STRUCTURAL OPTIMIZATION OF ADAPTIVE AIRFOILS USING EVOLUTIONARY ALGORITHMS

J. Seeger, K. Wolf
TU Dresden, Institute of Aerospace Engineering, 01067 Dresden
Germany

ABSTRACT

Adaptive structures offer a number of advantages for future aircraft. In case of airplane wings, the aerodynamic efficiency can be increased. Also, weight can be saved by using more flexible structures and controlling resulting aeroelastic problems by active members. Another example is the reduction of aerodynamic noise and vibration in helicopters by combining adaptive rotor blades with active control technology. A promising approach to realize this kind of application is to apply fibre reinforced composites with embedded actuators made from piezo-ceramic fibres. The design of such structures is a very complex task, since not only the basic structural design problem has to be solved. Additionally, optimal actuator locations have to be identified. The task to find structural configurations which combine minimum weight with maximum deflection leads to an optimization problem that has to be solved by numerical methods. The resulting problem involves a combination of discrete and continuous variables: the actuator placement task is conditioned by discrete design parameters whereas the structural problem is mainly characterized by continuous variables. In order to handle this kind of design problem the optimization code GEOpS/A has been developed, which is based on *evolutionary algorithms.* These methods are well suited for the optimization of structures that are characterized by a mix of continuous and discrete variables. The capability of the developed optimization procedure is shown by using an adaptive rotor blade section as example.

1. INTRODUCTION

Important drivers for the development of new aircraft are the need for more efficiency as well as the necessity to preserve natural resources. Furthermore, continuously increasing customer requirements regarding lower direct operating costs and improved aircraft performance play an important role. Therefore, new technologies as well as innovations in the engineering process have to be provided for future aircraft projects.

One of the evolving advanced technologies for airframes is the application of active and adaptive structures. Particularly, morphing airfoil sections in aircraft wings or helicopter rotor blades promise significant advantages compared to currently used structures. By adapting the airfoil shapes of aircraft wing sections to specific flight phases a considerable reduction of the aerodynamic drag can be achieved. In the long term even the omission of control surfaces might be possible. Regarding helicopters, rotor induced noise can be reduced by combining adaptive blades with active control technology. Also the passenger comfort can be increased by the application of active structures for vibration control. In the long term the use of adaptive blades might even lead to the omission of the swash plates which are typical for current helicopters.

The design process of adaptive structures is a very complex task. This is particularly true when laminated carbon or glass fibre composites are used as structural materials in which layers of piezo-ceramic fibres [1] are embedded as active elements. In this case two design tasks have to be solved simultaneously. The first one is to achieve a minimum weight design for the structure which has to fulfil all constraints. The second task is to find the distribution of the embedded actuators that needs the minimum of energy to produce a sufficient shape change of the structure. This coupling of problems leads to a considerably larger number of design variables compared to a classical structural design. Therefore, numerical optimization methods have to be employed in order to find appropriate solutions to this very complex task.

Optimization procedures mainly used for the placement of actuators or sensors in adaptive structures are based on *genetic algorithms* (GA). GAs are a class of optimization algorithms that use techniques similar to biological evolution and belong to the group of *evolutionary algorithms* (EA). Examples are given in the papers [2], [3] and [4], where GAs are employed to place actuators on frameworks. In [4] these stochastic methods were combined with a deterministic approach to predefine the actuator positions before starting the main optimization run. GAs also have been used for the placement of actuators made of *piezo-fibre-composites* (PFC) [5], [6] and [7].

A more complex task is to find simultaneously best solutions for the basic topology as well as the distribution of actuators. In [8] *simulated annealing* as well as *sequential linear programming* was employed to solve this task for a structural framework. The latter optimization method was also used in [9] to design an active twist rotor blade actuated by means of *macro fibre composites* (MFC). As design variables the chordwise position, length and thickness of the piezoelectric patches as well as parameters defining the geometry of the C-spar were considered. The skins of the blade were kept unchanged. The aim of the optimization approach was to get a design and placement of the active plies on the blade skins, which maximizes the amplitude of the induced static twist while preserving the dynamic properties of the passive blade.

In the present paper a new approach to optimize adaptive structures is presented. It is based on three different types of evolutionary algorithms, which are used in parallel. This permits to treat problems with complex design spaces and a large number of design variables. These variables define the topology of the structure, different materials as well as the properties and location of actuators. Known parameters are applied loads, the outer shape of the structure as well as support conditions. As an example, the method has been applied to design a 2-dimensional adaptive airfoil section, representing a rotor blade. The resulting optimization problem is described in detail and some results are given.

