Multi Objective Airfoil Design using Single Parent Populations

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Abstract

A new approach for multi criteria design optimization is presented in the paper. The problem tackled with this approach is the 2-dimensional design of an aircraft wing. To carry the derandomized step size control operator for evolution strategies also to multi criteria applications, three different selection schemes are proposed. Two of them fail to obtain a certain quality of outcome, but the third one leads to promising results. This third selection scheme more emphasizes the diversity among individuals than the other selection schemes.

1 INTRODUCTION

Aviation in general is not only one of the most important fields in industry, but also in science. Due to the many potential savings that are possible in this area many researchers from scientific organizations as well as from industry work here on production cost minimization, flight behavior improvement, etc. This results in a considerable impact from aviation on science itself and makes it that important.

One of the most referenced applications from aviation is aircraft wing design. Due to the development of computational fluid dynamic (CFD) methods, wing design is nowadays mostly done using computers, which provide a scalable preciseness for different design tasks. Nevertheless computers are nowadays not able to offer the computational power to calculate all needful properties of a whole aircraft with the mandatory precision in a reasonable amount of time. Therefore, the aircraft is divided into logical parts that are often designed independently. After receiving good and reasonable results on the several parts, these parts are put together again.

The insufficient computational power of computers is also the reason for working with two-dimensional problems to get basic results, before changing to the three-dimensional applications.

Different methods from optimization have been carried out on the current design problem, which is presented in detail in section 2. On a simplified problem considering only one flow condition resulting a one dimensional optimization problem, evolutionary algorithms (EA) [1] have been applied very successfully. Especially the derandomized step size control mechanism for evolution strategies (ES) [2] yielded the best results here. This special mutation operator is presented in section 3.1.

To carry this operator to multi objective tasks and, moreover, use step size adaptation in multi objective applications in general, three approaches are tackled in section 4.1.

First results can be found in section 5, where also first conclusions are drawn. One of the selection schemes is recognized to be a very promising approach, that should be further investigated on other test cases.

2 AIRFOIL DESIGN TEST CASE

In the current investigation a two-dimensional airfoil design problem for viscous flow is considered. The problem described is on of the test cases from the European research project AEROSHAPE. Here, all modeling issues concerning CFD, e.g. mesh size, mesh generation, used models, pressure calculation, etc. have been fixed and two regimes of flow conditions have been chosen. These regimes vary in the flow parameter settings and a suitable airfoil as a compromise for both conditions is to be designed.

In contrast to the airfoil design problem using only one regime of flow conditions (single point), the current task requires the application of multi criteria decision making methods. Therefore, genetic algorithms as well as evolution strategies have been used in conjunction with Pareto optimization techniques. In contrast to results already presented on the current test case [3, 4], the parameterization of the airfoil using Bezier points for determining the design has been improved. Here, some x-components of these points have been involved in the optimization process in addition to the y-components of all points.

The software and technical support for the fitness function calculation was provided by the European Aeronautic Defence and Space Company – Military Aircraft (EADS-M), one of the partners in the AEROSHAPE project. The two flow conditions are calculated using different models, namely the Johnson-King model for the subsonic flow (high-lift test case) and the Johnson-Coakley model for the transonic flow (low-drag test case).

The parameter settings describing the flow conditions in use are given in table 1.

Property	Case	high lift	low drag
M_∞	[−]	0.20	0.77
Re_c	[−]	$5 \cdot 10^6$	10^7
$X_{transition}$ (upper / lower)	[c]	3% / 3%	3% / 3%
α	[°]	10.8	1.0

Table 1: Summarized design conditions (c=chord length)

For the fitness function calculation two target airfoil designs are given, one for each flow condition. The fitness function reads as follows:

$$F(\alpha_1, \alpha_2, x(s), y(s)) = \sum_{n=1}^{2} \left[W_n \int_0^1 (C_p(s) - C^n_{p,target}(s))^2 ds \right]$$

with s being the airfoil arc-length measured around the airfoil and W_n weighting factors. C_p is the pressure coefficient distribution of the current and $C^n_{p,target}$ the pressure coefficient distribution of the target airfoils, respectively.

