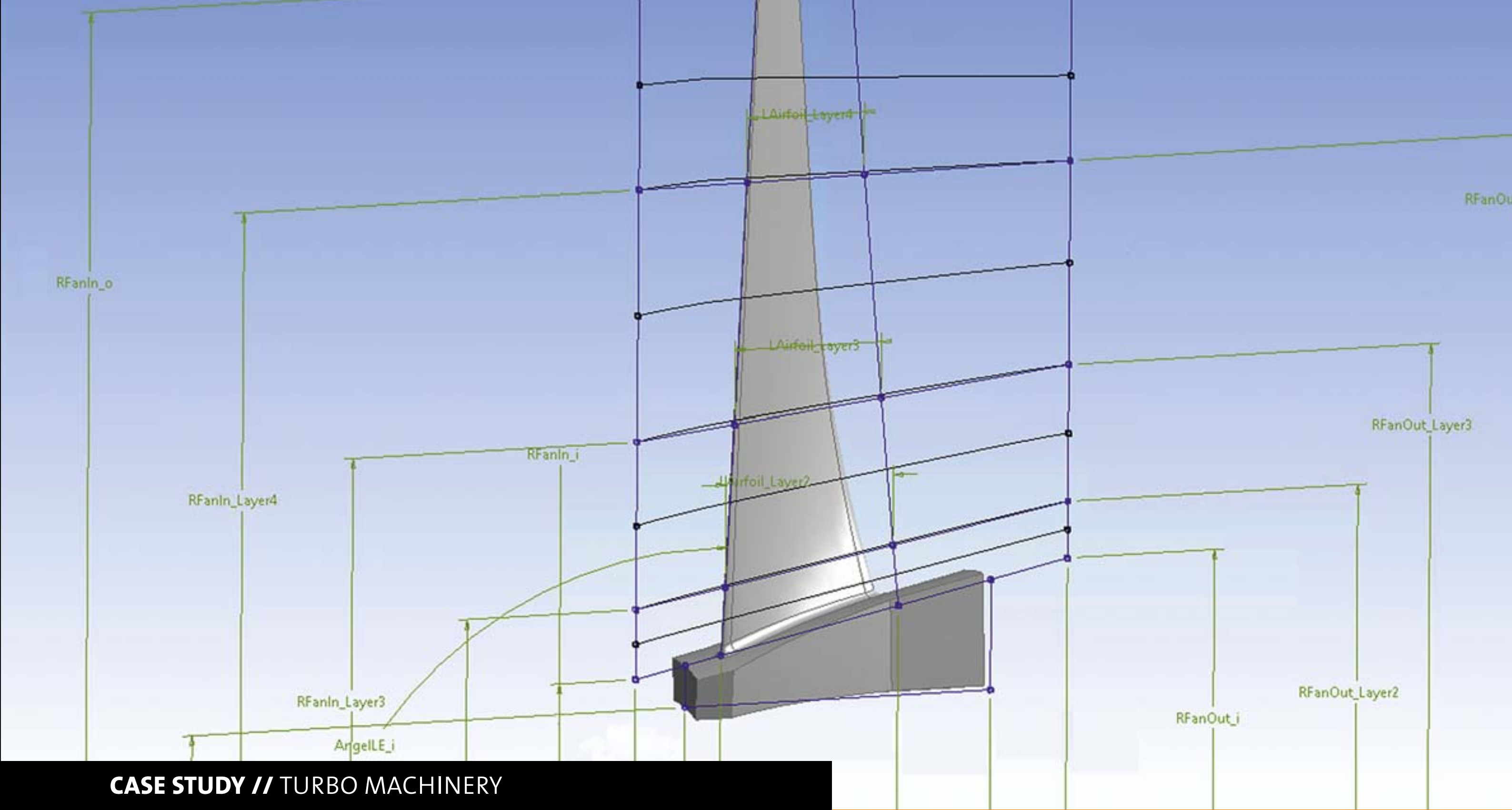

MULTIDISCIPLINARY OPTIMIZATION OF A CIVIL TURBOFAN JET ENGINE

Using ANSYS and optiSLang, the design of a turbofan jet engine was improved regarding polytrophic efficiency and mechanical stresses in the fillet and the blade of the fan.

