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EVOLUTIONARY DESIGN OPTIMISATION OF A TURBINE STATOR BLADE USING FREE FORM DEFORMATION TECHNIQUES

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ABSTRACT

Design optimisation methods are applied in various applications where the shape of an object has to be adapted with respect to aerodynamic properties. However, the description and parameterization of the often three dimensional shapes subject to the optimisation is a crucial point and often the key to a successful optimisation.

In the present paper a representation based on the method of free form deformation is proposed and combined with evolutionary computation methods in order to generate a system for the design optimization.

It is demonstrated that free form deformation methods are well suited for the optimisation of aerodynamic properties because of several reasons. One of these reasons is that they provide a highly efficient way of representing arbitrary shapes, while the complexity of the shape is decoupled from the dimensionality of the optimisation problem. Another reason is that it holds the advantage of a fast automatic mesh generation which is needed for automized CFD calculations.

To illustrate the efficient combination of FFD with evolutionary optimisation a test scenario has been set up in which a stator blade of a gas turbine is optimized.

Keywords: Computational Fluid Dynamics, Evolutionary Design Optimisation, Free Form Deformation, Representation, Turbine Blade

NOMENCLATURE

f	[ds]	performance index = fitness
t_1	[-]	pressure loss = 1- P_{out}/P_{in}
t_2	[°]	difference to target outflow angle
t_3	[-]	difference to target solidity
t_4	[mm]	difference to target minimum blade thickness
t_5	[mm]	difference to target minimum trailing edge thickness
w_i	[-]	weights for the different input data $t_1, t_2, \ldots t_5$
x, y, z	[m]	global coordinate system
x', y', z'	[m]	local cylinder coordinate system

1. INTRODUCTION

In order to apply evolutionary design optimisation methods, it is necessary to generate a fully autonomous system of optimiser driven design modification, calculation and quality evaluation.

Therefore, a representation is needed which produces valid designs and as far as Computational Fluid Dynamic (CFD) is involved for a flow simulation an automatic meshing process is of high importance.

Due to the stochastic components and the use of a population of solutions evolutionary algorithms need generally a higher number of quality evaluations than e.g. gradient based optimisation algorithms. At the same time, they allow a global search, are able to overcome local optima and are robust against noise in the quality evaluations. Generally, evolutionary algorithms show a good trade-off between convergence speed and global optimisation. In the present paper, an evolutionary strategy, more precisely the special variant using the covariance matrix adaptation (CMA-ES) [1] is applied as it has shown to be able to cope with a small population size while having a high convergence speed for real valued parameter optimisation problems. Its features are explained in more detail in Section 2.

In the present paper this variant of Evolution Strategy is combined with free form deformation (FFD) techniques as a representation as it provides several advantages for the optimisation of complex systems. While more classical representations such as spline descriptions define the geometry itself, FFD uses transformation equations to manipulate a given initial geometry. FFD allows a decoupling of a complex design description from the optimisation parameters because the parameters of the deformation functions are encoded instead of the geometry itself.

Therefore, the number of parameters is determined by the shape flexibility instead of the complexity of the represented shape.

Furthermore, FFD deforms a part of the design space instead of describing the shape directly. Therefore, it allows the deformation of the shape and simultaneously of the CFD mesh, which represents the design in the CFD simulation. As a consequence, no remeshing of the design is required which normally involves human interaction for complex geometries. The concept of FFD and its impact on an evolutionary design optimisation are described in more detail in Section 3.

To illustrate the combination of FFD and evolutionary optimisation a first test scenario has been built in which a stator blade of a gas turbine is optimized. The optimisation is outlined in Section 4 & 5. We draw some conclusions in the last section.

