulation model or other uncertainty effects can affect the design characteristics such that the design misses the target specifications. In order to improve the reliability in the optimal point next to the deterministic optimization the found optimal point is shifted such that a certain given probability of failure is not violated. To achieve this goal an additional constraint on the failure probability is imposed to the problem and a local optimization is initialized with the previous optimum as starting point and the same predefined objectives. Figure 5 illustrated the optimization process including a deterministic optimization followed by an additional local optimization with an additional constraint on the failure probability. Thus the target of designing a robust and reliable product behavior can be guaranteed with the requested probability given the used probability distribution of the inputs.

5. CONCLUSION AND RESULTS

The use of optimization methods and robust design has reshaped the virtual product development process. With the new software tools engineers have now the possibility to easily use sophisticated optimization algorithms and estimate the effect of input variations on performance and meeting required targets. Already in the early phase of the design process optimization methods and robustness analysis play an important role to develop high quality and reliable products. Considering the complete design processes various aspects have to be taken into account to capture and simulate the reality. The important steps in the decision making process to develop optimal and reliable products that have been discussed in this paper.

For the presented application example the initial mass could be reduced by 13 g starting with an initial weight of 453 g. Simultaneously not only the imposed constraints of the initial design on maximum buckling force and torsion angle could be achieved but even improved. The initial maximum buckling force was raised from 83.5 kN to 87.4 kN and the torsion angle was reduced from 0.1249 to 0.1221. Additionally staying below the initial values can be guaranteed in 95% of all cases when considering the given probability distributions for the input parameters. In Figure 6 the final design of the buckling arm is shown.

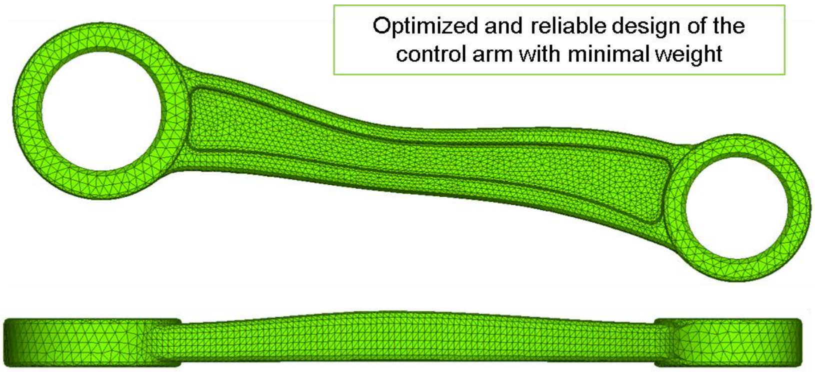

Figure 6 – Optimal design of the control arm achieved by parametric shape optimization

Using parametric shape optimization as a tool to derive the optimal model shape the question of parameterization techniques is the first step. Also the selection of parameters is very important in order to reduce the dimensionality of the problem and therefore to decrease the complexity of the actual optimization of model characteristics. Depending on the system behavior some system responses can react very sensitive to small perturbations of design parameters or other uncertainties and affect the predictive quality of the responses. This is one reason why the robustness and reliability to meet given target specifications or constraints has to be assessed and improved with efficient stochastic methods.

All described optimization algorithms and used techniques to create DOE tables, response surface models or robustness analyses are included in the software OPTIMUS [4]. The application example and parameterization technique was realized using the optimization tool OPTIMUS.

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