Motivation

This article contributes to the field of multidisciplinary optimization of turbomachines. Here, the focus is on the fan of a civil turbofan jet engine with a high bypass ratio. Conceptual design methods were used to determine the aerodynamic characteristics. For more detailed analyses, a numerical 3D-CFD and 3D-FEA model was set up for the take-off conditions of the fan (close to stall). Based on these results, the design was improved iteratively and manually regarding polytrophic efficiency and mechanical stresses in the fillet and the blade of the fan.

Recent developments in the product development process go beyond successive simulation and analysis of individual design solutions and results. Computational approaches for sensitivity analysis, optimization and robustness evaluation integrate a variety of simulation results to foster system understanding for engineering design.

The automation of the process and the numerical effort are challenges for such methods. The automated workflow is implemented in ANSYS optiSLang and ANSYS Workbench that includes a stable parametrized geometry model, automated meshing, CFD runs and post processing.

Due to the numerical demanding CFD simulations, an efficient method is necessary to enable parametric studies and optimizations with an acceptable numerical effort. To satisfy these requirements, the workflow is used to run a sensitivity analysis first in order to calculate meta-models for all relevant result quantities. With the help of the meta-models, a fast pre-optimization by using different objectives was possible. By using only the important parameters indicated by the sensitivity analyses, an efficient optimization algorithm could be chosen in order to run a final direct optimization with the numerical model.

Civil turbofan jet engine: conceptual design method and numerical CFD and FEA model

First, conceptual design methods were used to determine the aerodynamic characteristics. With the help of the software GasTurb, the main dimensions of the fan could be calculated based on the requirements of the engine (e.g. pressure ratio Π, Bypass ratio). Afterwards, the blade geometry (e.g. camber line, blade thickness) and blade angles are calculated as well as the inlet geometry is designed.

A jet engine operates at a great variety of different operating conditions. Depending on the desired travel Mach number, the spool speed and the mass flow rate change. Since the highest mass flow rates occur during the take-off (close to stall), these flight and thermodynamic conditions have been used in the design process.

For detailed analyses, a numerical 3D-CFD and 3D-FEA model was set up. For that, the parametric geometry was designed with the ANSYS BladeModeler. Global parameters for describing the main dimensions of the fan were kept constant, while 25 parameters could be used to define the shape of the blade itself. This included 5 parameters to describe the meridional plane, 8 parameters for the blade angles, 8 parameters describe the blade thickness and one parameter for the number of blades, blade lean circumferential and fillet radius.

The appropriate definition of parameter dependencies and bounds are essential in turbomachinery optimization. Therefore, usually the parametrization is not suitable after the first attempt. Consequently, for ensuring a stable geometry generation a Design of Experiments only for the geometries itself is useful. By statistical evaluation of failed designs, additional dependencies can be implemented, existing dependencies adapted and parameter bounds adjusted.

Exemplary for this parametrization is the meridional plane and the blade angles, which are explained in the following in more detail. Five airfoils at different span locations define the blade. Each airfoil has a length that is parametrized but not all are allowed to change within the Design of Experiments. Only the length at hub, shroud and the layer in the middle are adopted. The other lengths are adjusted accordingly. The leading-edge blade angles of the airfoils are are a second example, which varied independently at hub and shroud within the Design of Experiments. The other leading-edge blade angles are parameterized, but in order to ensure useful designs only hub and shroud are varied independently. The three angles at the layers in between are varied as parameters, but only in percentage within the current values of hub and shroud.