Due to the large calculation times for the Navier-Stokes simulations, only the restricted number of 1000 fitness function evaluations, being already a lot, is allowed.

For first investigations, only one flow condition has been studied. This leads to a *normal* single dimensional test case and a reduced calculation time of about half of the calculation time for both flow conditions.

3 EVOLUTIONARY ALGORITHMS

Evolutionary Algorithms are nowadays a widely spread stochastic optimization method. They have proven their practicability and efficiency in many optimization tasks. Furthermore, EAs are build on theoretical fundamentals today, reemphasizing their appropriateness. Nevertheless detailed knowledge about parameterizing these methods accordingly is essential.

This class of algorithms is subdivided into different methods according to the representation, genetic operators and selection methods used. In the present application genetic algorithms (GA) [5] have been tested next to evolution strategies. The genetic algorithm stems from a commercial design optimization toolbox called FRONTIER[1]. The algorithms included in FRONTIER are parameterized to solve design problems in general. The user is able to change basic strategy parameters in the graphical user interface of the FRONTIER tool, to receive different performances for the problem under investigation. For GAs these parameters are

- population size,
- mutation probability, and
- recombination type

among others, which are not that influential.

The best result for the single-objective low-drag test case has been a value of $1.44 \cdot 10^{-3}$. This result was computed using the new airfoil parameterization mentioned above (compare 2) and could be improved using evolution strategies. Best results could be obtained with ES using the derandomized step size control mechanism from Ostermeier et al. [6].

3.1 DERANDOMIZED STEP SIZE CONTROL

The mechanism of derandomized step size control in evolution strategies (DES) has been proven to be very successful, particularly in industrial applications with

[1]FRONTIER, the Open System for Collaborative Design Optimization using Pareto Frontiers, is a product of ES.TEC.O, a branch of ENGIN SOFT, Tecnologie per l'Ottimizzazione, AREA Science Park, Padriciano 99, 34012 Trieste, Italy (www.enginsoft.it/frontier).

only a restricted number of fitness function evaluations.

In contrast to the standard step size adaptation technique from ES, the derandomized mutational step size control accumulates information about the selected individual's mutation vector $\vec{z}$ over the course of evolution by adding up the successful mutations. The authors claim that the method enables a reliable adaptation of individual step sizes (i.e., n different standard deviations σ_i) even in small populations, namely, in (1,λ)-strategies with $\lambda = 10$ in the experiments reported. The proposed method utilizes a vector $\vec{z}^g$ of accumulated mutations as well as individual step sizes σ_i and a global step size σ according to [6]:

$$\vec{z}^g = (1-c)\vec{z}^{g-1} + c\vec{z}^* \ , \ \vec{z}^0 = \vec{0} \qquad (1)$$

$$\sigma' = \sigma \cdot \left(\exp \left(\frac{|\vec{z}^g|}{\sqrt{n}\sqrt{\frac{c}{2-c}}} - 1 + \frac{1}{5n} \right) \right)^{\beta} \qquad (2)$$

$$\sigma'_i = \sigma_i \cdot \left(\frac{|z_i^g|}{\sqrt{\frac{c}{2-c}}} + 0.35 \right)^{\beta'} \qquad (3)$$

$$x'_i = x_i^* + \sigma' \cdot \sigma'_i \cdot N_i(0,1) \qquad (4)$$

Essentially, equation (1) captures the history of successful mutations by a weighted sum of the mutations selected in preceding generations (i.e., $\vec{z}^{g-1}$) and the mutation vector $\vec{z}^*$ of the selected parent individual (notice that the method applies to (1,λ)-strategies, i.e., $\vec{z}^*$ is the mutation vector of the single best offspring individual produced in generation $g-1$). The vector $\vec{z}^g$ is then used to update both a global step size σ and individual step sizes σ_i according to equations (2) and (3).

Equation (4) then denotes the generation of offspring individuals from the single parent (with components x_i^*) in a way similar to the standard ES mutation mechanism using σ' and σ'_i. Concerning the choice of the new learning rates c, β, and β', both theoretical and empirical arguments are given in [6] for the settings $c = 1/\sqrt{n}$, $\beta = 1/\sqrt{n}$, $\beta' = 1/n$.

