MULTIDISCIPLINARY COMPRESSOR BLADING DESIGN PROCESS USING AUTOMATION AND MULTI-OBJECTIVE OPTIMIZATION

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Abstract

The compressor is one of the most important and challenging components within an aero engine. The design of a compressor is achieved by many multidisciplinary design iterations. The aerodynamic design process is usually subdivided into several stages, where the number of parameters and the complexity increase through the entire process. The first two steps consist of the mean line prediction and the through flow calculation which define global flow parameters and the basic annulus geometry. The subsequent blading process is needed to find appropriate blade shapes which fulfill the through flow requirements. In this stage of the aerodynamic blading procedure the feedback from the mechanical discipline is always mandatory because within the aerodynamic process only mechanical rules of thumb are used.

This paper shows, how the time consuming blading procedure can be accelerated by the use of different aerodynamic and mechanical design and analysis tools integrated into an automated process optimization environment. Furthermore, the application of modern multi-objective optimization strategies will be presented, which provide trade-off solutions between the contradicting design goals.

The results presented in this paper stem from German national funded VIT project which is currently carried out at Rolls-Royce Deutschland in close collaboration with the University of Cottbus in Germany (TU Cottbus).

Introduction

Generally, the aerodynamic design of an axial compressor is always a compromise between contradicting requirements like wide operating range, high efficiency, low number of stages and high surge margin. This is typical for multi-objective optimization problems. The blading process is a suitable mean to solve this design challenge. Usually, a geometry generation tool is used to design the blade sections which are then evaluated by a blade-to-blade CFD solver. The design of these sections is rather time consuming due to many iterations with different programs and tools. The individual blade geometries in a compressor are created by stacking several separate two dimensional blade sections along a specific stacking line. The resulting blade is then transferred into a CAD system to create an appropriate connection to the blade platform and is passed to a 3D stress calculation by means of a FEM solver. If the stress criteria are not fulfilled the aerodynamic design loop has to be restarted.

The paper shows examples of automization and optimization for the aerodynamic meanline prediction and 2D-blading and also for mechanical processes.

1. Compressor design process

The aerodynamic design process is a fundamental key element in the multi-disciplinary development of an axial compressor. It it usually subdivided into several design phases in which the underlying model order increases subsequently through the design process. Figure 1 shows the different phases of an aerodynamic design in a general view.

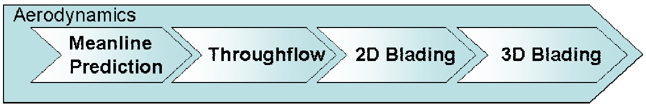


Figure 1. Compressor aerodynamic design process

The compressor design process starts with the aerodynamics, [1]. Here, the meanline prediction calculation process is the first step where typically an existing compressor design is taken as an initial starting point. Global parameters like annulus line, number of stages, stage pressure ratios are scaled or adapted to the new design problem to find appropriate flow parameter distributions along the mid-height of the compressor. The goal of the meanline calculation process is to find parameters which fulfill the compressor performance requirements for the design point and the off-design characteristics. In addition to the annulus line and the blade aerodynamics, blockage and surge margin predictions are outcomes from the meanline calculation, and are essential for the further design process.

Meanline prediction uses only a very simple one-dimensional model for the complex 3D-flow field. More precise approximation can be obtained by calculating the flow in two intersecting families of stream surfaces S1*j* and S2 as proposed by Wu [2], see Figure 2. From this point of view, meanline prediction can be interpreted as a one dimensional calculation on the intersection line of a mid-height S1*j* and the S2 surface.

Meanline prediction is followed by the throughflow design process which is a calculation on the S2 surface. The aim is to determine velocity triangles, i.e. gas inlet and outlet whirl angles, and flow conditions for several S1*j*-intersections in order to achieve desired stage characteristics along the S2 stream surface. The results of meanline prediction are used as initial guesses on the mid-radius line and basic aerodynamic parameters are then extended by radial distributions.

Based on these radial distributions of significant flow parameters, the following 2D blade-to-blade calculation is used to design 2D blade geometries which match flow angles and flow conditions on all S1*j* surfaces. These blade profiles are then stacked radially along a specific stacking line to create the 3D blade geometry. In this final stage, modern blade design principles like sweep and dihedral can be applied and highly sophisticated 3D flow calculations can be performed for individual blade rows and the whole compressor.