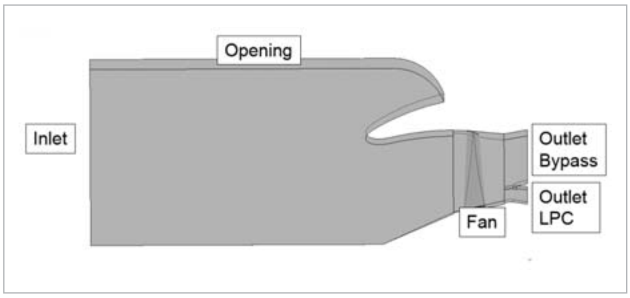

Fig. 1: CFD boundary conditions

The boundary conditions of the steady-state analyses of a periodic segment are shown in Figure 1. At the inlet, flight speed and ambient temperature for the take-off conditions are defined. The outlet is split in the bypass with static pressure and the LPC (low pressure compressor). At the opening, the ambient pressure is set. The meshing for the unchanged parts was conducted in ICEM. TurboGrid was used for the automated meshing of the fan domain. In CFD Post the output parameters like Π (pressure ratio) and polytrophic efficiency are defined.

Afterwards, a simplified FEA in ANSYS Mechanical is added to avoid implausible geometries from the structural mechanics point of view within the optimization process. In order to accomplish a reasonable numerical effort, a solid body is modeled instead of using a skeleton coated with CFK. Moreover, the deformation and the stresses in the blade and the fillet are of prime interest, the connection between the blade root and the hub disc is neglected in this analysis. The imported loads for the fan are the pressure on the blade coming from the previous CFD calculation and the rotational velocity. The cylindrical support and the cyclic symmetry are the boundary conditions.

Based on these results, the design was improved iteratively and manually regarding polytrophic efficiency, Π (pressure ratio), total deformation and mechanical stresses in the fillet and the blade of the fan. Figure 2 depicts the flow around the airfoil at different operating points and span locations. It can be proven that the flow meets the blade at the right angle.

Results of the sensitivity analysis

As a framework for geometry model, meshing and solver runs (including the mapping of the pressure field to the FEA) the ANSYS Workbench is used. This model was integrated in ANSYS optiSLang for an optimization workflow.

In order to ensure that the geometry and mesh can be generated and the solver covers the whole design space properly, a sensitivity analysis was carried out in ANSYS optiSLang. The design space was defined by the lower and upper bounds of the parameters. A sensitivity analysis scans the space and evaluates the variance of the inputs (e.g. geometry parameters) in relation to the output parameters (e.g. Π pressure ratio). For this purpose, the Design of Experiment is generated by an optimized Latin Hypercube Sampling [1]. For each sample, the output parameters are evaluated by the solver. With help of the Metamodel of Optimal Prognosis (MOP) approach [2] an optimal mathematical surrogate model (meta-model) was generated for each scalar response value.

In total, 188 of 200 designs for the sensitivity analysis are calculated successfully. In order to ensure the evaluation of the convergence, for each design relevant physical quantities are extracted. Consequently, 149 designs could be indicated as converged and after neglection of outliers 138 designs are used to generate the MOP. Figure 3 shows the MOP for the polytropic efficiency with a CoP of 78% which used 18 input parameters (that have a significant influence on the response) to build the meta-model. The leading edge radius at the hub (LERadius_i) and the length of the airfoil at layer 3 (LAirfoil_Layer3) have the highest influence for the given parametrization. It has to be noted that the importance of parameters will change by using different parameter variation windows. In this example, the design was manually pre-optimized and therefore the variation window for the blade angles was set rather