2. EVOLUTIONARY DESIGN OPTIMISATION

Evolutionary algorithms belong to the group of stochastic optimisation algorithms. They mimic the principles of Neo-Darwinian evolution, see e.g. [2], by applying operators for reproduction, mutation and/or recombination and selection to a population of possible solutions (e.g. a vector of continuous parameters, the objective variables). Adaptation of solutions is realized by variation and by selection of the best solutions for the next generation. The variations can be classified as purely stochastic (usually called mutation) and combinatoric/ stochastic (usually called recombination or in the context of genetic algorithms crossover). Schematically, the evolutionary cycle is depicted in Figure 1, already with respect to the present turbine blade optimisation.

Examples for evolutionary algorithms are Evolution Strategies (ES), Genetic Algorithms (GA) or Genetic Programming (GP), respectively.

Among the advantages of evolutionary algorithms are robustness against noisy or discontinuous quality functions, the ability to escape from local optima and to enable global search.

In this paper, a special variant of Evolution Strategies, the Covariance Matrix Adaptation (CMA-ES), is applied which has the advantage of a high convergence rate for real-valued problems while requiring only a small population size. This is particularly advantageous for problems that require very time consuming fitness evaluations like CFD simulations. The successful application of the CMA-ES to CFD shape design has been shown previously e.g. for a two-dimensional turbine blade optimisation [4]. Mainly three features distinguish the CMA-ES from standard evolutionary strategies.

Firstly, the stochastic influence in the mutation step is reduced by introducing only one stochastic source which is used for modifying both, the object as well as the strategy parameters. Secondly, the so-called cumulative step-size adaptation is applied which extracts information from past generations to speed up and stabilize the adaptation of the strategy parameter. Thirdly, an adaptation of the full covariance matrix of the probability density vector of the normally distributed mutations takes place. Therefore, correlated mutations can be realized which can significantly increase the convergence speed of the algorithm [1], [4], [5].

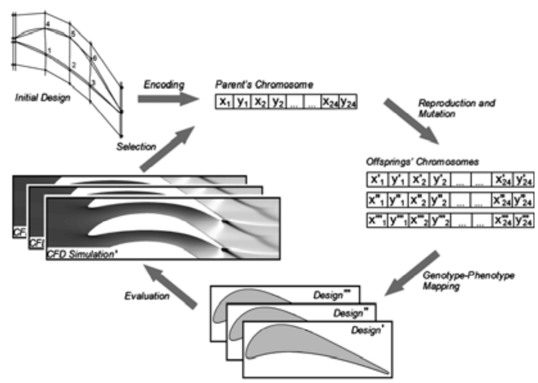

Figure 1. The generation cycle in evolutionary design optimisation [3]

3. FREE FORM DEFORMATION (FFD)

3.1. FFD in computer graphics

Free Form Deformation has been introduced initially in the field of soft object animation (SOA) in computer graphics. The special feature of FFD is that it uses transformation equations to apply modifications on a given geometry instead of a direct definition of the shape. Hence, not the geometry itself is parameterized but spline equations are formulated to realize the deformations. This is especially advantageous if the geometric description is very complex. An FFD system comprises in general a lattice of control points, the so called control volume, spline knot vectors and spline degrees. The altering of the geometry is then realized by a modification of the control points. Different FFD systems have been developed in the past three decades which differ mainly in the underlying spline functions and the shape of the control volumes.

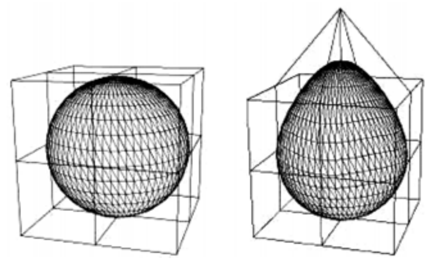

Figure 2. Free Form Deformation [6]

A basic FFD system has been introduced in the 80s by Sederberg and Parry [7]. They used trivariate Bernstein polynomials in combination with parallelepiped control volumes which enable a very efficient formulation of the transformation equations. It allows to neglect a complicated calculation of the geometry in spline parameter space which can be a costly process if e.g. B-splines are used. To achieve more flexibility Coquillart [8] extended the FFD system to arbitrarily shaped control volumes which consequently require B-splines as basis functions because of their local definitions. Additionally, more local modifications of the design are achieved which is advantageous for the object designer and for the optimisation algorithm in a design optimisation because the influence of a control point on a local region of the design is increased.