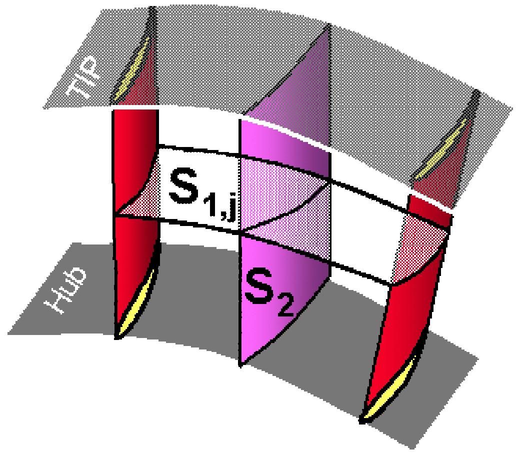


Figure 2: Definition of S1*j* and S2 planes

As soon as a blade geometry exists, it has always to be checked if the mechanical behavior of the blade, i.e. maximum mechanical stresses, thermal stresses, frequency behavior or life assumption are fulfilled. For that reason the blades are transferred to mechanical FEM tools via CAD systems in which the blade is positioned on its platform and fillet radii are applied. Figure 3 shows a sketch of a compressor mechanical design system.

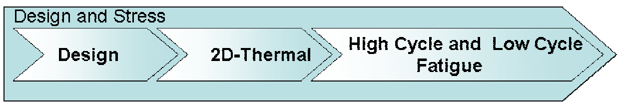


Figure 3. Compressor mechanical design process

Nowadays more and more efforts are under way to improve the performance and to reduce the development time of a compressor or an individual blade row by the use of an automated optimization process during the aerodynamic and mechanical design.

In the following, three different approaches will be described in which process automation and multi-objective optimization was used:

2 aerodynamic approaches:

- Meanline optimisation
- 2D blading optimization and

1 mechanical approach

- Optimization of thickness distribution

In all examples in the presented investigations the process automation was realized by the use of the commercial process integration software tool iSight from Engineous Software Inc. [3]. This software has been chosen as a front-end and control tool to integrate the different parts of a complex design process. The software supports task management, decision making, definition of the design analysis process and data exchange. It automates the execution control and data exchanges with arbitrary analysis tools where design analysis may be split into multiple programs running in a heterogeneous computational environment. Design decisions are guided by sampling methods, like Design of Experiments (DoE) and Monte-Carlo Simulation(MCS), as well as local and global optimization strategies.

Numerical optimization based on Genetic Algorithms and Lagrange-Newton, [4] methods is used to improve a given Rolls-Royce design of a 9-stage high pressure research compressor with respect to conflicting design goals like effciency, surge margin and overall pressure ratio.

2. Meanline optimization

As already mentioned, one of the most important design part within the aerodynamic process shown in Figure 1, is the meanline prediction. Here, the most influencing design decisions are made on significant parameters like mass flow, annulus geometry, number of stages, stage widths, blade aspect-ratios, blade solidities and stage pressure ratios.

Figure 4 gives a rough overview of the realized process implementation for the meanline prediction.

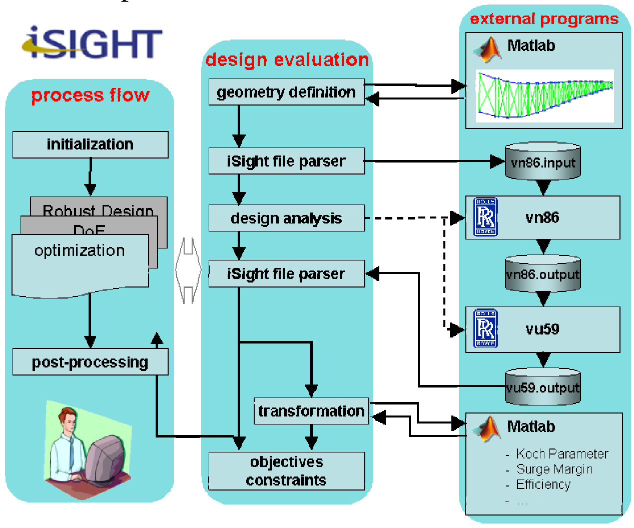


Figure 4: Sketch of the meanline prediction process realized with iSight

Design changes are performed with respect to the annulus geometry and the stage pressure ratio distribution.

The program iSight is used to define the process flow consisting of initialization, an optimization loop and post-processing. The optimization routine interacts with a design evaluation process which is also defined with and controlled by the task manager iSight. When the optimization program requires a new design evaluation, the task manager invokes a Matlab script which calculates the new annulus line geometry and the stage pressure ratio distribution. This information is parsed into an input file and the meanline prediction calculation can start. The outcome is bundled in an output file, where the task manager extracts basic information required for constraint and criterion evaluation which is performed by another Matlab script. The optimization loop proceeds until the desired optimized design is found.