2. OPTIMIZATION APPROACH

2.1. Fundamentals

Structural optimization involves the task of finding the best structural design, taking into account given restrictions. In order to achieve this aim an initial design solution has to be changed. The potential for change is expressed in terms of permissible ranges of a group of design variables which form the design vector **x**:

$$\mathbf{x}=(x_1, x_2, \ldots, x_n).$$

The design variables x_i are parameters which represent the geometry and other properties of the structure. Depending on the type of problem, design parameters have to be expressed either as continuous or discrete variables. The n design variables constitute the design space Ω:

$$x_i \in D_i \subset R^1, i = 1(1)n$$
$$\Omega := D_1 \times D_2 \times \ldots \times D_n \subset R^n.$$

The aim of the optimization process is to find among all feasible design vectors **x** the one that minimizes or maximizes an objective or fitness function $f:\Omega \to R$

$$\min f(\mathbf{x}) \text{ and } \mathbf{x} \in \Omega \tag{1}$$

The design space Ω is restricted by inequality and equality constraints:

$$\mathbf{g}(\mathbf{x}) \geq \mathbf{0}, \mathbf{g}(\mathbf{x}) = (g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_m(\mathbf{x}))^T, \mathbf{g}:\Omega \to R^m$$
$$\mathbf{h}(\mathbf{x}) = \mathbf{0}, \mathbf{h}(\mathbf{x}) = (h_1(\mathbf{x}), h_2(\mathbf{x}), \ldots, h_l(\mathbf{x}))^T, \mathbf{h}:\Omega \to R^l.$$

In case of structural optimization problems typical constraints are stress and strain allowables or deformation limits. The constrained optimization problem is given by:

$$f(\mathbf{x}) \text{ and } \mathbf{x} \in \Omega, \mathbf{g}(\mathbf{x}) \geq \mathbf{0}, \mathbf{h}(\mathbf{x}) = \mathbf{0} \tag{2}$$

Regarding the constraints the whole design space Ω is divided into two disjoint sets, a feasible region Ω_f and an infeasible one Ω_{inf}:

$$\Omega_f := \{\mathbf{x} \in \Omega | \, \mathbf{g}(\mathbf{x}) \geq \mathbf{0}, \mathbf{h}(\mathbf{x}) = \mathbf{0}\} \subseteq \Omega$$
$$\Omega_{\text{inf}} := \Omega \setminus \Omega_f$$

For the problem considered here the constraints are not available in a closed form. Therefore, a penalty approach [10] is applied. A positive penalty term $P(\mathbf{g}(\mathbf{x}),\mathbf{h}(\mathbf{x}))$ is added to get the functional value of $f(\mathbf{x})$, if constrains are violated:

$$f(x) := \begin{cases} f(\mathbf{x}) & \forall \mathbf{x} \in \Omega_f \\ f(\mathbf{x}) + P(\mathbf{g}(\mathbf{x}),\mathbf{h}(\mathbf{x})) & \forall \mathbf{x} \in \Omega_{\text{inf}}. \end{cases} \tag{3}$$

2.2. Evolutionary Algorithms

Evolutionary algorithms (EA) mimic the principles of the biological evolution process. The optimization process starts with a population of different design solutions. Based on the information from these parent individuals, an offspring population is created by using a number of evolutionary operators. The selection of the better individuals leads to a progress in the optimization. The selection is based only on the computed values of the objective function. Therefore no derivative information is required. This makes it possible to find optimal solutions in discontinuous design spaces with combined discrete and continuous design variables. Although the basic principle is the same for all types of evolutionary algorithms, they differ considerably in the coding of the design variables and the way operators are working. In the presented research *genetic algorithms*, *evolution strategies* and *differential evolution* have been employed. A short description of these evolutionary algorithms is given in the following. More detailed information can be found in [11].

Genetic algorithms (GA) are based on binary coded design variables, which are combined in strings or chromosomes. These strings are modified by operators in order to find better solutions. Applying crossover, the main operator of the GA, string sections of different individuals are changed between each other as shown in the upper part of Fig. 1. Another operator is the genetic mutation. This operator swaps single bits of the binary string (see lower part of Fig. 1). That means smaller and bigger changes in the design variables depend on the location of the mutation. The newly generated design alternatives are considered in the following selection process in which the new parent population is formed. The creation of new individuals and the selection process alternate until a stop criterion terminates the optimisation run. Due to the binary-coded parameters this kind of operator is particularly well suited to discrete and combinatorial problems like the placement of actuators.