The usual workflow of such an FFD system is outlined as follows. At first a control volume has to be constructed which encloses either the whole object or the specific part of the object which is modified in the deformation step. In the second step the geometry has to be transferred into the parameter space of the control volume, a procedure which is also called “freezing”. When an object is frozen the u, v and w coordinates of the geometry in spline parameter space are calculated. This is usually done by Newton approximation which is regarded to be the fastest approach but it can also be done by similar gradient based methods [8], [9]. Finally, the object is deformed by moving a single or several control points to new positions and evaluating the spline functions to calculate the modified geometry.

3.2. FFD in evolutionary design optimisation

The choice of an adequate representation in evolutionary design optimisation depends on various requirements. It is important to keep the number of optimisation parameters as low as possible because a smaller parameter set implies usually a faster convergence of the optimisation process. In most cases this conflicts with the flexibility of the representation. An adequate and efficient representation finds a good trade-off between minimality and completeness. A second aspect is the strong causality which is frequently quoted in this context [10]. The representation defines the properties of the map from the genotype space (the object parameter space) to the phenotype space (the space of possible designs). These properties are important because they influence the structure of the search space and therefore the search process. In this context, strong causality refers to the property that similar causes (in our case small mutations on the genotype space) lead to similar effects (in our case small differences of the designs in phenotype space). Especially for evolutionary algorithms this property is meaningful since it supports the self-adaptation of the step sizes which is one reason for the high performance of Evolution Strategy for the optimization of continuous parameters.

For the present problem FFD has been chosen. Since these methods are based on transfer functions instead of defining the geometry explicitly, the optimisation parameters are decoupled from the geometric description of the design in opposite to representations based e.g. on surfaces or splines.

When dealing with a CFD or FE solver for performance evaluation there is one additional constraint on the representation. In this case in every generation for each offspring a computational grid has to be computed which is the basis for each CFD simulation. With respect to a fully automized environment this can be a very time consuming (or even impossible) process if the geometry is highly complex. FFD provides the advantage of generating the geometry and the CFD mesh simultaneously [6]. Since everything within the control volume is deformed, also the grid points of a CFD mesh are modified. Since the structure of the grid is kept, the mesh is directly available for simulation.

4. 3D TURBINE BLADE OPTIMISATION

Subject of the optimization is a turbine stator blade which is part of a gas turbine developed for the propulsion of a small business jet. An illustration of the turbine is shown in Figure 3. In order to reduce the weight of the engine only one turbine stage is used with a ultra-low-aspect-ratio (ULAR) stator with only 8 blades. The blades have been already target of design optimization. For more detailed information on the turbine functionality and on a design optimization approach using spline representation the reader is referred to [11], [12] and [13].

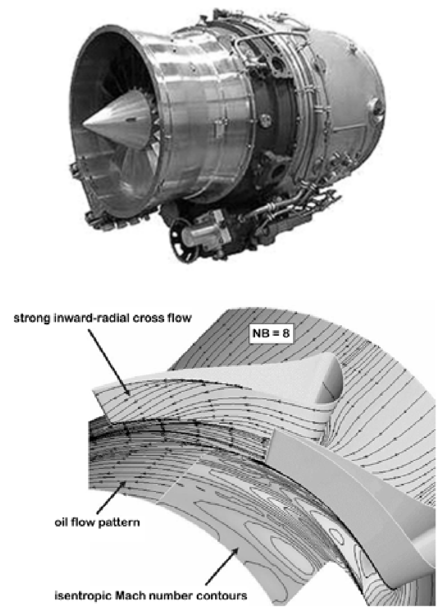

Figure 3. Gas Turbine and its fluid dynamics in one blade section [12]

In order to optimize the blade shape using FFD a lattice of control points has to be constructed in which the target geometry is embedded. Due to the rotational symmetry of the turbine only one of the eight turbine blade sections is encoded.