2.1 Parametrization

Parametrization is an important step to reduce the number of design variables to a minimum, but keeping the design freedom at a maximum. Reduction is required to save computational costs, and additionally to guarantee technical feasibility of the obtained designs. Further it smoothes the design problem and thus increases the chance to find a global optimum solution and not to be trapped in one of the multiple local minima. On the other hand, parameter reduction can be considered as imposing implicit constraints on the design problem leading to suboptimal solutions only. The decision on design parametrization, therefore, is a trade off with major influence on the final result.

In the specific case of meanline optimization, the geometrical annulus lines and the stage pressure ratio distribution was described as parametric curves in 2D-space with. Bezier-splines [5]. These are chosen because of their mathematical simplicity and their properties concerning continuity and differentiability.

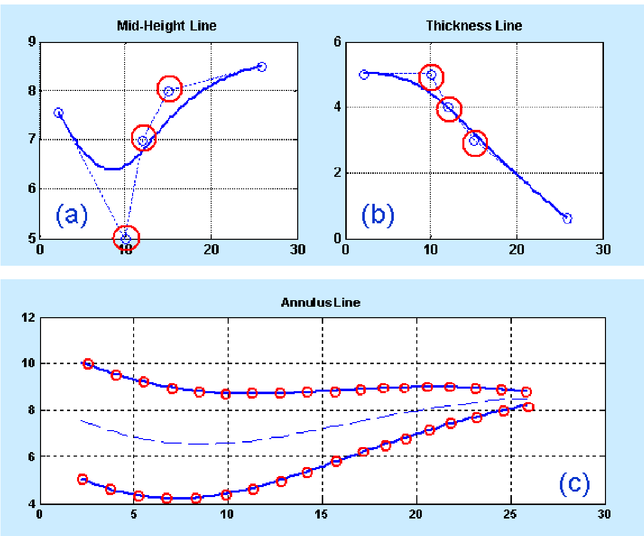


Figure 5: Parametrization of the Annulus geometry. Definition of annulus by mid-height line (a) and annulus thickness (b), resulting annulus geometry (c) as point string data for a 9-stage compressor

Figure 5 shows the parametric annulus mid-height (a) and annulus thickness (b) distributions based on Bezier-splines with five control points, respectively. The resulting smooth annulus geometry is drawn in Figure 5c. In order to use this annulus geometry within the meanline prediction program, the hub and casing annulus lines have to be transferred into discrete point string data which is also shown in Figure 5c.

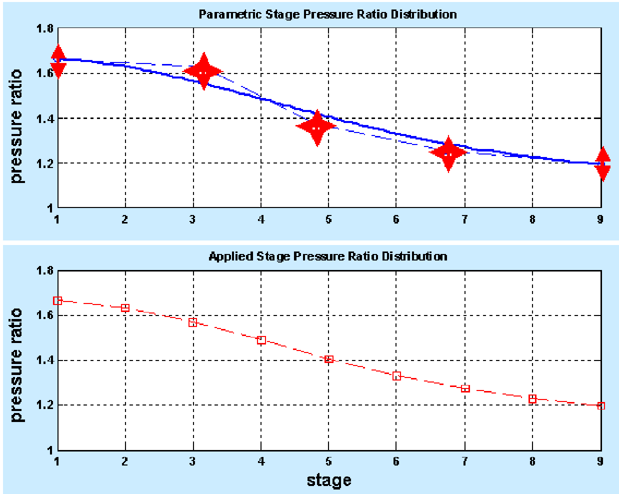


Figure 6: Stage pressure ratio para- metrization (upper) and distribution (lower)

The same kind of Bezier-spline representation can be used also for parametrization of non-geometry curves like the stage pressure ratio distribution which is used as an input for the meanline prediction. Figure 6 shows the parametrization of the pressure ratio distribution with 5 Bezier control points and the resulting pressures as input for the meanline calculation for each of the 9 stages.

2.2 Meanline Optimization

The goal of meanline prediction is to find model parameters leading to appropriate flow and loading conditions. The whole suite of parameters describing the compressor model can be split into design variables, which are assumed to be adjustable in order to fulfill design requirements, and system constants, which are kept constant during the design process. Such a decision depends on the design goals and the sensitivities of the criterion functions on parameter changes. In most cases, however, the sensitivities are unknown and the decision has to be based on experience or design exploration.

As already mentioned, in the following design investigations the design variables will be the coordinates of the control points describing the annulus lines and the pressure ratio distribution.