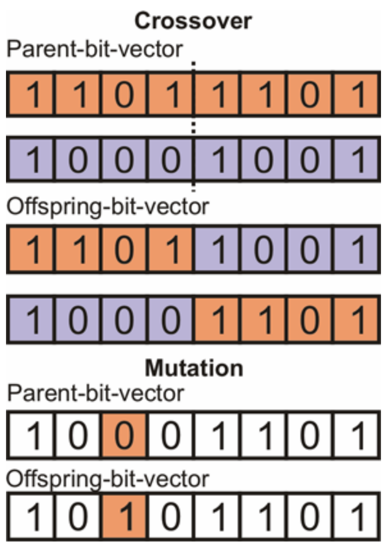

Figure 1: Crossover and mutation operator of GA

To search in design spaces with combined continuous and discrete design variables, the application of *evolution strategies* (ES) is more preferable. This method is based on real valued coding. The mutation is the most important operator of the ES. It is based on a Gaussian probability function centred at the point of the original design parameter (see Fig 2). Based on this distribution a step size is determined to create a new individual. Small step sizes are very common. Large ones are rare, but possible.

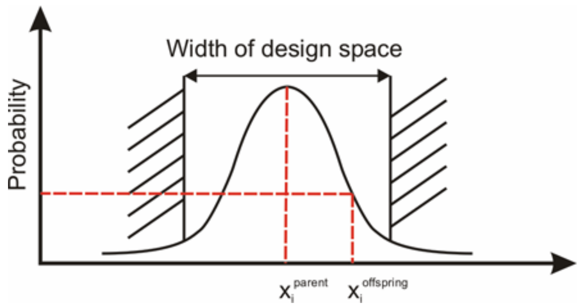

Figure 2: Mutation operator of ES

Another operator called recombination allows to exchange design information between several individuals. Different types of the recombination operator are implemented in the optimization tool. In order to generate an offspring individual, single design parameters of specific individuals are taken over or mean values are computed. For a better understanding, these facts are illustrated in Fig 3, where the creation of an offspring individual is presented. The shown individuals consist of three design variables that are modified by these two operators. Afterwards, a selection operation follows that works in the same way as with GAs.

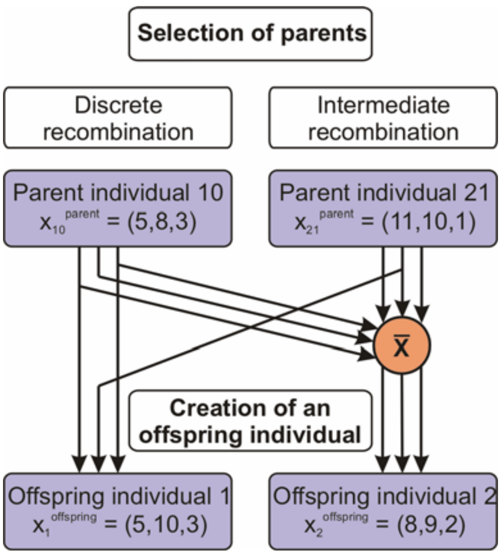

Figure 3: Discrete and intermediate recombination operator of ES

The *differential evolution* (DE) is the third type of evolutionary algorithms that have been applied in the present research. This method is closely related to the *evolution strategies*. The differential evolution is also based on real-coded design variables. The determination of the step size in the mutation process involves the computation of differential vectors between the design points of the parent individuals (see Fig. 4). An increasing homogeneity in the population causes a reduction of the step size and finally enforces a precise adjustment of the optimised individuals in the final phase of the optimisation. Thus, the DE represents an intermediate state between the stochastic algorithm types such as GA and ES and purely deterministic mathematical algorithms. Also DE uses selection operators which are different from the other two methods. The new parent population is formed by the comparison of each parent individual and its offspring. The DE is well suited for not-convex continuous problems and offers advantages for local search.

