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1. Introduction

During the last decades CAE based optimization has become a standard technology. A current focus is the enhancement of bringing robustness and optimization together for the design - Robust Design Optimization (RDO).

With the increase of computing power and the efficient parallelization for Computational Fluid Dynamics (CFD) simulations more and more CFD applications like for turbo machines, combustion engines or electric devices appear using RDO for the analysis.

For turbo machines the efficiency is the most important criterion, for the combustion engines the fuel consumption is one of the most important criteria, and for example the cooling rate of a flow for the high voltage battery is among the important criteria for electric cars.

All these criteria or output parameters do not depend only on a single set of values for the input parameters, which could be optimized to something like the ideal operating situation. Therefore usually not single ideal operating conditions are important but rather the operating map or curves, mapping the most important input variables to the output variables.

For example with regard to fuel consumption the instant economy varies in a large range depending on the specific driving situation and on the characteristics of the vehicle, like for a car with a turbo charging system for example on the characteristics of the operating map of the compressor of the turbo charger.

For the CFD simulations a sensitivity analysis in combination with the generation of meta models can be used to analyse these operating maps. The accuracy of the meta models and the robustness of these calculated operation maps have to be examined carefully in detail.

Therefore the prediction quality of meta models becomes increasingly important. For a closer examination with regards to robustness evaluation the sensitivity analysis also has to include scattering variables.

Finally with the approach of using meta models to establish operating maps a new technique can be introduced that is also very helpful for the engineers not doing themselves the CFD simulations.

In Chapter 2 we will provide a basic introduction of Robust Design Optimization. The application of RDO in CFD will be shown in Chapter 3 with an example from turbo machinery. In Chapter 4 the concept of operating maps and their presentation by meta models will be introduced and as an example the possible application to the design of turbo chargers will be discussed.

2. Robust Design Optimization

Optimization and Robustness

Nowadays optimization is well established in engineering. Dependent on the task, different optimization categories like form, topology or parametric optimization are useful. In this paper we refer to the parametric optimization. The availability of parametric models increases however still this is a fundamental issue for the broader usage of parametric optimization. The target for the optimization is often the reduction of material consumption. This pushes the design towards the boundaries of allowable stresses, deformations or other critical design responses. At the same time safety margins are asked to be reduced and products should be cost efficient and not over engineered. Of course a product should not only be optimal under one possible set of parameter realizations. It also has to function with sufficient reliability under scattering environmental conditions. In the virtual world we can proof that e.g. with a stochastic analysis, which leads to CAE-based robustness evaluation (Most et al. 2015). The combination of CAEbased optimization and robustness evaluation leads to the area of Robust Design Optimization (RDO).

The main idea behind that methodology is, that uncertainties are considered in the design process. These uncertainties may have different sources like, in the loading conditions, tolerances of the geometrical dimensions and material properties caused by production or deterioration. Some of these uncertainties may have a significant impact to the design performance which has to be considered in the design optimization procedure.

A sensitivity analysis is very useful to explore the variation space as a preprocessing step. By definition, sensitivity analysis is the study on how the variation in the output of a model can be apportioned, gualitatively and guantitatively, to different sources of variation of the input of a model (Saltelli et al. 2008). In order to quantify this contribution of each input parameter to each response variable under real world CAE conditions like non-linear, noisy problems having a large number of parameters and suffering of loss of single designs evaluations, variance based methods are very suitable. With these methods the proportion of the output variance, which is caused by an input variable variation, is directly quantified. That approach can be applied in the same manner in the domain of optimization parameters. by representing continuous optimization variables with uniform distributions as well as in the domain of uncertainties by using adequate distribution functions and correlation models. Therefore, variance based sensitivity analysis is very suitable as an optimization and robustness preprocessing step to investigate and identify variable importance as well as to estimate the amount of unexplained variation of response values which may occur from CAE solver noise, inappropriate extraction of responses as well as unidentified functional correlations to the input variation.

In contrast to local derivative based sensitivity methods, global variance based approaches quantify the contribution with respect to the defined total variable variation. Unfortunately, sufficiently accurate variance based methods require a huge numerical effort due to the large number of necessary simulation runs. Therefore, often meta-models or simplified regressions are used to represent the model responses by surrogate functions in terms of the model inputs. However, many metamodel approaches are available and it is often not clear which one is most suitable for which problem (Roos et al. 2007). Another disadvantage of meta-modeling is its limitation to a small number of input parameters. Usually the approximation quality decreases for all meta-model types dramatically with an increasing dimension. As a result, an enormous number of samples is necessary to represent highdimensional problems with sufficient accuracy. In order to overcome these problems, Dynardo developed the Metamodel of Optimal Prognosis (Most and Will 2008, 2011). In this approach the optimal input parameter subspace together with the optimal meta-model type are automatically determined with help of an objective and model independent quality measure, the Coefficient of Prognosis (CoP).