Typical design goals for compressors are polytropic efficiency, overall pressure ratio, compressor length, weight, stresses, etc. The major design criteria in the following investigations are the

- overall polytropic efficiency [1] η_{poly}, c
- and overall pressure ratio

$$\Pi_c = \prod_{i=1}^{N} \Pi_i$$

where Πi are the stage pressure ratios of the individual N stages.

Optimizing the compressor with respect to just these two design criteria will yield stability problems which can be avoided by introducing the

- surge margin *SM* at design point defined as

$$SM = \frac{\Pi s - \Pi c}{\Pi c} .100\%$$

where Π_c is the design pressure ratio and Π_s is the pressure ratio at the surge line for equal mass Flow , Figure 7.

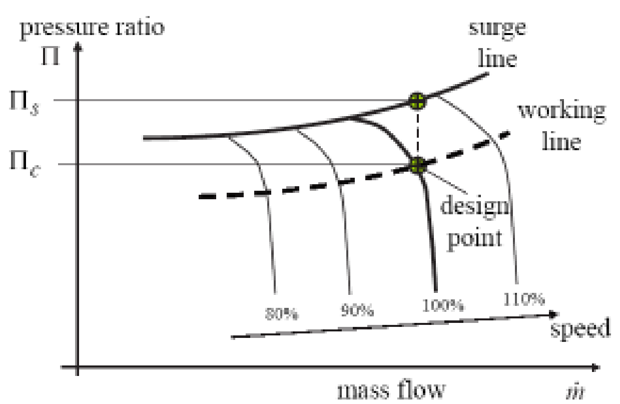


Figure 7: Compressor map and significant parameters for the surge margin definition

Beside of these criteria, which are typically maximized, some more constraints with respect to blade loading, flow conditions such as inlet and outlet Mach number and stability measures like the Koch parameter [6], de Haller number or Diffusion Factors have to be taken into account.

For a 9-stage compressor which is investigated here, this results in 73 inequality constraints which have to be taken into account by the optimization routine. If the optimizer uses an active set strategy, the constraints may be provided as described, because the algorithm will concentrate on active and violated constraints automatically. Else, it is better to group the constraints by minimization and maximization over all stages.

2.2 Meanline Optimisation

Two approaches are used in the optimization. In the first, the total pressure ratio was kept constant and the optimization objectives were to maximize the efficiency and the surge margin of the compressor by varying the geometry. In the second approach the overall pressure ratio was added as a objective. Both optimization results were compared to the results of a human designer.

The result of the first approach is shown in Figure 8 for two different optimization methods:

1. multi-island genetic algorithm MIGA,
2. NLPQL method [7] (which is a Lagrange-Newton type algorithm [8],[9].)

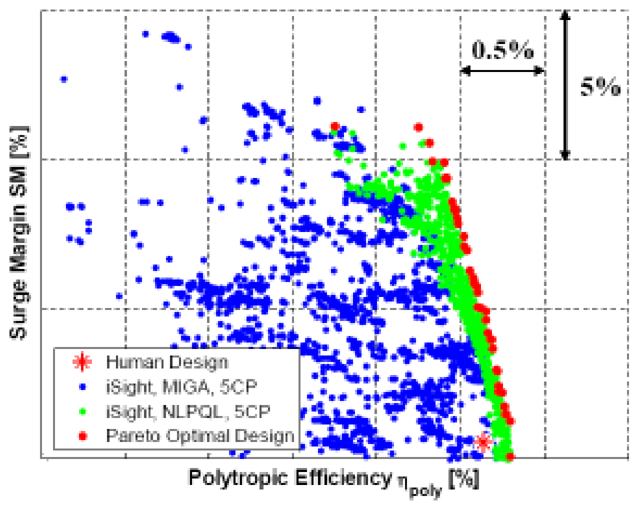


Figure 8: Meanline optimization; Results of MIGA and NLPQL method and comparison to human design

As can be clearly seen, a Pareto-optimal front is developed and the results for the efficiency and the surge margin are superior in comparison to the human designer. The NLPQL algorithm produces a Pareto-optimal front which is more dense than obtained from the MIGA approach, where the density can be controlled by choosing adequate step sizes for increasing the surge margin constraint. Beside this, the optimal solutions found by the deterministic NLPQL method are obviously more reliable than results from the stochastic MIGA approach.

In the case of this multi objective optimization the designer is now able to discuss on trade-offs between polytropic efficiency and surge margin.