It is important to note that not only the blade geometry itself but the mesh necessary for the CFD simulation is deformed. Therefore, the control volume is constructed in such a way that it includes the grid which is in the passage between two blades, i.e. it spans from the suction side to the pressure side of two neighboring blades. As mentioned above, in this way the CFD mesh can be directly gained from the deformation and a remeshing is omitted. In the present example, the re-meshing costs would have not been crucial for the optimization because of the ‘simple’ structured grid consisting of parallelepiped volumes but if the grid structure is more complex containing edges and ridges the omission of a costly remeshing procedure is very advantageous.

The design evaluation of a blade consists of two steps. At first geometric constraints are tested such as blade thickness. In a second step, the flow is simulated by CFD to determine the flow characteristics.

The distribution of control points is depicted in Figure 4.

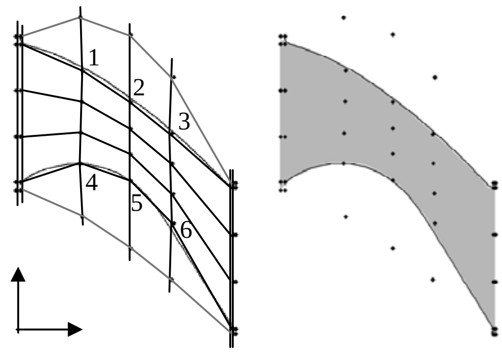

Figure 4. Blade geometry embedded in a lattice of control points [3]

Twelve control points have been taken from the lattice as optimization parameters. Six control points are on the hub section and six are on the casing section. All remaining control point positions are linear interpolated. To simplify the calculations and because of the bending of the turbine blade the global x, y and z coordinates of the design and of the knots of the CFD grid have been transferred to a local cylinder coordinate system x’, y’ and z’ which is depicted in Figure 5.

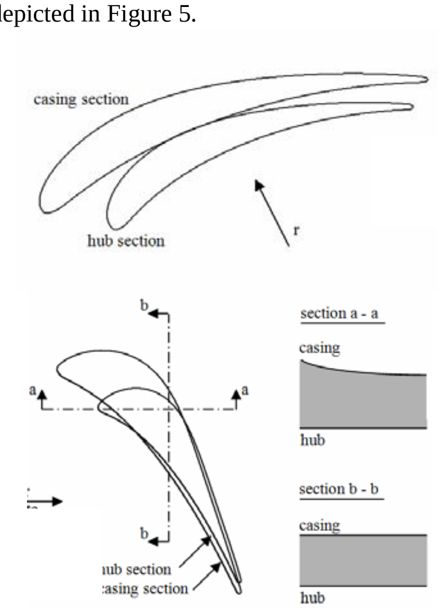

Figure 5. Transformation of global coordinate system to cylinder coordinates (a-a and b-b denote the positions of the cross sections a - a and b - b respectively)

4.1. Definition of optimisation parameter

The lattice is fully three dimensional and an example of the cross-section is depicted in Figure 6.

