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Generation of geometry tolerances in turbocharger blades

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Abstract:

In technical design it is important to take into consideration not only the performance of a nominal design, but also any tolerated designs with deviations. The larger these deviations can be tolerated, the cheaper the design will be. The aim of the following study is to optimise tolerance of turbine wheels of small gasoline turbochargers, which means to tighten them where necessary, and release them where possible. Using ANSYS Workbench (including BladeGen for 3D blade design) and OptiSLang enhanced with Python scripts, an automatized procedure for FEM calculations on non-nominal geometries can be set up. This paper will describe the geometry generation and verification with statistical methods. The ANSYS Workbench is used to generate CAD and FEM models of the turbine wheels. These FEM models are used to control the deviations of non-nominal versus nominal geometries using contact algorithms. Various numerical measurement algorithms have been implemented to ensure comparable deviation features to existing quality measurement methods. This enables later calibration with production data. Special feature is the blade thickness measurement in 3D. SoS algorithms/random fields have been used to create realistic blade shapes based on only 2 variation parameters. A practical number of measurement points have been chosen to control the variability of the non-nominal geometries. With this information, a MOP solver can be set up using only a small number of non-nominal geometries. The MOP solver then easily creates a large number of certain types of non-nominal geometries, e.g. close to maximum tolerance geometries. This saves a lot of time compared to manual creation of a sufficient number of worst case geometries that can be used for up-following structural analysis processes.

1 Introduction

The goal was to develop a fully automatized procedure of generation of 3D-CAD geometries of turbocharger turbine wheels including different kind of real production imperfections. The procedure incorporates evaluation of particular deviations and differences from nominal blade geometry, hub body geometry and backface geometry. Since the turbine design is integrated, the blades and hub are a single part. The wheel is manufactured by investment casting, so different sources of deviations have to be considered. Tool tolerances, casting process parameters, shrinking of wax and metal during solidification and cooling as well as finishing process steps have influence on the final geometry. Each geometrical feature, like massive hub body or thin blade body, machined or unmachined surfaces have different deviations. In the numerical system, the process of deviations acquiring can be reproduced for many different virtual geometry designs and the space of designs' deviations can be statistically evaluated. Based on these statistical evaluations it can be stated with quantified probability in which interval ranges the geometrical deviations occur.

The original numerical simulation process for turbine wheels design has been split up into geometry generation and FEM analysis. Geometry generation needs to be parametrized to be able to set up an automatized repeatable design generator. Utilizing a progressive technology of statistical metamodeling implicitly included in optiSLang a statistical metamodel of optimal prognosis (MOP) describing relations between input parameters (geometry modification) and output parameters (geometry deviations) can be established. Using such statistical metamodel as solver instead of geometry generation process the whole procedure can be increased rapidly. Incorporation of virtual simulations of geometrical deviation into the process of turbocharger development has a certain positive impact on better understanding of the deviation causes and deviation statistical properties. This knowledge leads to better performing turbocharger design and elimination of unnecessary tight tolerances. On the other hand, robustness of several design features can be evaluated and improved.

2 Contact-element based algorithm for tolerances evaluation

Algorithms for deviations evaluation represent a core of the whole process. There were designed four different algorithms to measure four different types of deviations. Assuming production deviations it is necessary to measure distances between the external surfaces (see Fig. 11), thickness differences, curves and points distances. ANSYS classic environment was chosen for algorithms implementation for its robustness and wide variability in customization. Contact and target finite elements (designed and derived in ANSYS for performing nonlinear structural analysis) are used to determine distances between the defined surfaces (gaps resp. penetrations in terminology of ANSYS). Based on this feature differences between the nominal and design geometry are calculated and further processed. The results are available for all nodes of the FEM mesh, but it is advisable to pick a certain number of relevant nodes for the evaluation of production scatter. Interesting postprocessing nodes might be located either on edges that can be measured with tactile instruments or topological points that can also be checked by optical measurement systems. To be able to understand the system behaviour, a reasonable amount of nodes needs to be selected intelligently. Full surface results are nevertheless an interesting source of information when selecting designs for further analysis. Through the use of numerical contact algorithms and distance calculation, they resemble the typical postprocessing results of optical 3D scans.