In Figure 9 an enlargement of Figure 8 is shown in the vicinity of the human design. The improvements are 0.16% points in efficiency for constant surge margin, or 4.4% points in surge margin for invariant efficiency,

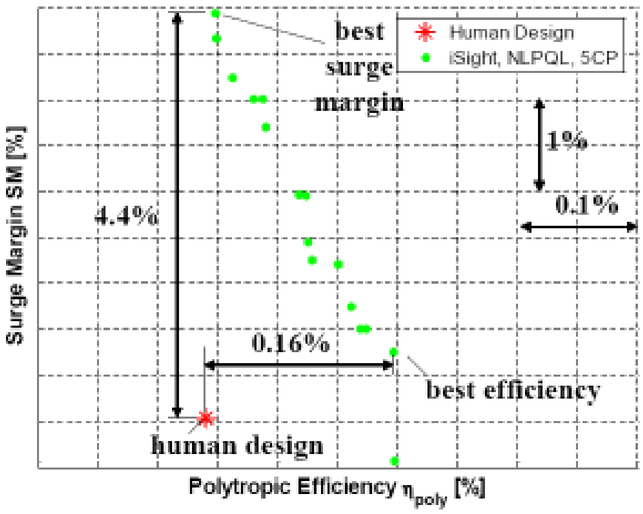


Figure 9: Pareto-optimal results with NLPQL

In order to gain more design freedom, the stage pressure ratio distribution is introduced as an additional design quantity besides the annulus geometry, where it is parameterized through Bezier-splines with five control points. Again the multi criterion optimization problem is transformed to a scalar problem where effciency is maximized and the other two criteria are ignored. Figure 10 shows a sketch of the feasible solutions in the three-dimensional criterion space where the overall pressure ratio as the third criterion is marked by the color.

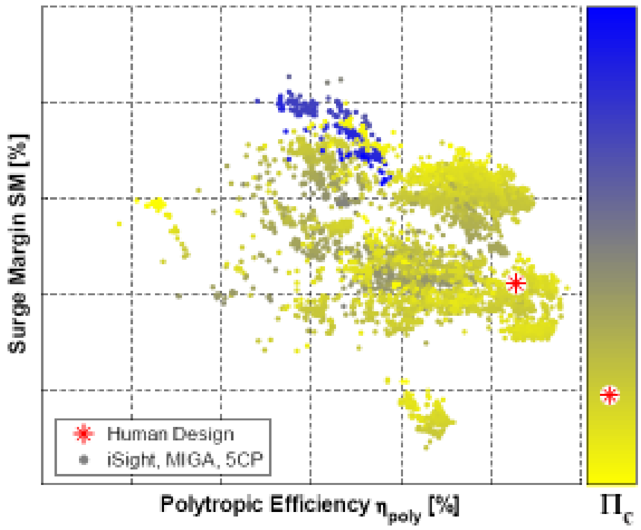


Figure 10: Multi-criterion optimization with respect to efficiency, surge margin and overall pressure ratio

Due to the increased design freedom, improved designs can be found compared to the earlier solutions. E.g., the surge margin can be increased by absolutely 4.9% points without loosing efficiency and overall pressure ratio compared to the human design, which is clearly better than 4.4% points in Figure 9. It should be noted, that this improved design is obtained just by the genetic algorithm MIGA. Another design point can be found where the overall pressure ratio can be increased by 2% without loosing efficiency or surge margin. Further, there exist designs which are improved with respect to all three criteria simultaneously.

3. Compressor Blade Design Optimization

The second automation and optimization example is the 2D blading procedure. Starting from the one-dimensional meanline prediction, where global flow and geometry parameters are determined, the through flow calculation follows in order to obtain radial parameter distributions. Based on these, the subsequent blade to-blade calculation is used to design two dimensional blade geometries which fulfill the given flow angles and flow conditions on several radial stream surfaces. Finally, the three dimensional blade geometry is generated by stacking the individual blade profiles along a specific stacking line including additional design rules like bow and lean to consider 3-dimensional flow phenomena.

The usual 2D blading procedure by a human designer is to apply profile changes according to the respective deflection task from the throughflow calculation and to calculate the flow field in the S $_{1,j}$ plane (Figure 2) with a 2D-blade-to-blade-solver. After that the flow field can be analyzed and appropriate changes to the profile geometry can be applied. This manual and very time consuming procedure was automated using the procedure which is shown in Figure 11.