The automated MOP/CoP approach solves three very important tasks of a parameter sensitivity analysis: the identification of the most important combination of input parameters, together with the best suitable surrogate function with regards to the optimal forecast quality and a quantification of this forecast quality.

Parametric Optimization

In parametric optimization, the optimization parameters are systematically varied by mathematical algorithms in order to get an improvement of an existing design, ideally approaching a global optimum. The values of the design parameters have lower and upper bounds and may be continuous or discrete. In real world industrial optimization problems, the number of design parameters can often be very large. Unfortunately, the efficiency of mathematical optimization algorithms also decreases with an increasing number. With the help of sensitivity analysis as a preprocessing step it is possible to identify the parameters which contribute most to a possible improvement of the target function for the optimization. Based on this identification, the number of design parameters may be dramatically reduced and an efficient optimization can be performed. Additional to the information regarding important parameters, a sensitivity analysis may help to decide, whether the optimization problem is formulated appropriately and if the numerical CAE solver behaves as expected.

Robustness evaluation

Optimized designs may become sensitive to scatter e.g. in geometry and material parameters, boundary conditions and loads. Therefore, it becomes necessary to investigate, how the optimized design is affected by scattering model input parameters. Design robustness can be checked by applying a systematic perturbation analysis, like Latin Hypercube Sampling, based on a randomly generated sample set and a suitable definition of the scattering parameters. Therefore, robustness measures as mean value, standard deviation, safety margins to failure criteria as well as the probability of failure need to be introduced. In terms of using variation based measures we call the approach variance based robustness evaluation. In terms of using probability based measures we call such a procedure probability based robustness evaluation, also known as reliability analysis.

Robust Design Optimization

The combination of robustness evaluation and optimization can be done in several ways. We call it an iterative Robust Design Optimization (RDO) when deterministic optimization is combined with variance-based robustness analysis at certain points during the optimization process. Of course this requires the introduction of safety factors, which should assure that a sufficient distance to the failure criteria is given during the

deterministic optimization. These safety factors may be adjusted iteratively during the iterative RDO process and a final robustness and reliability proof is mandatory at least at the end of the procedure. This procedure is the state-of-the-art in the majority of publications on real world RDO projects (Roos et al. 2009).

If the safety margins fluctuate within the optimization domain, e.g. due to several interacting failure phenomena, an iterative procedure may require a large number of iterations. In such a case, an automatic approach where the robustness criteria are estimated for every candidate in the optimization domain, a so-called nominal design, may be more efficient with respect to the CPU requirements. That procedure we call simultaneous RDO approach. Since the robustness evaluation is performed as an internal loop within the global optimization loop, this approach is sometimes also called "loop in loop" RDO.

3. Example: Turbomachinery

Challenges in turbomachinery design

There are many variables involved in turbomachinery design, each causing a complex effect on the final product performance. Today's most common design methods start with a one-dimensional analysis and include engineering experience to obtain an initial design having a reasonable efficiency level of approximately eighty five percent.

The next step is usually a computational fluid dynamics (CFD) simulation. This provides a more detailed look at the flow velocity as well as direction and pressure conditions. It also identifies issues such as recirculation which cannot be detected with one-dimensional analysis. However, to run such a simulation takes normally a considerable amount of time and each run provides diagnostic information about just one design iteration.

These results from the CFD simulation are usually reviewed to modify and improve the design in a more intuitive way. However even outstanding experts are rarely capable of achieving a 90%+ efficiency level which can be found in today's best-in-class designs. Attaining this level requires a much more sophisticated analytical process. By using CFD combined with RDO, hundreds or even thousands of potential designs can be analyzed automatically. Even with the latest computing hardware, it is still a challenge to deal with the large amount of computing time and resources required to conduct such simulations. Consequently, turbomachinery designers want to address this challenge with optimization algorithms that reduce the number of simulation runs required to explore the design space and to identify the best designs. There are many different optimization algorithms delivered as black box applications which often require considerable mathematical expertise to operate. These algorithms can also fail to find an optimal solution because of limitations in their capacities.