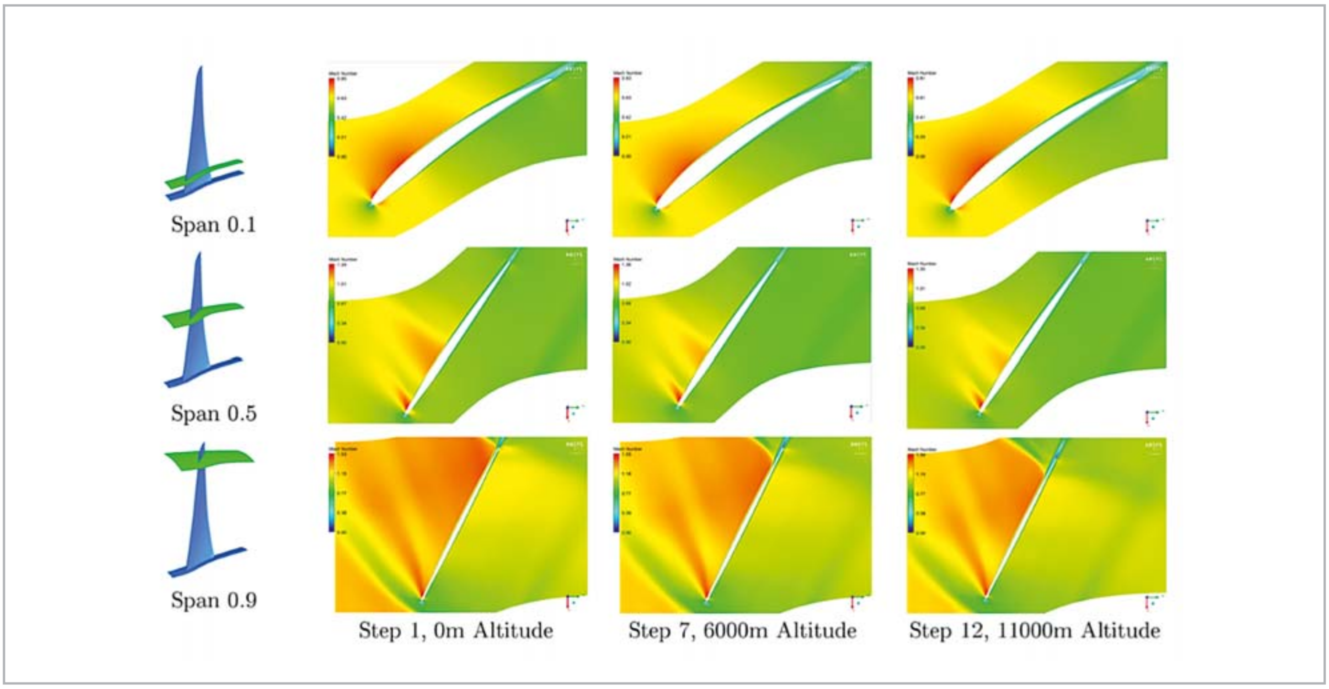

Fig. 2: Flow around the airfoil at different span locations and operating points

narrow. Thus, they have an influence (e.g. ReaktionRatio_o or betaIn_o), but not a dominating one.

Optional subsequent strategies that derive from the analysis are: a) increasing of the number of designs of the sensitivity in order to get a more accurate meta-models with a higher CoP value (this is very likely since the number of important variables is high and only 200 designs have been evaluated), b) to conduct a second sensitivity analysis in a narrower design space defined by the parameters of the best designs of the first sensitivity or c) to do a pre-optimization on the given MOP and use this improved design for a direct optimization. Due to the numerical demanding CFD simulations, the third strategy was chosen.

Optimization

The main objective was the increase of the polytrophic efficiency. Due to the requirements of the jet engine itself, the pressure ratio Π should be above 1,2. Moreover, the unaveraged stresses in the blade and the fillet should not exceed 1000 N/mm² and due to the tip gap of 6 mm the radial deformation of the blade must be under that value.