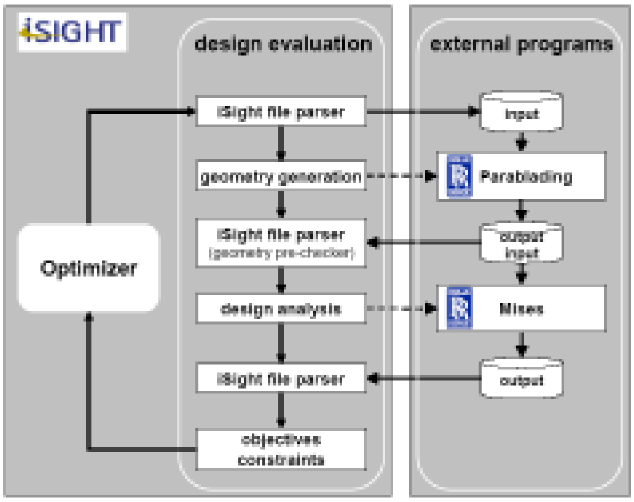
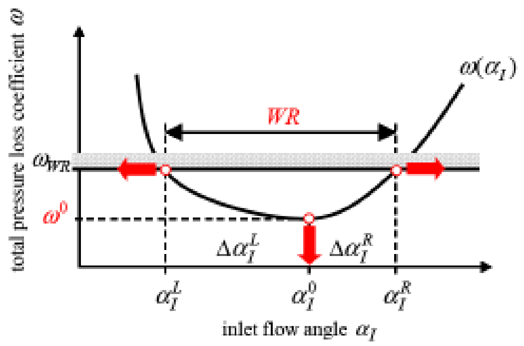


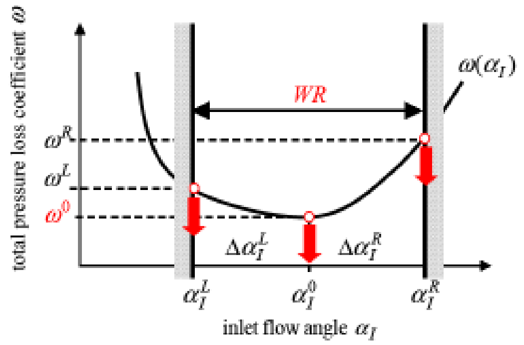
Figure 11: Aerodynamic blade design process integrated into the *iSight* environment

As can be seen, the general structure of the procedure does not changes. The program iSight is used to define the process flow consisting of initialization, an optimization loop, and post-processing. When the optimization program requires a new design evaluation, iSight invokes an in-house geometry generation and modification program Parablading [10] and the flow analysis package Mises [11]. Both programs are integrated in a common environment. As can be seen in the process flow chart, Figure 11, the task manager controls and automates the execution and data exchange between the individual design tools as well as it provides several local and global optimization strategies for finding better design solutions.

In the current multi-objective optimization problem one design goal is to find an appropriate blade profile geometry fulfilling given design inlet flow conditions with minimum pressure loss where the other design goal is to maximize the blade working range WR defined in such a way that the loss does not exceed a prescribed loss level due to inlet flow angle variation. An issue of this design objective formulation is that many Mises calculations with variable inlet flow angles are needed to determine the working range value WR. In order to reduce the number of flow calculations and therefore to accelerate the complex multi-objective blade optimization process, two alternative problem definitions are investigated, see Figure 12. The aim of both definitions is on the one hand to reduce the loss ω at design flow conditions and on the other hand to increase the working range WR



a) maximizing $\Delta\alpha_I^L + \Delta\alpha_I^R$ at constant working range loss level ω_{WR}



b) minimizing $\omega^{R,L}$ with prescribed constant working range WR

Figure 12: Alternative definitions for solving the multi-objective aerodynamic blade design problem

For the formulation a) in Figure 12 the Figure 13 shows as an example the working range WR versus the profile loss for more then 10000 functional evaluations of Mises. Over 5000 Mises solutions were feasible. The presented multi-objective optimization approach has found improved designs with respect to both objectives.