Due to the complexity of turbomachinery development, parameters leading to optimal solutions are often located in spaces surrounded by relatively inefficient designs. Therefore, optimization algorithms that push efficiency towards higher levels often fail to identify the optimal solution, because, while avoiding surrounding low-efficiency designs, they tend to shift temporarily towards design spaces of reduced efficiency.

Another fact making turbomachinery development complicated is that the structural design process must be performed simultaneously in order to ensure the design will be able to handle the resulting loads. Typically, design and structural engineers work in different departments with different tools. Both frequently make design modifications. This might create the risk that the two groups work on different files causing extra expenses and delays in the downstream process.

Integrated approach

This chapter explains an integrated approach for optimizing the design of a centrifugal compressor while ensuring sufficient robustness towards manufacturing variations. The design geometry, including the blades and hub body, was defined in ANSYS BladeModeler, which is fully integrated into the ANSYS Workbench environment. The design was defined in a number of 2-D sketches, either at span-wise positions or at arbitrary user-defined positions. Thus, a full 3-D design was interactively generated providing quantitative information such as blade angles and throat area.

In this application, the geometry of the blades was defined by the meridian flow path consisting of two parametric sketches, one for the hub and another for the shroud. The location of the leading and trailing edges for the rotor, as well as the return guide vane, were defined based on the meridian plane. Angle and thickness distribution of the hub and shroud layer defined the shape of the blades (Figure 1). There were a total of 17 input parameters.



Figure 1: Parametric geometry

Computational fluid dynamics

A key advantage of the integrated approach is that both the flow and the structural groups work with the same design geometry using the same environment. This saves a considerable amount of time by eliminating the need for sending modifications back and forth to enter them into the model. The integration also includes the structural simulation, as well as the flow simulation, into the optimization process. Thus, for example, the optimization can be configured to select the design with the highest efficiency while also considering specific static and dynamic mechanical properties.



Figure 2: CFD simulation results

Based on the mesh resolution defined by the user, ANSYS TurboGrid was used to automatically generate the mesh for the computational fluid dynamics (CFD) simulation. The model included one passage per component with a profile-transformation rotor-stator interface as well as with chronological periodic interfaces. The total pressure and temperature were defined at the inlet, while the mass flow rate was defined at the outlet. Assuming an ideal gas, ANSYS CFX was then used to solve the model. The output parameters, such as total pressure, temperature ratio and isentropic or polytrophic efficiency were determined using CFX-Post. Figure 2 shows typical simulation results.

The transient rotor-stator capability resolved the true transient interaction between components in regard to maximum accuracy. It can be applied to individual pairs of blade passages or to the entire 360degree machine. Setup and use was as simple as it had been with the other frame-change models. It was also possible to combine transient and steady-state frame change interfaces in one computation. This was complemented by the inclusion of the second-order time differencing, which provided greater transient accuracy. Furthermore, transient blade row (Time- and Fourier transformation) models allowed unequal pitch systems to simulate multi-rows using only a few blade passages and less than the full 360-degree geometry.

Structural analysis

The mechanical model used one segment of the rotor with cyclic symmetry reducing computational time without any loss of numerical accuracy. The model was fixed at the inner radius. The rotor was loaded by centrifugal force and fluid pressure using results of the CFD simulation. Data handling and fluid-structure coupling were automatically performed in ANSYS Workbench. After the completion of the static simulation, a pre-stressed modal analysis was performed. The results of the mechanical simulation included the eigen frequencies, the maximal displacement and the von Mises stress (examples are shown in Figure 3). The design requirements included an upper limit of those stress and eigenvalues that did not match the rotational velocity in order to avoid resonance.



Figure 3: Mechanical displacement and stress

Sensitivity analysis

With the flow and structural models set up, the next step was to automatically simulate the minimum number of design points needed to map out the complete design space. Thus, not only the design meeting the spec, but also those providing the highest possible level of performance while meeting other constraints, could be confidently identify. The software tool optiSLang was used for sensitivity analysis, optimization, robustness evaluation and reliability analysis. The optiSLang inside ANSYS Workbench integration runs simulations by importing parameters automatically, minimizing the required user input.