Figure 1 shows 4 runs of $(1+10)$-ES using this kind of step size control after the change of the airfoil parameterization already mentioned in section 2 (compare [3, 4]). The best solution so far could be improved in all 4 runs. This shows, that the derandomized step size control mechanism is a very successful method for the given application. Therefore, the usage of this method should also be continued or at least tried on the multi objective test case.

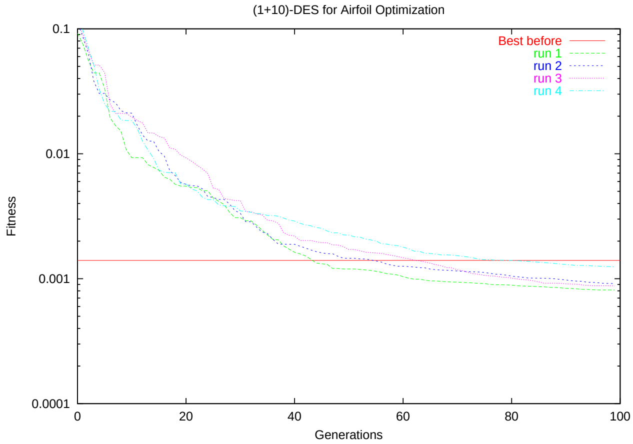

Figure 1: 4 runs of a $(1+\lambda)$-DES in comparison to the best result so far (horizontal line)

4 MULTI OBJECTIVE EVOLUTIONARY ALGORITHMS

Due to their population-based approach, EAs are very promising methods if more than one value to describe the quality of an individual is required. The first overview on multi criteria decision making using EAs was given by Fonseca and Fleming in 1995 [7]. In the following text, their definitions concerning dominance, Pareto-optimality, Pareto-sets, and -fronts are used. The term *Pareto-front* is additionally defined as the set of non-dominated individuals.

Next to the definition of Pareto-dominance etc. an archive to store the individuals, e.g. non-dominated ones, over a number of generations plays another important role in Multi Objective Evolutionary Algorithms (MOEAs). This archive gives the algorithm the chance to compare current solutions to older non-dominated ones and select these older individuals, if the chosen selection mechanism does not find a better one in the current population. Roughly, this archive implements a kind of plus strategy from evolution strategies nomenclature, taking not only the current offspring population into account for the selection step, but also individuals from preceding generations. In the case of using archives, not only parents are taken into account, but all individuals from the whole history of the current evolution process qualified for the incorporation in the archive, e.g. by being non-dominated.

Problems that arise from using archives are the number of individuals stored in this archive. Here, new methods for selecting individuals to be stored and also to be deleted from the archive are in discussion [8]. Another problem arises when using step size adaptation. Falling back to older individuals from the archive could lead to replacing good step sizes in the current individuals and moreover to forget useful information gained from the evolution process. This is the main reason, why there normally is no step size adaptation in MOEAs.

Our approach to deal with the airfoil optimization problem therefore does not use an archive. No information, except for the parent individual is carried on into the next generation.

4.1 SINGLE PARENT MULTI OBJECTIVE DES

Since the single objective version of the DES approach has been successfully applied to the single point airfoil design problem, a transformation using this approach for multi-objective design seemed quite natural. Therefore, a lot of different subjectives have to be taken into account, especially:

- One single parent has to be chosen from a population respecting all different and sometimes conflicting fitness function values.
- The strategy must not focus in approaching one single global optimum but the whole Pareto-front of non-dominated individuals.

Selecting one individual from a set of individuals each having more than one fitness function value is in the end only a special case of selecting a new population in MOEAs. The first step in the selection scheme is almost clear, if the Pareto concepts are applied. If there is one and only one non-dominated individual, select this one for becoming the parent of the next generation.

If there is not only one non-dominated individual in the population, there must be more than one non-dominated individuals. Due to some logical considerations the case that there is no non-dominated individual is not possible.