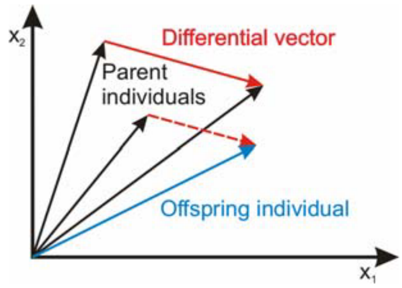

Figure 4: Generating a new individual by DE

As described in the paragraph before, all of the mentioned evolutionary algorithms have their special field of application. In order to combine the advantages of these methods all of them are implemented in the developed optimization tool named GEOpS (*Genetic and Evolutionary Optimization of Structures*). The sequence of operation of a typical optimization run is shown in Fig. 5. It is possible but not always necessary to use all algorithms in parallel. Depending on the kind of problem also a single method can be applied.

2.3. Multiobjective optimization

The design of adaptive structures results in the task of finding best solutions for the basic topology as well as for the distribution of actuators. This leads to conflicting objectives which have to be optimized simultaneously. An example is the requirement to combine minimum weight with maximum deflection. This kind of problem can be solved by employing multiobjective optimization methods.

Since it is unlikely that the same set of design variables will result in the best values for all objectives, some trade-off between the solutions is needed. The resulting weighting problem can be overcome by using the concept of *Pareto* optimality. A design vector **x** is Pareto optimal, if there exists no other feasible design vector which would decrease a objective function value without causing a simultaneous increase in at least one other criterion. This concept almost always gives not a single solution, but rather a set of solutions called the Pareto optimal set. The design vectors corresponding to the solutions included in the Pareto optimal set are called non-dominated. The plot of the objective functions whose non-dominated design vectors are in the Pareto optimal set is called the Pareto front (see Fig. 6). The solution with the shortest position vector can be regarded as the best compromise solution.

Evolutionary algorithms are particularly suitable to solve multiobjective optimization problems, because they deal simultaneously with a set of possible solutions (the population). This permits to find several members of the Pareto optimal set in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of the traditional mathematical programming techniques. Additionally, *evolutionary algorithms* are less susceptible to the shape or continuity of the Pareto front (e.g., they can easily deal with discontinuous or concave Pareto fronts), whereas these two issues are a real concern for mathematical programming techniques.