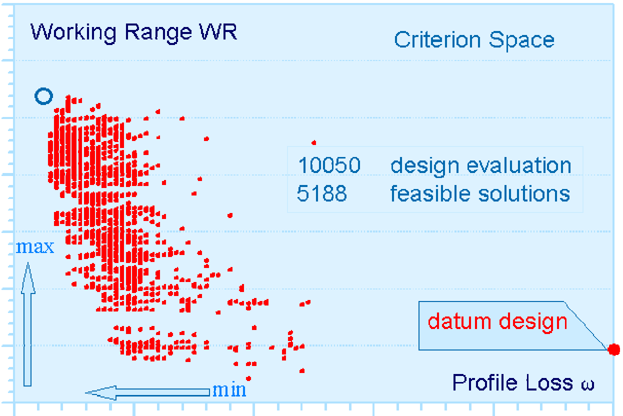
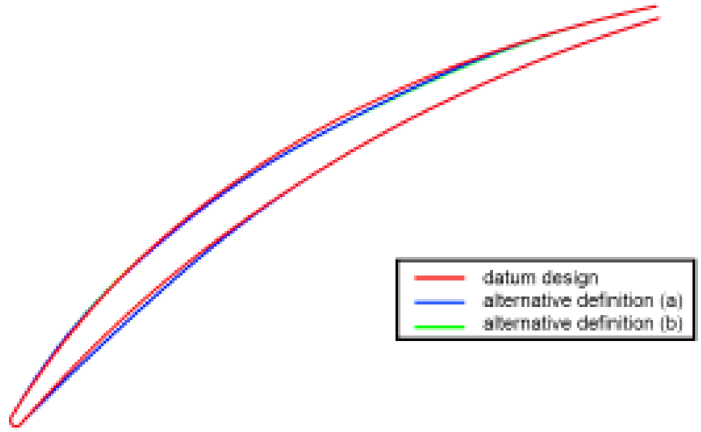


Figure 13: Working range versus loss distribution for formulation a) from Figure 12

In order to illustrate the potential of the alternative formulations a Pareto-optimal solution is evaluated and compared with the datum design. As can be seen in Figure 14, the optimized blade section geometries are nearly identical and since the cross section area is considered as a mechanical constraint within the optimization, a redistribution of the loading towards the blade leading edge can be observed compared to the datum design. The loss distributions in Figure 14 show a reduction of approximately 5% at design flow conditions and an increase of the working range of about 1.5° on a comparable loss level. Both alternative definitions show promising results.



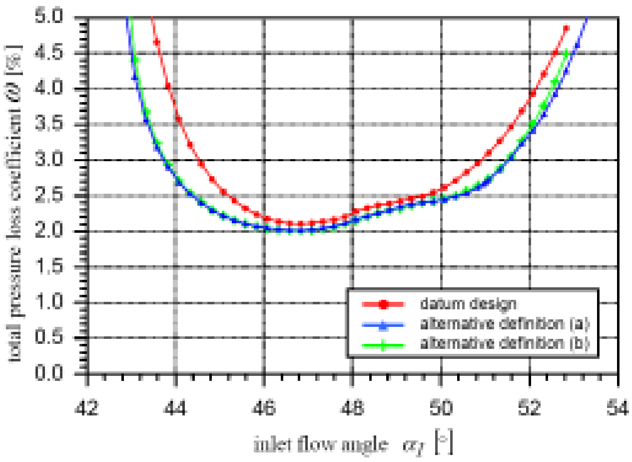


Figure 14: Comparison between datum and optimized blade geometry (upper);Comparison of the loss distribution between datum and optimized designs

4. Mechanical Blade Optimization

The last automation example in this paper is the mechanical optimization of blade thickness distribution and fillet radii.

Within the 2D blading procedure the two dimensional blade geometries are parametrized by means of B-splines [7] and are then radially stacked to form a 3D blade geometry. Thus, the 3D blade is described fully parametrically. The transfer to the CAD system is realised via so called Knowledge Fusion (KF) system which is a “Knowledge Based Engineering”-part of the UG CAD-system. The KF interface in both programs, parablading and UG is then used to exchange the geometries which are described with exactly the same B-spline control points.

After the blade is transferred to the UG CAD system, it is then assembled on its platform and root with appropriate geometrically parameters, especially the fillet radii. Within this automatic approach, the aerofoil can be modified and the whole blade including platform and root can be regenerated easily and automatically. For every new blade a subsequent FE-analysis is then performed. The result of this analysis are mechanical requirements like the minimum amplitude frequency (af-strength), eigen-frequencies and flutter sensitivity.

For the optimization procedure, the thickness distribution of the blade is also described in parametric manner using B-spline description within the program Matlab. This ensures a smooth thickness distribution which is shown in Figure 15.