The meta-models are used for pre-optimization, since the forecast quality of the efficiency is almost 80%. Different formulations of objectives and constraints can be easily tested, adapted and fast evaluated. In the left Figure 4 the convergence of the Evolutionary Algorithm by using the MOP and the improvement of the objective is shown. This calculation of more than 3500 design evaluations is done in minutes, while one CFD run takes hours. As shown, the algorithm starts in an area with lots of constraints violations (red) and moves in a subspace with less constraint violations (green) in the local search at the end. The best design

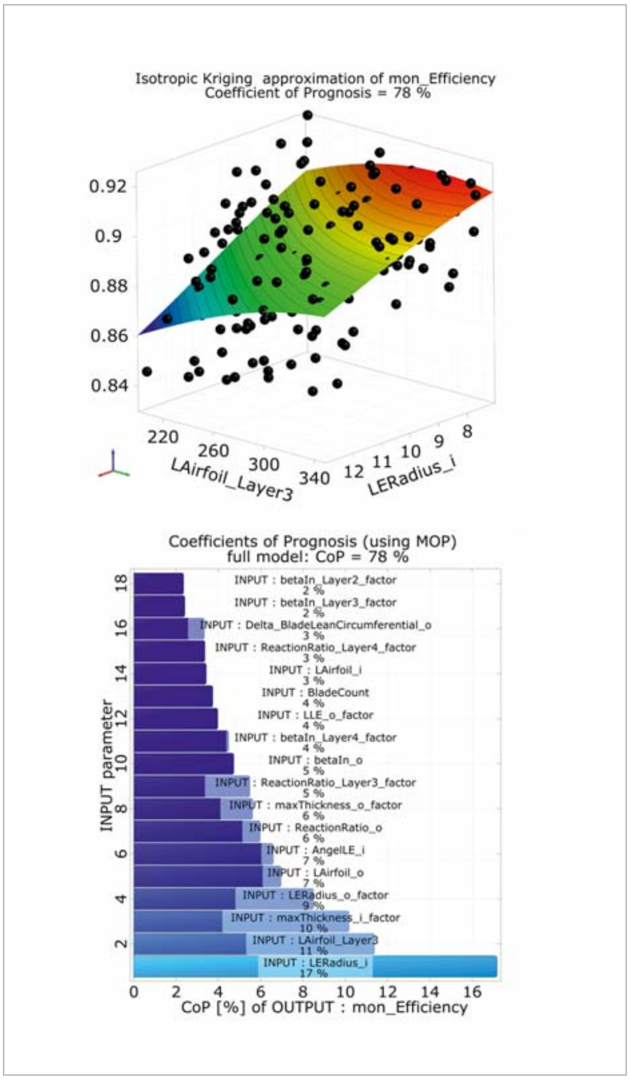

Fig. 3: Meta-model (top) and important parameters (bottom)

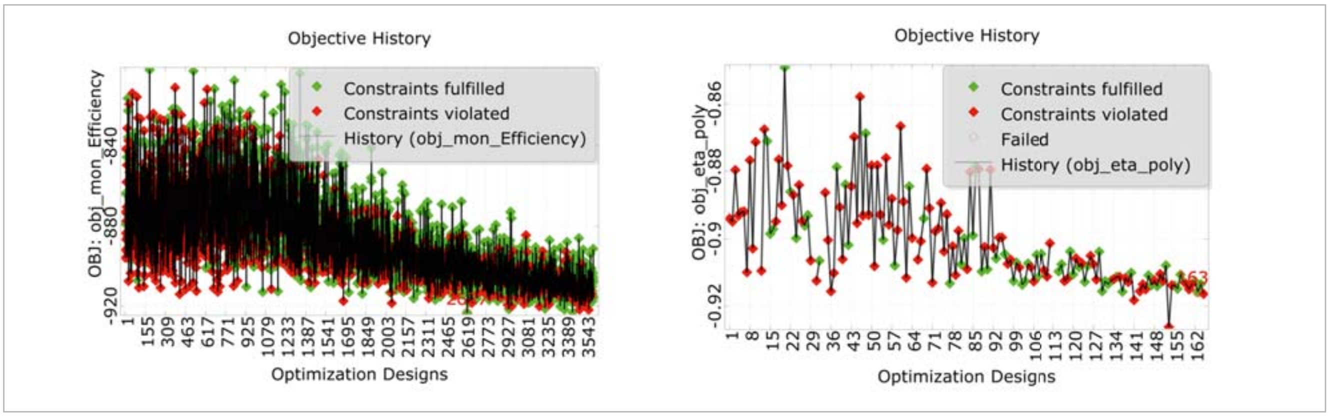

Fig. 4: Convergence history of Evolutionary Algorithms in the MOP (left) and direct optimization using an ARSM algorithm (right)