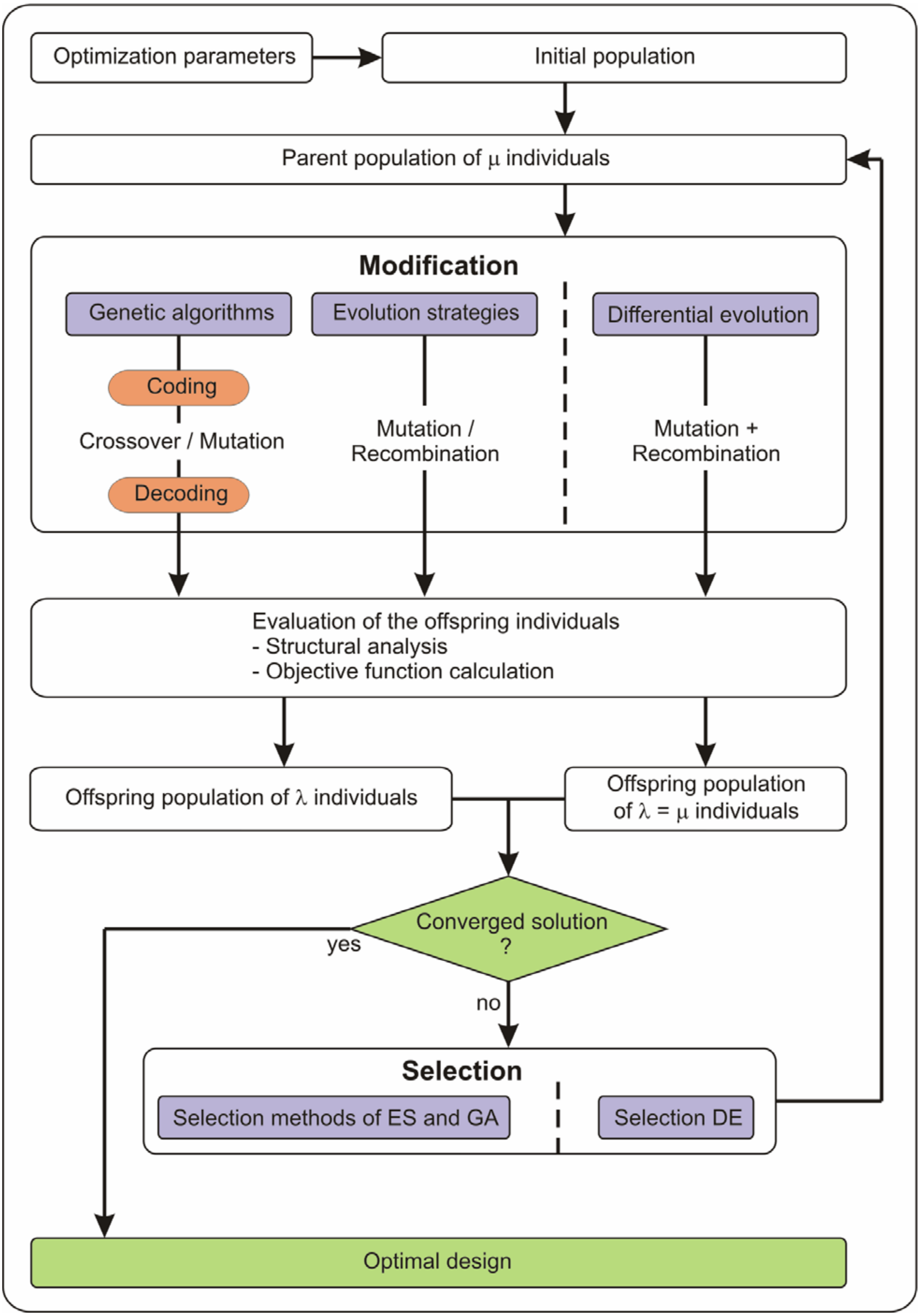

Figure 5: Flowchart of the optimization within GEOpS

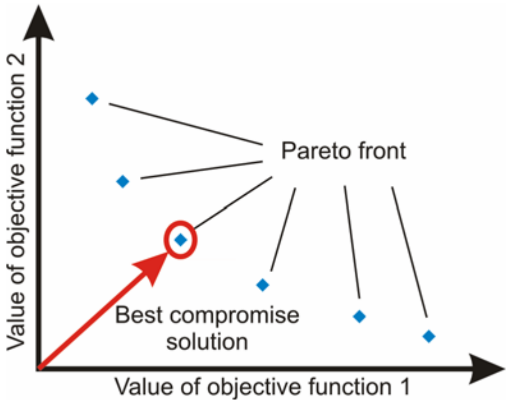

Figure 6: Schematic of a Pareto front

2.4 Parallel Computing

The application of *evolutionary algorithms* results in considerable computational effort. Therefore, means are required to speed up the optimization process. The inherent parallel structure of EAs makes them ideal candidates for parallelization. Since the algorithms work on the individuals of the population independently, it is straightforward to parallelize several aspects of the optimization procedure.

As mentioned before, it is necessary to evaluate the fitness of the individuals for an efficient selection. For more complex structural optimization problems such as adaptive airfoil sections normally finite element analysis codes are used which requires a considerable computational effort. Due to the population-based approach of EAs all newly created individuals are available at the same time. This permits to evaluate them in parallel. In GEOpS the *Message Passing Interface* (MPI) is used to execute the parallel evaluation. MPI represents a standard for parallel computation in multi-processor environments. Therefore, PC-clusters, PCs with multi-core CPUs as well as high performance computers can be employed. The example given in Fig. 7 shows the allocation of seven evaluations to three multi-core computers that are connected via *Ethernet.*

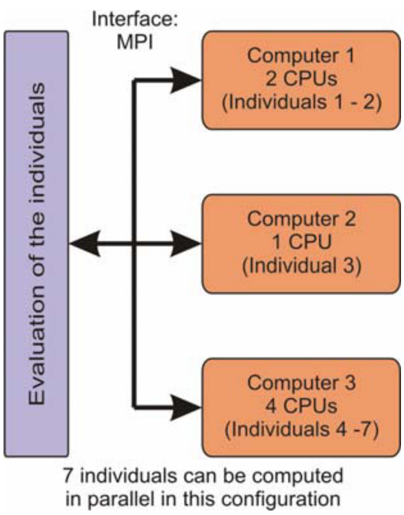

Figure 7: Parallel evaluation of individuals

2.5 Design Space Adjustment

Another way to speed up the optimization is the application of a technique called design space adjustment. In GEOpS a rather simple approach is used: the feasible region of the design space is reduced during the optimization run, depending on the parameter range of the best individuals (i.e., structural designs). An example for this method is given in Fig.8. For the vertical / inclined webs of an adaptive airfoil structure the initial design space has a range from 0 to 10. If the best individuals of the population have only 3 to 5 webs after a number of iterations, it can be assumed that the best solutions will be in this interval. Therefore, the design space can be reduced. In order to prevent a premature stagnation of the optimization a margin of safety is introduced for the new interval. In the given example an additional web is added on both sides, so that the new boundaries of the design space are 2 and 6. Hence, in further iterations only individuals with a number of webs taken from this interval will be created.