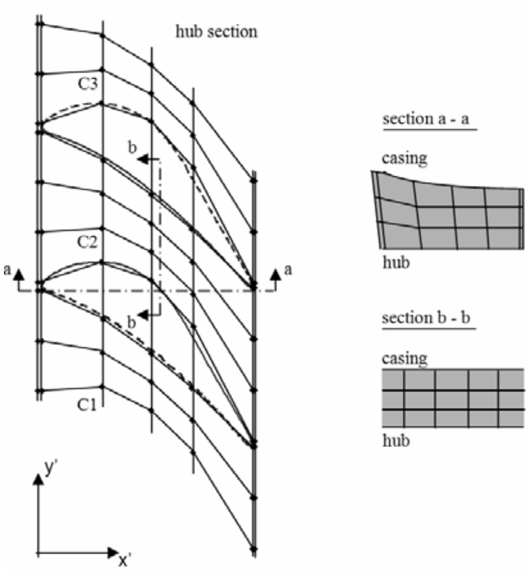

Figure 6. Illustration of the three-dimensional control volume

The continuous lines in Figure 4 and 6 illustrate the blade shape: the continuous upper line is the pressure side and the continuous lower one the suction side of two neighbouring turbine blades. The grey regions in the right part of Figure 6 mark the area of the knots and volume cells of the CFD grid. In Figure 6 two blade contours are depicted to show the position of the blades with respect to the control volume. In this test scenario, the number of optimization parameters is kept as low as possible because here the target is to demonstrate the feasibility of the representation via free form deformation. As a consequence the movements of the chosen control points effect more or less global design changes of the blade which can also be seen in Figure 8. A higher degree of local changes can easily be realized by refining the control point lattice but with all its consequences on the optimizer, e.g. the increasing number of parameters.

In local x'-direction seven control points have been set. In local y'-direction six control points are introduced. Due to the rotational symmetry of the design additional points are introduced to realize periodic boundary conditions for the splines which results in 10 control points for that direction. For a detailed description the reader is referred to [3]. In z'-direction four control points have been positioned which resulted in a total number of 7x10x4 = 280 control points.

Although all of these control points are important for freezing and deforming the geometry and the CFD mesh, only 12 points had to be considered for optimization. Six of these points are shown in Figure 6 for the hub section and another six points have been chosen analogously at the casing section. In total 24 parameters (x and y coordinates of the 12 points) have been considered in the evolutionary optimization and were encoded in the chromosome. To maximize the influence of these control points on the blade geometry they have been positioned as close as possible to the boundary layers of the blade so that the mutation of the control points provides a high impact on the design. The present optimization was motivated to analyze in how far these global design changes influence the performance.

Based on these control point settings the initial CFD grid and the blade geometry have been frozen, i.e. the coordinates of the grid knots have been calculated in spline parameter space.

4.1. Performance evaluation

The quality of each blade is evaluated using the 3D Navier-Stokes flow solver HSTAR3D [11]. The used CFD grid is restricted to 175 x 52 x 64 = 582400 cells which allowed an estimation of the quality of one generation of individuals on a cluster of 32 CPUs in a reasonable time of about five to six hours.

In each generation the parameter that are stored in the chromosome of each of the eight individual of a population are decoded and used for a transformation of the initial CFD mesh.

After deforming the initial CFD grid for all eight individuals numerical solutions for the flow patterns are calculated based on the resulting CFD grids and the overall quality is estimated based on the fitness function described in the following.

$$f = w_1 t_1 + \sum_{i=2}^{5} w_i t_i^2 \rightarrow \min \qquad (1)$$

The main optimization criterion is the minimization of the pressure loss w_1. To keep the blade geometry within feasible constraints four additional values w_2 to w_5 have been extracted from the CFD calculation and blade geometry respectively The quality of the blade are calculated according to (1). Instead of hard constraints which would exclude illegal designs the constraints define penalty terms in the formulation of the fitness function which are determined by the outflow angle, a maximum solidity, a minimum blade thickness and a trailing edge thickness. The weighting coefficients were chosen like in [12], [13].

4.1. Results of the optimisation

The course of the fitness (note: in a minimization problem like equation (1) fitness values are minimized) and the step size are depicted in Figure 7. A total number of 134 generations has been calculated resulting in an overall optimization time of approx. six weeks. In the first ten generations a (1,6)-strategy has been used but was extended to a (1,8)-strategy starting with generation

11 because of the high variance of the fitness values. Generally, a population size of 10 is recommended for the used strategy but could not be realized due to restrictions of the computational resources. The fitness value of the initial blade is about 10.69 and is marked by the dashed line in the fitness graphs.