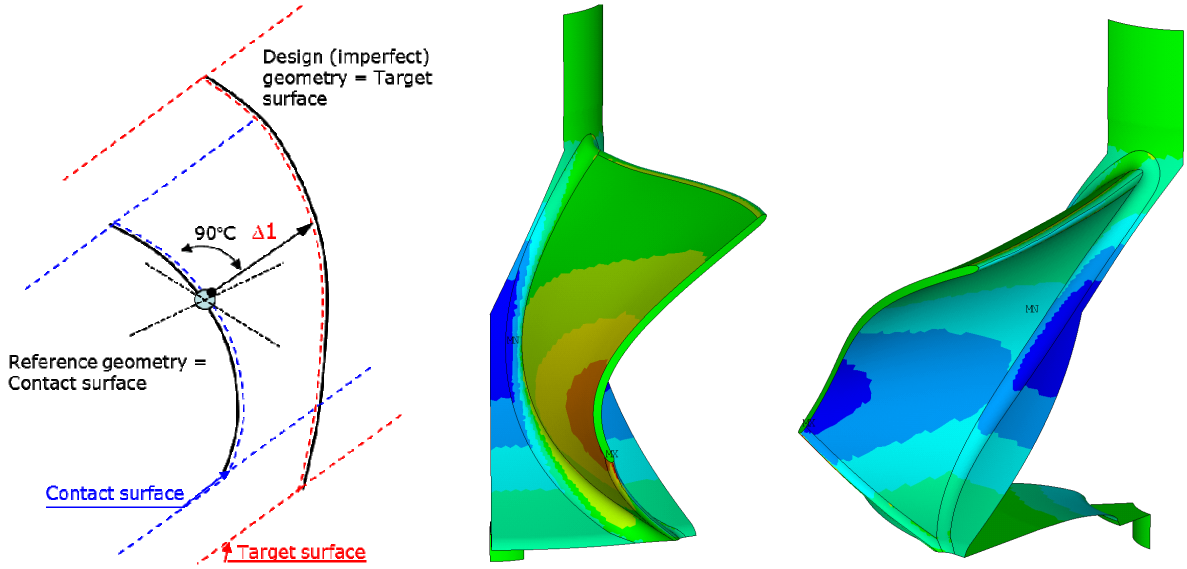

Fig. 1 Example of external surfaces deviations on the blade and hub body

3 Process integration

As the core of the process is the deviation-measuring technics prepared in classic environment of ANSYS it was a crucial task to set up the process of gaining the deviations from the moment of geometry creation in BladeGen and DesignModeler until the deviation values extraction automatic. It was the only way how to post-process the results from hundreds (thousands) different designs. Some design features like blade thickness are exclusively defined in BladeGen, while others like fillet radii are exclusively defined in DesignModeler. Both systems have their own interfaces and file formats. Also, in case of impossible geometries, different exit conditions have to be recognized. These inherent properties of the task make it necessary to have a generic control system for the numerical process chain.
The key control system determining the time flow of the process is optiSLang4. OptiSLang4 enables the user to compose the sophisticated structure of particular actors representing the various actions that are supposed to happen during the flow run (see Fig. 2).