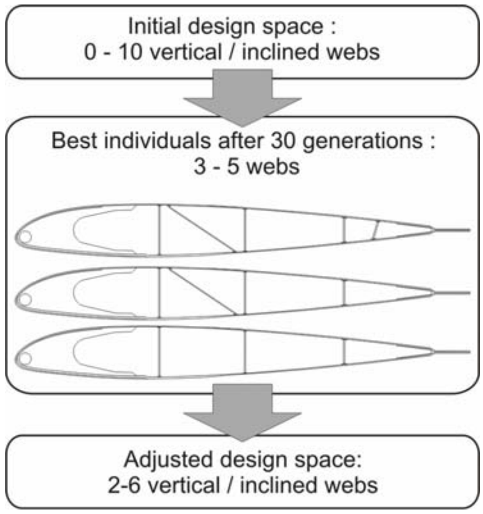

Figure 8: Adjustment of the design space

3. OPTIMIZATION PROBLEM

In the following, an example for the application of GEOpS to an adaptive structure is given. The structure chosen is an airfoil section (Fig. 9) that is typical for a rotor blade. Nevertheless, the principle approach can also be applied to the optimal design of adaptive wing sections.

The aim of the optimization was to find a minimum weight design that allows for a maximum change in airfoil camber by using state of the art piezo-fibre-composites. The design space was limited by a number of constraints. Most of them are connected to the requirement to match as close as possible specific properties of a passive reference airfoil section. This is necessary to preserve the performance of the reference blade.

3.1 Structural Concept

The basic structural elements of the airfoil section are shown in Fig. 9. The structure consists of a massive C-shaped spar, thin skins forming the outer shape and vertical, inclined and horizontal webs. The main task of the vertical and inclined webs is to support the thin skins. The horizontal as well as the inclined webs may also form mechanisms. All thin walled structural elements are made of laminated graphite/epoxy material. The massive front spar can be assumed as rigid. As a result, only the part from 25 % chord to the trailing edge is flexible. PFCs are placed only in this section. Layers of piezo-fibres can be bonded on the surface or embedded in the skin and web laminates.

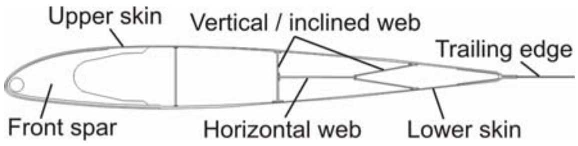

Figure 9: Main structural elements of the adaptive airfoil section

3.2 Structural model

Both a finite element model as well as an analytical model was developed for the evaluation of the adaptive airfoil section. This two-staged approach was chosen because of the complex deformation behaviour of the structure and the need to save time. The finite element analysis was used to determine the deformation and the strains. The global bending stiffness, the centre of gravity and the mass were calculated analytically.

During the optimization process basic design parameters are changed. In order to evaluate the effect of these design changes on the structural deformation a parametric finite element model is required. Thus, a parameter controlled pre-processor was developed which provides finite element meshes of 3-dimensional blade sections (Fig. 10). Skins and webs are modelled using layered shell elements, while the front spar is idealised by 10-node solid elements. The shell elements have to be able to handle laminated composite material as well as thermal loads. The latter is required to simulate the piezoelectric effect of the actuator material by using a thermal analogy. For the given example the Ansys code was used as finite element solver.