	Manual optimized	Best Sensitivity	Opt. on MOP (validated)	ARSM (Direct optimization)
Polytrophic Efficiency [%]	90,94	92,01	92,63	92,83

Fig. 5: Polytrophic efficiency in optimization process

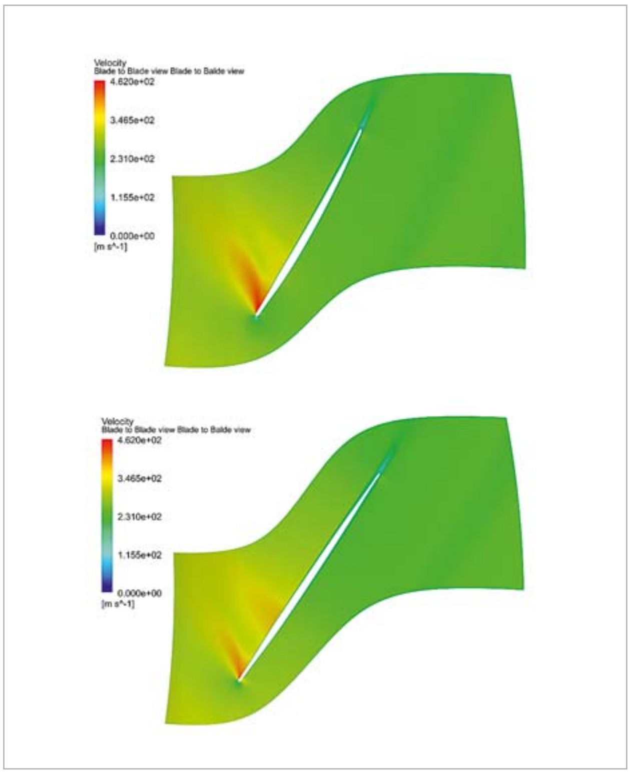

Fig. 6: Flow around an airfoil at span 0,5: manual optimized (top) and best design after optimization (bottom)

has improved the polytrophic efficiency by 1,7% from 90,9% to 92,6% (Fig. 5). After finishing the MOP-based optimization, the best design candidates need to be validated with CFD/FEM runs.

Based on this pre-optimized design an Adaptive Response Surface Method (ARSM) was applied in a second step using CFD/FEM design evaluations. The start design was the best design from the pre-optimization and the algorithm used the reduced number of parameters, which were indicated as important in the sensitivity analyses. Within a few iterations a further improvement was possible to an efficiency of 92,8%, which is an increase of 1,9% compared to the manual optimized design. Again, all the mechanical constraints were fulfilled and also the needed pressure ratio (Π) was reached. In Fig. 6 the velocity field is shown an 0,5 span. In both designs, the flow meets the blade at the right angle and the maximum velocity is lightly reduced in the best design of the optimization.

Summary

A civil turbofan jet engine with a high bypass ratio was manually optimized by conceptual design methods and with the help of a 3D-CFD and 3D-FEA model. This design was used as a basis for an optimization procedure with the objective to increase the polytrophic efficiency while the pressure ratio (Π), mechanical stresses in the fillet and radial deformation had to fulfill given constraints. By conducting a sensitivity analysis, pre-optimization on the metamodel and direct optimization, the polytrophic efficiency could be increased by 1,9% from 90,9% to 92,8% while the given constraints were still fulfilled.

A possible next step is to add desired altitudes for the jet engine, which means for the optimization to include multiple operating points in one design evaluation.

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