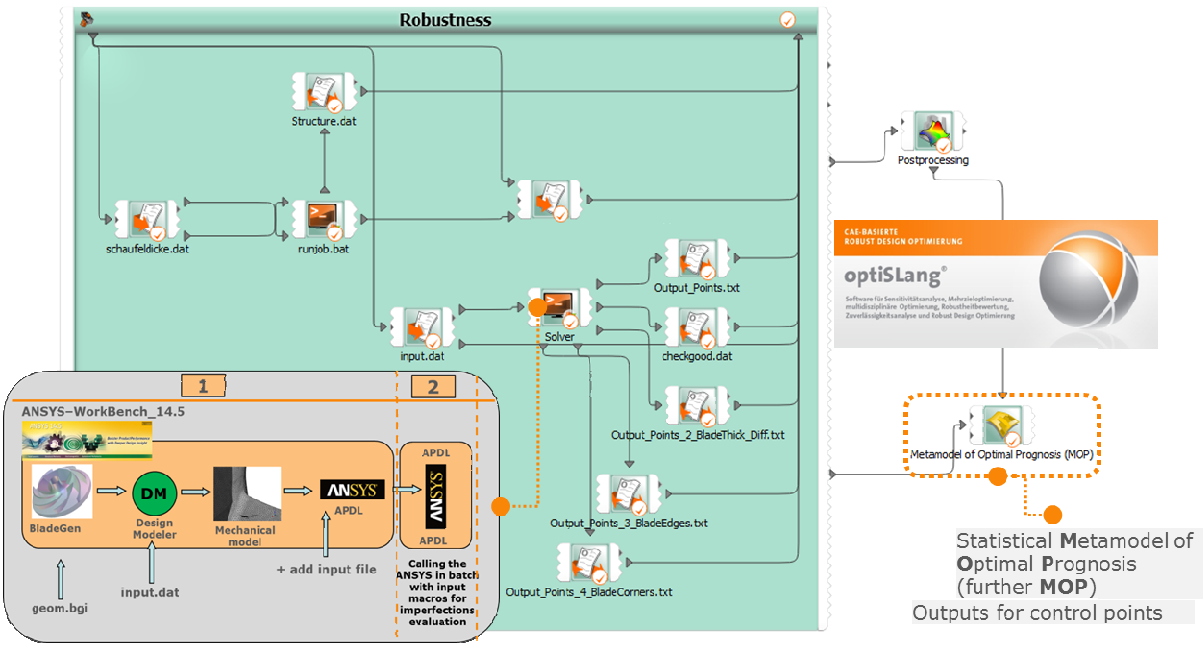

Fig. 2 Process flow in optiSLang

The process starts by the creation of the correlated input parameters set. Parameters are spatially correlated using the random fields' technique (see Fig. 3). Correlation dependencies designed by random fields secure that the geometrical deviations result in "reasonably" imperfected blade design (see Fig. 3). Designed blade surfaces with higher density of surface waves are not in compliance with turbochargers produced. Other parameters like blade length are generated randomly.

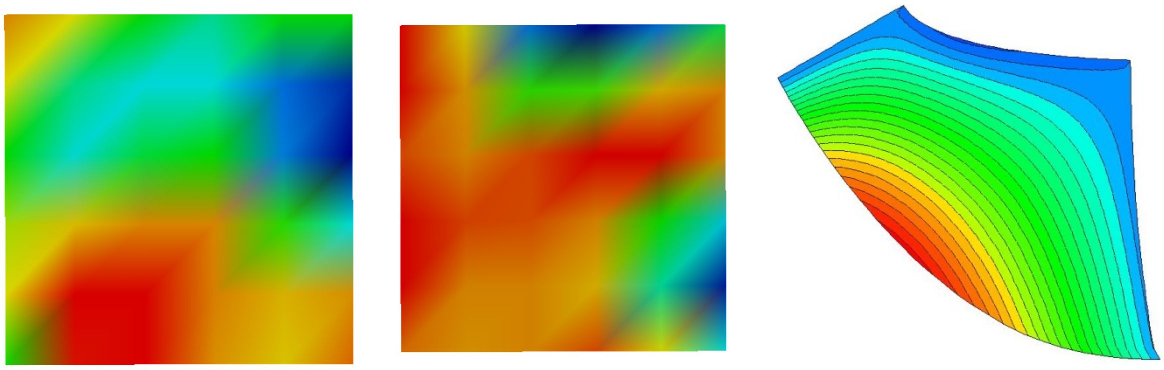

Fig. 3 Example of random fields' realizations (left), correlated thickness distributions (right)

After the preparations of input parameters the main part of the process is started (see Fig. 2 – main solver part). A new blade design is produced by BladeGen based on the correlated input parameters and other parameters passed on into the BladeGen tool. The blade is then finished in DesignModeler, connected to the hub body with a fillet radius, fitted with a backface and nose and prepared for exporting to ANSYS solver. Deviations are calculated using ANSYS and sent to optiSLang4 as responses. OptiSLang4 evaluates the statistical quantities and creates a metamodel of optimal prognosis for chosen responses.