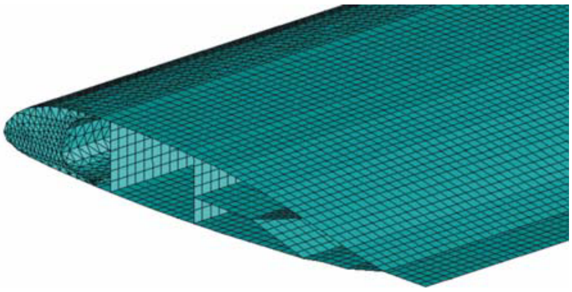

Figure 10: Finite element model of the airfoil section

In the presented study only the deformability of the cross-section was of interest. Therefore, a quasi-2D model was generated by constraining any displacement in span direction. For the underlying optimization problem the spar can be considered as rigid. Thus, only the thin walled part of the airfoil section was considered in the model (Fig. 11). Additionally, the range, where active material is usable, can be restrained. This is done by defining two airfoil stations as lower and upper limit as shown in Fig. 12.

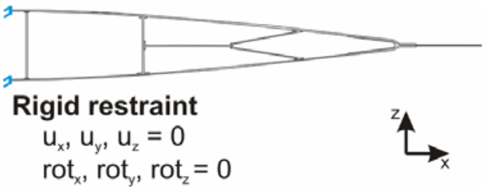

Figure 11: Constraints of the finite element model

The design space of the example is defined by a total of 225 design variables that can be changed during the optimization process. A summary of these parameters is given in Table 1. Main topology parameters are the number and positions of webs. Skins and webs are composed of unidirectional tapes or fabric made of graphite/epoxy material. The laminate lay-up schemes are variable, being constrained by the rule that the fibre orientation in the plies is restricted to 0, ±45, 90 degrees. PFC layers can be placed on the skins as well as on the web structures. For the piezo-ceramic material used a thickness of 0.31 mm, a density of 4.5 g/cm³ and a piezoelectric coefficient of 0.9E-6 mm/V were assumed. An electrical field of 1500 V/m was applied.

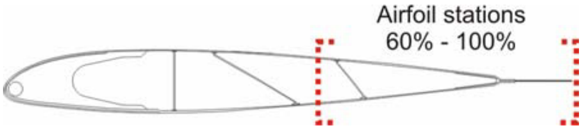

Figure 12: Schematic of airfoil stations

Table 1: Design variables used

Parameter description	Data type
Number of vertical / inclined webs	Integer
Position of vertical / inclined webs	Real
Horizontal webs	Logical
Length of trailing edge	Real
Active material of upper skin - Position of active areas on upper skin - Direction of the applied electrical field	 Real Integer
Active material of lower skin - Position of active areas on lower skin - Direction of the applied electrical field	 Real Integer
Active material of webs - Position of active areas on webs - Direction of the applied electrical field	 Real Integer
Active material of trailing edge - Direction of the applied electrical field	Integer
Laminate lay up of upper skin - Ply material - Ply angle	Integer
Laminate lay up of lower skin - Ply material - Ply angle	Integer
Laminate lay up of webs - Ply material - Ply angle	Integer

Additional to the forces introduced by the active elements air loads have to be considered. This is particularly important for the lay-out of the thin skins. In the present study a simplified approach was used to keep the computational effort limited. A static pressure distribution was applied on the surface that is representative for the basic airfoil. The two step procedure shown in Fig. 13 was used to distinguish between deformations resulting from air loads and active materials, respectively. In the first step only the air load is applied and the displacements of the structure are saved. In the second step the electrical field is added. The difference between the results of both steps yields the displacements generated by the actuators in the flow field.

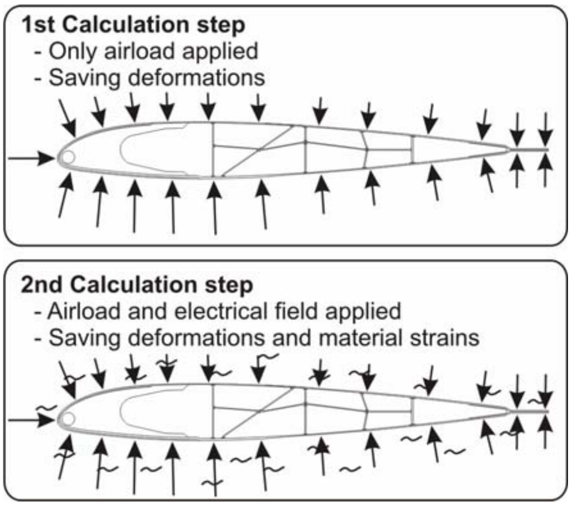

Figure 5: Schematic of load application

3.3 Objectives and constraints

In this example two objectives had to be met: to get a maximum change in airfoil camber with a minimum weight structure. Consequently, two separate objective functions were defined. To solve this problem a multiobjective optimization according to section 2.3 was applied, yielding a Pareto front as result.