A global sensitivity analysis uses a designed experiment to evaluate the reliability of the numerical model and identifies the most important input parameters. The Metamodel of Optimal Prognosis (MOP) algorithm uses Latin Hypercube Sampling to scan the multidimensional space of the input parameters. A Latin Hypercube is an n-dimensional object representing n different analyzed design parameters where each sample is the only one in its axis-aligned hyperplane. In this case, there were about 50 design parameters and about 100 design points were solved in order to create the MOP. This model represented the original physical problem and enables analyses of various design configurations without any further simulation runs.

The selected integration platform provides a seamless data transfer between applications and process controllers that sequentially simulate all of the design points and collate the outputs. Parametric persistence between the software components makes it possible to automate the optimization process including file transfer, mapping between physics, boundary conditions, etc. When the user clicks the Update All Design Points button, the first design point, containing the first set of parameter values, is sent to the parameter manager of ANSYS Workbench. There, the design modifications are processed from the CAD system to postprocessing. The new design point is simulated and output results are passed to the design point table where they are stored. The process continues until all design points are solved and the design space is defined for later optimization.

The Coefficient of Prognosis (CoP) determines whether the meta model is reliable or not. This calculation also determines which input parameters have a strong influence on the outputs. The response surface graphically depicts the influence of the relevant parameters on the system's performance and shows where the highest efficiency is located. Figure 4 shows the CoP and the response surface. In this case, the CoP was 84%, which indicated that the model was admissible but still could be optimized. The sensitivity analysis generated an efficiency of above 89% based on relatively rough simulations run parallel on a computing network overnight. This is about the maximum level that a highly experienced designer could expect to achieve within a reasonable time period.



Figure 4: Coefficient of prognosis and metamodel

The sensitivity analysis also showed that the eight most significant parameters account for nearly all result variations. This information was used to decisively reduce the time required for the detailed simulation by eliminating the variables that do not appear to have a significant impact on the results. For verification, the engineer can also check the numeric model, such as by examining the upper and lower bounds of the design parameters.

Design optimization

With the entire design space examined and the most promising region selected, the next step was running a more detailed simulation. optiSLang's optimizer provides a wide selection of algorithms. In this case, the sensitivity analysis showed that the practical designs were located in a relatively small area of the design space. The Adaptive Response Surface Method (ARSM) was selected because of its efficiency to generate optimal solution based on starting points that are already in the vicinity of the optimum. If the sensitivity analysis had shown many design space areas containing practical designs, it would have been necessary to choose a different algorithm.

	Initial	SA	ARSM	EA
Pressure Ratio	1.3456	1.3497	1.3479	1.3485
Efficiency [%]	86.72	89.15	90.62	90.67
# Simulations	-	100	105	84

Table 1: Design optimization

The direct optimization with ARSM generated another 1.5% improvement in the efficiency level to 90.62%, which is truly a best-inclass result. This level of efficiency is beyond what could be reached by using manual methods regardless of the designer's experience. With ARSM, approx. 10 simulations can be run parallel resulting in a required time of about three days.

Using all parameters, a second optimization was performed with an Evolutionary Algorithm (EA) as a contol point to check whether the elimination of design parameters in the first optimization was appropriate or not. The EA simulation hardly provided any further improvement, confirming that the additional input parameters have a negligible effect on the results.

Robustness evaluation

So far, the simulation dealt with an idealized setting where, according to the CAD geometry for example a 50 degrees angle is assumed to be exactly 50 degrees. In real world manufacturing, of course, one blade will have an angle of 50.1, the next 49.9 and so on. All of the other design parameters, including material properties, also vary. In order to determine the effect of this variance, we need to design a probability distribution that will simulate the real world manufacturing output. A Gaussian distribution is often used to model manufacturing tolerances while a log normal or Weibull distribution is common for material properties. Again, a Latin Hypercube sampling distribution was used because of its efficient ability to estimate the outputs of a large number of possible designs based on a small sample of actual simulations.



Figure 5: Robustness evaluation of pressure ratio

The robustness analysis results showed that an estimated 13% of the manufacturing volume had a pressure ratio outside the limits. The CoP was 83 percent, which indicated that the results are reliable. The robustness analysis indicated that the fluctuation of pressure was primarily caused by the rotational velocity, the so called myomega variable shown in Figure 5. Controlling this parameter will have a major impact on pressure distribution. It was also worth noting that the pressure ratio was tilted towards the lower limit. Shifting the distribution in the direction of the higher limit will significantly reduce the proportion outside the limits. The other design parameters caused negligible effects which means there might be potential for opening up manufacturing tolerances in order to reduce costs.