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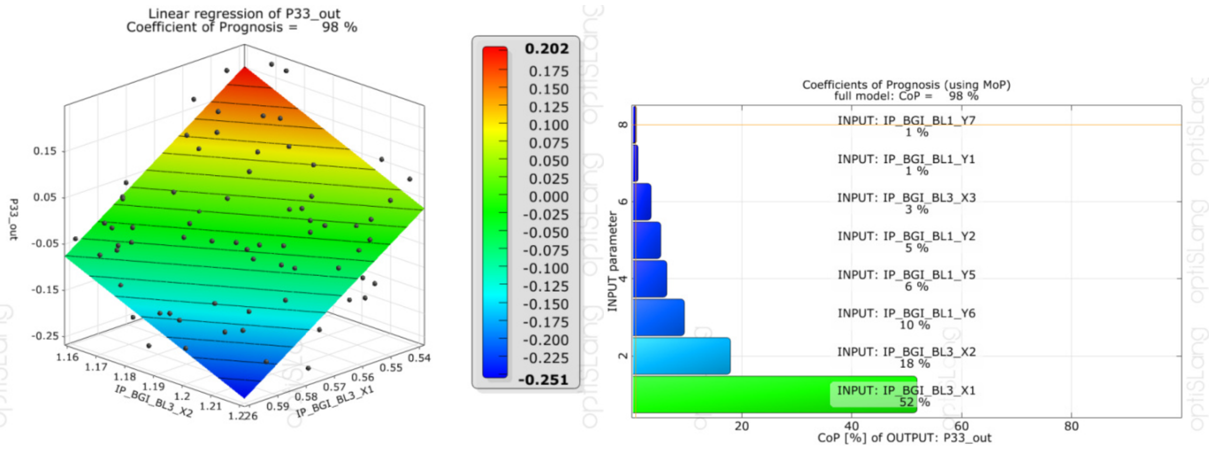

Fig. 4 MOP for chosen response (left), coefficient of prognosis (right)

The process flow integration is based on windows and Python scripts.

4 Strategy of producing non-nominal geometries

The process described in chapter 3 can be performed as sensitivity (robustness) analysis. Results of such a procedure are the statistical quantities representing the dependencies between the input and output parameters. Since not all parameters of the geometry generation relate directly to a length or position, it is useful to have a tool that quantifies scatter of the actual measured feature versus the input parameter. Especially when splines are used in geometry generation, this is a necessary information when tuning the deviations to typical manufacturing values. Over these statistical quantities the MOP can be created for more important purposes:

1. Quantify the explainability of the output parameters.
2. Determine the dependencies between input and output parameters.
3. Statistical verification of the deterministic procedure.
4. MOP can be used as a substitutive solver.

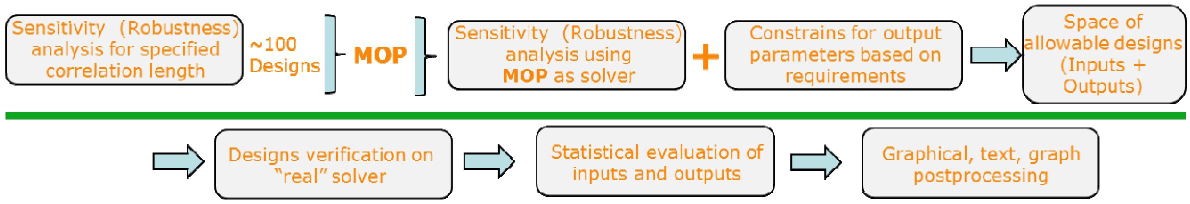

Fig. 5 Strategy for deviations evaluation

Utilizing MOP as solver it is possible to calculate a sufficient amount of designs in a reasonable time. Designs calculated this way are cross-checked by parallel performing of the full process. After collecting all the responses different responses' filters are applied to create a space of allowable designs.