The feasible design space is limited by a number of constraints which are considered as penalty factors in the objective functions (equation 3). A considerable part of the constraints were applied to match as close as possible specific properties of the airfoil section of a reference blade:

- the tension as well as the horizontal and vertical bending stiffness is limited by upper and lower bounds
- the location of the centre of gravity should be in between upper and lower limits.

Additionally, the maximum strains in the structure must not exceed the strain allowables of the materials.

Another group of constraints is related to the shape change of the airfoil. Any airfoil can be separated into its thickness distribution and a zero-thickness camber line as shown in Fig. 14. The shape of both the camber line as well as the thickness distribution in the deformed state can be defined by arbitrary functions. The type of function strongly depends on the aerodynamic effect aimed at. Both shapes are enforced in the optimization process by penalty factors. In the example presented only the camber line is considered as variable while the thickness distribution is kept constant. The shape of the deformed camber line is represented by a continuous function that allows a smooth change of curvature.

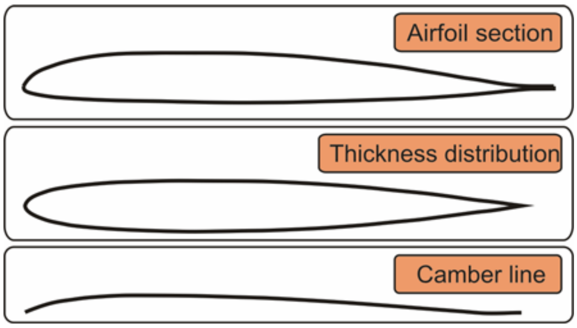

Figure 6: Separation of an airfoil section

3.4 Result

The developed optimization procedure was applied to the example structure, resulting in a set of solutions, which form a Pareto front. One Pareto optimal design taken from this set is shown in Fig. 15. Since one aim of the study was to explore the potential of piezo-ceramic fibres, the design with the maximum deflection of the camber line has been chosen.

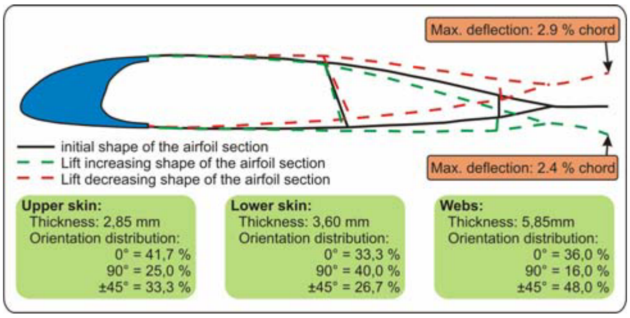

Figure 7: Design with maximum deflection

The optimization was performed with populations consisting of 60 individuals. In every 30th generation the design space was adjusted and the optimization method switched between ES/GA and the local search with DE. A total of about 1000 generations was required to get the solution. This is attributed to the huge number of design variables involved.

The obtained structural design offers a reasonable shape change for the application in a rotor blade. This is achieved by PFC layers that are arranged in pairs to form bimorph actuators (Fig. 16).

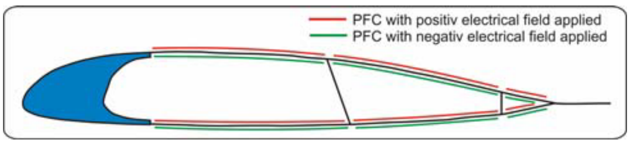

Figure 8: PFC distribution of the example

4. CONCLUSIONS

The design of efficient adaptive structures is a very complex task, because several problems have to be solved simultaneously. Thus, the intensive use of numerical simulation and optimization methods is required. In order to handle this kind of problems the optimization code GEOpS/A has been developed. It is based on evolutionary algorithms, which are well suited to solve optimization problems typical for adaptive structures. The tool has been particularly developed to combine both the design of minimum weight structures and the optimal placement of actuators.

The capabilities of the developed optimization code were evaluated through an example. An adaptive airfoil section of a rotor blade was designed based on piezo-fibre-composites as active materials. It could be shown that a reasonable change in camber could be achieved through the application of the optimization approach. This result proved that the developed optimization code is an efficient design tool for complex adaptive structures.

ACKNOWLEDGEMENTS

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