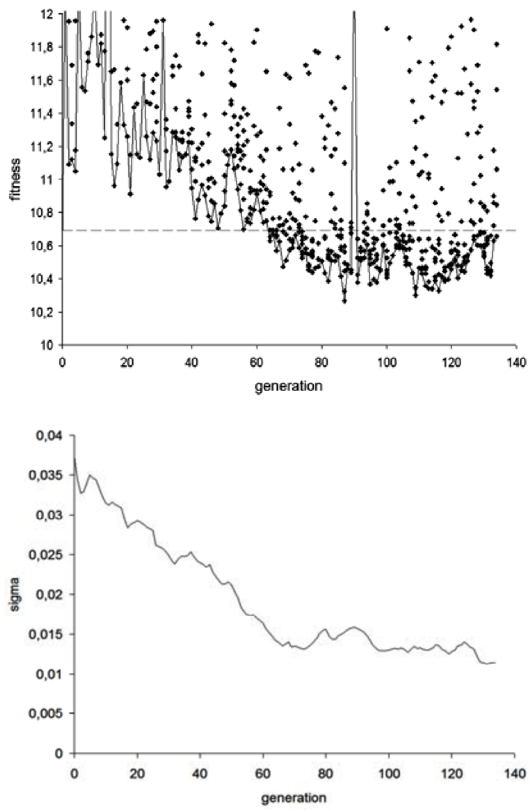

Figure 7. Result of the optimisation run. Upper figure: Fitness values of single evaluations (note: minimization problem). The best individuals in each generation are connected by a line. Lower figure: mutation step size.

It can be seen that in the beginning the fitness values of the designs are higher than that of the initial design (baseline). During the optimization the initial fitness value is recovered by generation 60. The reason is likely to be a sub-optimal choice of the initial step size. This is not a principle problem because the step size is adapted during optimization. However, it delays the convergence and basically wastes computational resources during the early stages of optimization. This is supported by the fast decrease of the step size until generation 60, thereafter it is kept nearly constant. In general the initial step size depends on the experience gathered for the problem at hand. However it can be observed that the step size adaptation in the CMA-ES algorithm finds a proper setting.

The best value of 10.27 is found in generation 87, which corresponds to a performance gain of 4%.

The initial blade and the shape of the best design of generation 87 are depicted in Figure 8 to visualize the changes which occurred.

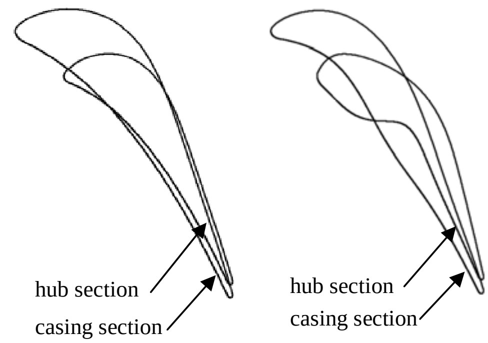

Figure 8. Initial and optimized shape of the turbine blades [3]

5. CONCLUSIONS

In the present paper the techniques of free form deformation have been combined with evolutionary design optimization. This combination is especially promising if coupled with CFD or FEM simulators for calculating the performance of the designs under realistic conditions. In contrast to a direct definition of the shape geometry, e.g. with the help of splines or spline surfaces, for free form deformation the geometry is embedded in a control volume and the shape modifications are calculated via transformation equations. Hence, for many complex systems the number of optimization parameters can be reduced drastically. The additional possibility of deforming the shape geometry and the CFD/FEM mesh simultaneously is highly advantageous because the grid structure is kept and a re-meshing procedure is avoided. The easy and successful applicability of this representation and the comfortable integration in autonomous evolutionary design optimization has been illustrated by the example of a turbine blade development.

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