5 Sensitivity analysis

Sensitivity analysis provides basic statistical properties of the inspected problem. As a first step a set of input and output parameters has to be defined. In-between the functional dependencies are expected. Using LHS it is possible to cover the desired design space (within the input parameters' ranges) with a reduced number of samples (50-200, see Fig. 6). Structural mechanics evaluation of the non-nominal designs expects extreme cases to be the most interesting. Therefore a non-centrally emphasized sampling is helpful. This is even more relevant when high nonlinearities are involved. The effect of one parameter may be much higher in a border area of the design space than in the center or on the opposite side. Information about this can only be available when the sampling combines boundary values of several parameters at the same time. Therefore the higher number of samples is evaluated the better quality of statistical properties is to be expected. The dependence of the number of input parameters is low, but with a number of around 50 input parameters it is advisable to do at least 100 successful designs with LHS. To be able to achieve this even under the presence of instabilities, a larger number is requested in optiSLang accordingly. The run can be aborted when the number of successful designs is reached. Performing sensitivity analysis following valuable information is provided:

1. Stability of designed process workflow (eventual manifestation of conflicts)
2. Relations between input and output parameters are determined
3. Utilizing the MOP on the design space it possible to determine the importance of the input parameters on each of the output parameters. Additionally the participation of the input parameters is quantified. Dependencies determined between inputs and outputs can be highly nonlinear as well.
4. Obtaining high values of Coefficients Of Prognosis (COP) for the responses it is proofed that defined responses can be well explained by the defined input parameters. In an opposite case the reasons for low values of COPs should be considered. This way the whole process is subjected to statistical verification.
5. MOP represents the mathematical dependencies between the inputs and outputs. Knowing these dependencies it is possible to use such statistical metamodel as a substitutive (significantly faster) solver. Results obtained from such a solver contain a certain error expressed by the COP.

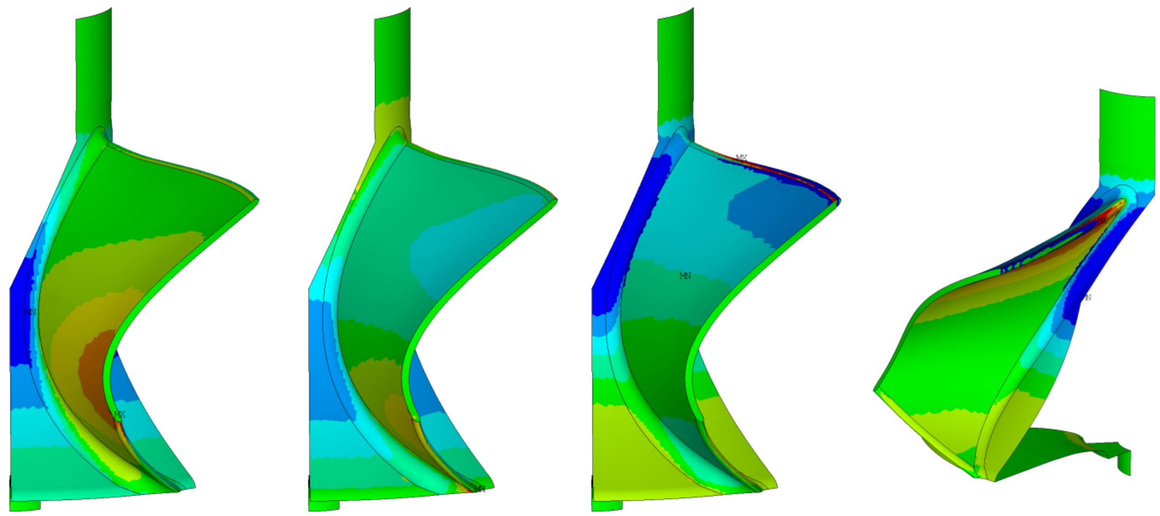

Fig. 6 Variability of the parameterization

Sensitivity analyses were successfully carried out either using the whole designed procedure or substitutive MOP as solver.

6 Metamodel of optimal Prognosis as Generator of non-nominal geometries

The metamodel of optimal prognosis is a statistical metamodel containing special features suitable for using in a wide spectrum of probabilistic problems. As any statistical model it is able to predict the values of responses with a certain quality of approximation.