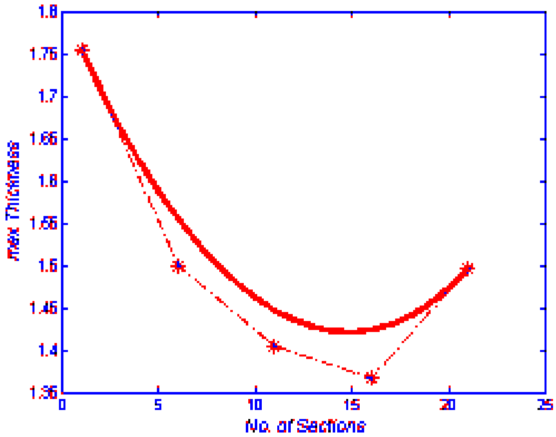


Figure 15: Blade thickness distribution parameterized by a B-spline with five control points

All programs used (Matlab, Parablading, Unigraphics NX2 as CAD-System and ANSYS10 for the FE analysis) are again embedded in the automation and optimization environment iSight. Figure 16 shows the process which is implemented here. Firs of all a new thickness distribution is calculated followed by 3D aerofoil creation according to the new thickness. The blade is then transferred to the CAD system for the assembly with the platform and root and is passed to the FE analysis.

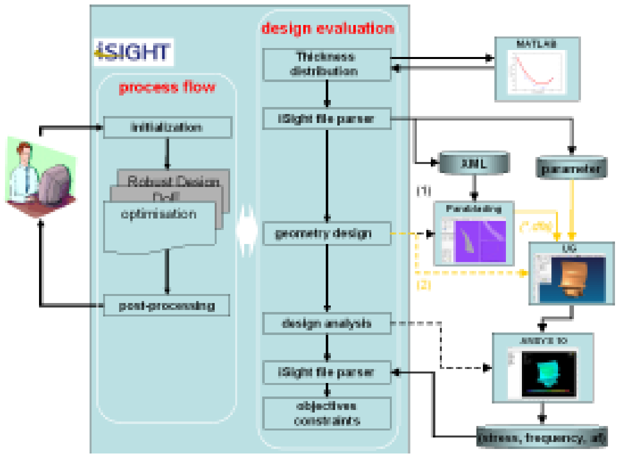


Figure 16: Integrated mechanical blade design process.

In the mechanical multi-objective optimization problem, one design goal is to find a minimum mass of a blade, which fulfills mechanical constraints. The other design goal is to achieve a low flutter sensitivity which can be expressed through high values of the flutter parameter λ. This parameter is defined as:

$$\lambda = \frac{\omega C}{U}$$

where ω is the angular frequency of the relevant mode shape, C the true chord length of the aerofoil and U the relative gas velocity at the inlet.

One result of such an optimization procedure is shown in Figure 17.

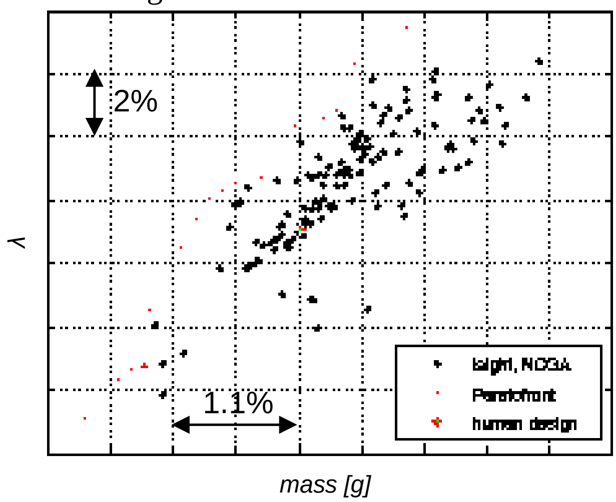


Figure 17: Pareto-optimal results with NCGA [12] (17 Generations and population size: 10)

The solution shows a noticeable pareto-front. Starting form the human design (green symbol), a better solutions can be found with respect to the flutter parameter λ at constant mass. On the other hand, also the mass can be lowered at constant flutter parameter. This procedure can be of valuable help for the designer to judge different designs. It should be noted, that this improved design is obtained just by the genetic algorithm NCGA (Neighborhood Cultivation Genetic Algorithm). Other gradient based algorithms will be used in the future.

5. Summary and outlook

This paper shows several examples of multi disciplinary optimization processes which are used during the blading design of an axial compressor. These are aerodynamic meanline and 2D blading optimization but also mechanical optimization of blade thickness distribution.

In every case the first step is a proper parametrization of the geometry to achieve a reduction in optimization parameters. Then, all subsystems used (geometry modification and analysis tools) are automated using the process integration software iSight. This tool also offers different optimization algorithms which are used to optimize the specified problem.

Using these automated processes, the designer has now the choice to look into different optimized designs for trade offs rather then to drive programs manually.

In the future, the presented processes will further be bundled into one multidisciplinary process and optimization chain which will then include both aerodynamic and mechanical constraints.

6. Acknowledgements

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