This example from turbomachinery showed how an automated process can be applied to achieve robust design optimization with reproducible methods. The process provides automatic geometry regeneration, highquality meshing for each possible design, automatic solver execution as well as automatic post-processing.

4. Operating Maps and Meta Models for Turbo Charging Systems

At the present time the internal combustion engine is widely used for passenger cars and commercial vehicles applications. Today's newly developed combustion engines must meet five key demands. The engine should cause low costs, have a long life cycle, provide a good response with a low fuel consumption and meet the actual emission targets. To achieve these objectives, increasing of the engine power absolute and specific becomes more and more important. To fulfill the core requirements in engine development, today almost all diesel engines for commercial applications use an exhaust-gas turbocharger. During the design process, the combination of a radial turbine and a centrifugal compressor has a decisive influence on the economic operation of a combustion engine.

For matching an exhaust-gas turbocharger with an engine the performance values, such as number of cylinders, power, mass air flow, fuel consumption, boost pressure, exhaust back pressure, etc. are needed for engine design points for the target engine. Based on the performance values, at first a suitable compressor wheel and compressor housing geometry combination is selected. The compressor map (Figure 6), which is determined based on the selected compressor components is either based on measured data or as a result of numerical data, which are determined with the help of 1D and 3D-CFD programs.

The compressor map has three limitations that restrict the map width and height. These are the surge-line and the choke-line, which exist due to the aerodynamics and the maximum compressor speed u_{cmax} . The maximum compressor speed is limited by the allowable mechanical stresses in the impeller.



Figure 6: Compressor map with extended map range

At the surge-line the flow tears by low mass flow and high pressure ratio that the delivering of fresh air flow is interrupted. The air mass flow run backwards through the compressor until a stable pressure ratio is reached with a positive mass flow rate, so the pressure is built up again. By periodic repeating of this procedure, the term "pump" is derived.

At the choke-line the flow reaches the speed of sound at the narrowest cross-section at the inlet of the compressor wheel. If this condition is reached, a further increase in flow-rate is not possible even by increasing the compressor speed. All flow-curves run to the maximum flow rate value at a pressure ratio of $\Pi_{CT}=1$.

With the help of the identified compressor map the engine design points are investigated whether the map range of the map is sufficient. Depending on the application of the engine, a wide range of the compressor map is needed. If the map range is not adequate a new impeller has to be designed to get an extended compressor map (Figure 6) to reach the requirements.

The impeller geometry is generated by special turbo machinery design software. The redesign of the existing impeller can be done by an automatic optimisation by numerical methods by using 3D-CFD simulations in combination with an optimiser (Frese et al. 2012). Therefore the MOP procedure is applied to the compressor. Figure 5 shows that the CoP of the total pressure ratio Π_C and the total temperature ratio Θ_C is pretty high for both operation points. A value over 80% is known as a good and reliable result. Common reasons for a small value are a too small number of design points or "numerical noise" in the simulation. The "numerical noise" was reduced by ta best practice study (Frese et al. 2012) and the monitoring of the analysis showed a stable value of the CoP. The isentropic efficiency η_{Cis} , a more sensitive result than the other ones, has significant smaller values; i.e. we can rely to the MOP in terms of Π_C and Θ_C , but we need to be careful about η_{Cis} .

It is important to be aware that all results are with respect to the chosen input parameters and their lower and upper limit!

The efficiency is the most important output parameter for the optimization and this is the reason, why the MOP is not used for optimization (It would be the fastest way!); a direct algorithm is chosen, see below.



Figure 7: Coefficient of Prognosis (CoP) and important input variables on isentropic efficiency, total pressure and temperature ratio for both operating points OP1 and OP2

All further analysis steps are done for the relevant parameters only, which can also be seen in Figure 7. Figure 8 shows the analysis, based on the Meta-model:



Figure 8: Meta-model for a) ηCis OP1 b,c) ηCis OP2 d) Anthill plot ηCis OP1 vs. OP2

The isentropic efficiency of OP1 depends mainly only on one variable x_1 , Figure 8a, while at OP2 it is a function of three important variables x1, x2 and x3, Figure 8b and 8c. It can be seen that a larger value of x_1 would result in a better efficiency at OP1 while it would reduce the value at OP2, i.e. we have a conflict of optimization goals. Figure 8d shows an Anthill Plot, the efficiency at OP1 vs. OP2, where one can see the assumed Pareto Front. If one chooses a certain point on the Pareto Front, one variable can only increased by decreasing the other one.