The prediction quality of an approximation model may be improved if unimportant variables are removed from the model. This idea is adopted in the Metamodel of Optimal Prognosis (MOP) proposed in (Most and Will 2008) which is based on the search for the optimal input variable set and the most appropriate approximation model (polynomial or MLS with linear or quadratic basis). Due to the model independence and objectivity of the COP measure, it is well suited to compare the different models in the different subspaces.

As it is possible to reach high precision of MOP (quantified by COP) it is very convenient then to be used as a substitutive solver representing dependencies between input and output qualities. In case of the presented process of a turbine wheel's deviations calculation it takes about 25-30 minutes to complete one design containing unique geometry variation. The main fraction of this time is used for distance calculation between thousands of nodes, but also the geometry generation in DesignModeler is costly due to the interface with BladeGen on the one hand and 3D fillet generation on the other hand. After solving a sufficient amount of various wheel designs (in this case ca. 120) and building up the metamodel over the design space it was stated that over 90% of output parameters have prognosis coefficients (COP) higher or equal than 85% (see Fig. 4). Based on this knowledge it was feasible to use MOP as a substitutive solver with the expectation of obtaining reasonable results' quality. Utilizing MOP as solver in the process workflow caused dramatic acceleration in design realization performance. Compared to full process workflow the speed-up with MOP is 1000x and more. Due to such a speed-up it was possible to carry out sensitivity (robustness) analysis containing 2000 designs and more in less than 1 hour. This performance gained significantly higher amount of designs than it would be possible only with full workflow which brought into the light valuable statistical information about the relations between the geometry variations and appropriate deviations.

7 Filters

One of the consequences resulting from MOP utilization is the higher amount of produced output data. To get an overview of design realization scattering there exist many ways of data postprocessing. Histograms of frequencies of occurrence (Fig. 7) can be displayed for each of the output parameter. Each histogram can be approximated by the best-fitting type of statistical distribution. Once the statistical distribution is attributed probability of response occurrence in a specified continuous interval can be easily determined.

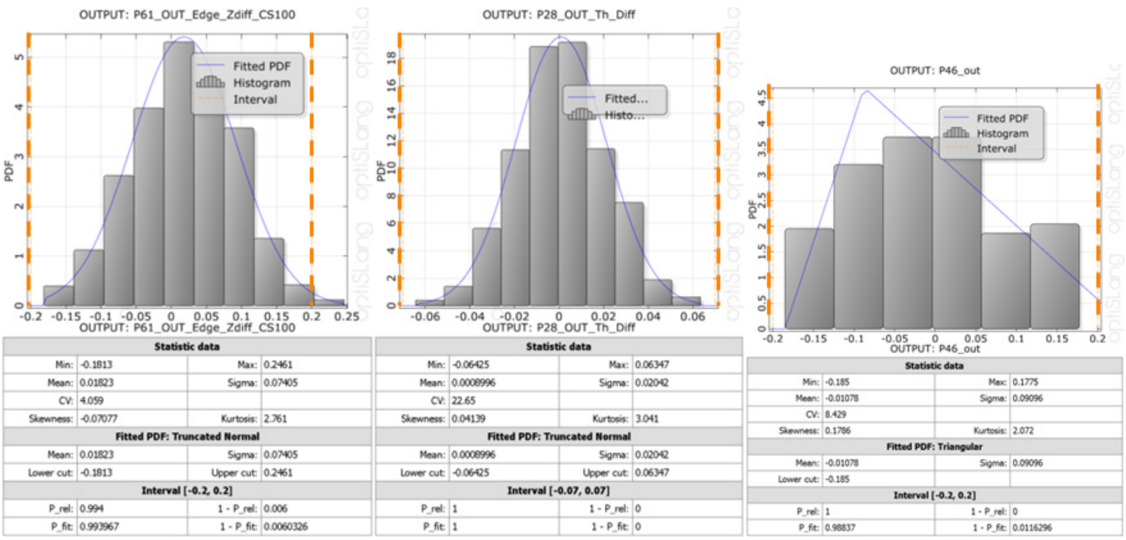

Fig. 7 Statistical distribution attribution

Sorting the designs' outputs according to the chosen criteria is a way how to aggregate the result information from the whole design space. In optiSLang4 it is convenient to use the constraint conditions feature in order to sort or filter the designs according to responses' ranges. Intending to implement a filter which will sort out all the designs which have at least one of the responses (from selected set of appropriate responses) out of a given interval (symmetric, defined by bound = β) it is necessary to set up for all involved responses following conditional constraining equations:

$$ABS(Value_{Desing}) \leq Value_{required} \rightarrow ABS(P18\_OUT\_Th\_Diff) \leq \beta$$
$$\rightarrow ABS(\text{"}all\ other\ related\ responses\text{"}) \leq \beta$$

By the application of the formerly described filter on the design space only the designs fulfilling the conditions for all the responses remain. The others are considered to be invalid. The primary deficiency of this basic filtering technique is the fact that a design can be only valid (status=1) or invalid (status=0) and it is not known how many responses have violated the allowable bounds for each design by how much. In order to obtain the information how many responses have violated the bounds for each design to be able to estimate if the violation is only local or if it occurs at larger area it was necessary to create a new actor (in optiSLang4) which contains a Python function summing up the violations for each design. The advantage is deeper insight into the probability of limit violations occurrence. An example of another useful filter is the "two belts filter". Also, a certain tolerance on the allowed deviations of 20% has been introduced. The purpose of this filter is to sort out all the designs with responses outside the two defined intervals (see Fig. 8).

$$\rightarrow ABS(\text{All related responses}) \geq 0.8 \times \beta \ \wedge\ (\text{All related responses}) \leq 1.2 \times \beta \ \wedge (\text{All related responses}) \geq -1.2 \times \beta$$

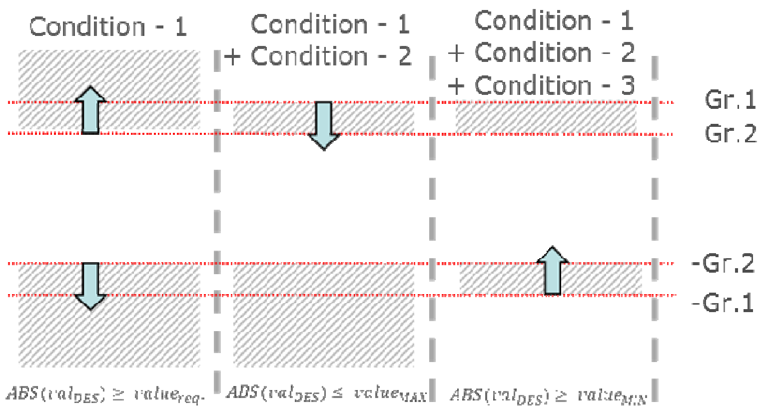

Fig. 8 Example of “two belts filter”

Filters based on constraining equations can be implemented either in GUI using predefined interface or the Python scripts can be prepared in advance and later on these can be inserted in optiSLang4. The opportunity of using Python scripts at any moment of creation of an optiSLang4 workflow enables preparation of higher amount of responses, conditions, parameters etc.

8 Summary

The process of turbine geometry generation incorporates various geometry parameters participating on geometry definition in BladeGen and subsequently in DesignModeler. Parameters determining the thickness distribution over the blade are additionally mutually correlated using a random field strategy in order to create geometry designs which are appropriate compared with real specimens. For virtual measurement of these deviations several automatized algorithms were developed. After developing all the necessary parts of the process these were assembled into one flow driven by OptiSLang. Such flow enables to generate unique geometry designs. Sensitivity analysis of the proposed workflow qualified and quantified dependencies between the input and output parameters. Using statistical meta-modeling it was possible to create a statistical meta-model (MOP) representing input-output relations. It was proofed that the established MOP is precise enough to be used as substitution for the whole process of blade designs' generation. This highly advantageous feature facilitated generation of thousands of designs which led to better statistical evaluation. For effective sorting of response ranges filters based on python scripting were designed, integrated and used.

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