The Sensitivity Analysis can be summarized:

- 1. The Meta-model is reliable, due to the CoP values of Π_C and Θ_C
- 2. A reduced set of parameters was found, 3 out of initial 15.
- 3. The Meta-model is plausible, with respect to physics

This result is the basis for the optimization procedure: The fastest way, using the MoP directly (instead of doing numerical simulations), is not recommended, because of the small CoP of the efficiency; i.e. a direct optimization algorithm is required. We found Pareto conflict for the efficiency, for further resolution of this a Pareto Optimization is required.

Because these algorithms require a high number of design evaluations we did not use it in here. We resolved the conflict in terms of objectives by constraints:

- "old" objective: η_{Cis} OP2 = max and η_{Cis} OP1 = max
- "new" objective: η_{Cis} OP2 = max and η_{Cis} OP1 > η_{Cis} OP1 $_{initial}$ 1%

The new objective means, that the efficiency at OP2 should be as big as possible, while we accept a smaller one at OP1.

As Optimization algorithm we choose the Adaptive Response Surface Algorithm (ARSM). The main properties of this algorithm are:

- Finds the optimum, depending on the start point. From the Sensitivity Analysis we can see, that there is a global optimum
- Efficient for a small number (up to 10-15) of input variables (the Sensitivity Analysis showed that 3 input variables are important)
- Very robust algorithm

The ARSM works like that:

- 1. Sample the design space with a certain number of designs and solve them
- 2. Build a "simple" response surface and find the best point
- 3. Reduce the size of the design space around the best point and do next iteration, back to 1.

After 6 iterations, with 45 design evaluations we see a converged solution, see Figure 9:



Figure 9: Convergence of the Adaptive Response Surface Algorithm. Convergence plot of the objective function, design in parameter space and Anthill plot of evaluated designs

The result shows us, that x_2 becomes a small, while x_3 a large value; one can also see on the Meta-model. For x_1 , "carrying" the conflict, we result in a medium value. The final optimized design increased the efficiency at OP2 to 2%, while 0.5% at OP1 is "lost". Figure 9 shows also a better resolution of the Pareto conflict, because the ARSM is "driven" to the border of what is possible. Design 38 is the best in terms of the objective function, nevertheless there are other interesting designs computed.

Figure 10 a) shows the measured compressor maps of the initial and optimised impeller geometry.





Figure 10: Comparison of measured compressor map for initial design and optimised design: a) compressor map; b) difference in total isentropic compressor efficiency between optimised and initial design

The comparison shows that the surge-line and the speed lines below $u_c=420$ m/s don't deviate form the initial map. Only the speed line and therefore the total compressor pressure ratio at u_{cmax} is lower than the initial one. This is caused by the backward curved main blade which reduced the maximum pressure ratio. Besides the reduced pressure ratio the flow capacity could be increased, which could be seen by the expanded flow curves above $u_c=420$ m/s.

To reach the optimisation goals the total isentropic compressor efficiency at OP1 has to be reduced to increase the flow capacity. This approach leads to efficiency lost and gain in the optimised compressor map.

Therefore the delta isentropic efficiency $\Delta \eta_{\text{CisT}}$ is used, which is defined by the efficiency of the optimised design $\eta_{\text{CisT opt}}$ minus the efficiency from the initial design = $\eta_{\text{CisT ini}}$.

Figure 10 b) shows difference map of the measured efficiency between both designs in which the map range is lower than in Figure 10 a) because only the intersection is displayed. The results show that a gain of efficiency up to 2.5% could be identified above $m_{cn} = 0.9$ by a simultaneous reduction of the efficiency of 1.5% in the largest range of the map. Only at the lower map boundary (red ellipse Figure 10 b) the efficiency breaks down by 3.5%.

5. Conclusion and Outlook

This paper discussed the introduction of RDO for applications including 3D-CFD simulations. The current approach for RDO with CFD applications is in the most cases iterative RDO, meanwhile simultaneous RDO for CFD is still very challenging.

An example from turbomachinery showed how a MOP/CoP based automated process is used to achieve robust design optimization with reproducible methods.

The usage of meta models with a high prediction quality will become an important instrument for the analysis of operating maps and in general for the understanding and exploitation of the technical possibilities to produce an improved robust design.

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