For the case with more than one non-dominated individuals, further approaches are possible. One possibility, which was tried in the current investigations, is to choose the individual, which dominates most of the other ones. Another selection scheme would be to select the individual next to the origin of the fitness function space, the global optimum for both fitness function values in this special redesign test case. In fact this global optimum remains unreachable if different target airfoils are considered. Another scheme tested is the selection of the individual with the greatest distance to the other individuals in the fitness function space. Again, different strategies can be applied here: comparing the fitness to all other individuals or to the individuals on the same level, e.g. all non-dominated individuals, all individuals dominating the same number of other individuals and so on.

Up to now all the formulations and specifications for the new method of multi objective DES hold for two cases: A comma strategy as well as the elitist plus strategy. Due to hard restrictions concerning the allowed number of fitness function evaluations, the elitist (1+10)-DES is used. Combined with the choice of this selection scheme is the hope, that it performs better than the comma strategy, because only improvements with respect to the selection mechanism in use are possible.

One drawback of the applied techniques is that the sum of different fitness function values can become worse in following generations. This might happen, if one non-dominated individual is selected due to other selection schemes, e.g. the distance to the other non-dominated individuals.

In the current investigation, the following selection schemes have been compared:

Scheme 1: If more than one non-dominated individual is in the population, the number of individuals dominated is taken into account. If there is one individual with a maximum number of dominated individuals, this one is chosen to become the parent of the next generation. If there are more than one with the same maximum number of individuals dominated, the distance to the origin of the fitness function space is taken into account. In this special case, the individual with the smallest distance to the origin, which is the global optimum due to fitness function formulation, is selected to become the parent of the next generation.

Scheme 2: This selection scheme is similar to Scheme 1 presented above, but instead of the distance to the origin, the distance to other individuals from the population has been taken into account. More precisely, the individuals with the same number of dominated individuals are compared to each other. Therefore the distance of one individual to the other ones is calculated and added. The one with the greatest sum, thus the one with the greatest sum of distances to the other individuals, is selected and becomes the parent of the next generation.

Scheme 3: In the third selection scheme investigated here, the second criteria from scheme 2, the number of individuals dominated, is omitted. If more than one non-dominated individual is in the population, the one with the greatest distance among all non-dominated solutions is selected to become the parent of the next generation. Therefore, the distance of each non-dominated individual to the other ones is calculated and added similarly as in selection scheme 2.

5 RESULTS

For each of the presented selection schemes, different optimization runs have been performed. Each of these runs can be compared to one another by the results achieved. Most important for the comparison of results is the obtained Pareto-front.

Prior to these ES results, figure 2 presents the geometry obtained with the multi objective GA in the FRONTIER tool. The thick solid line denotes the best engineering geometry. The symbols present the Bezier control points by which this airfoil geometry is achieved. It can be well recognized, that the resulting geometry is a compromise between the two target (subsonic and transonic) geometries (narrow lines shown in figure 2).

Figure 2: Airfoil geometry (thick) and two target airfoils (thin)

Additionally, figure 3 exhibits the pressure distribution obtained for the best airfoil in subsonic and transonic flow. Again, the results indicate a compromise between both targets and, furthermore, that the optimized shape tends to come closer to the subsonic shape in the front part of the airfoil and follows better the transonic shape in the rear part.

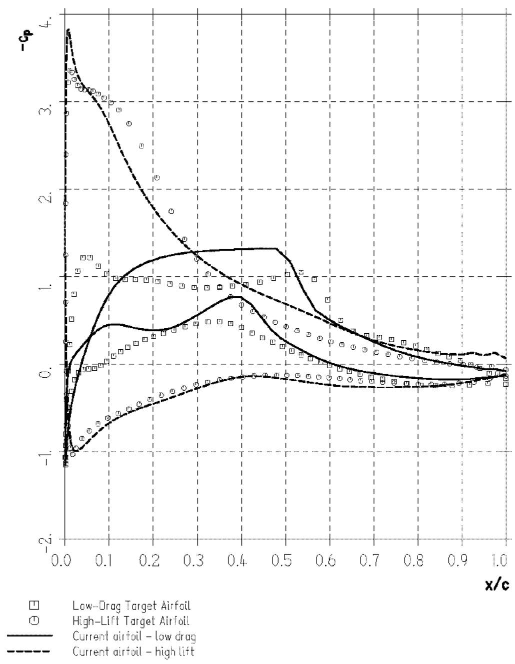

Figure 3: Pressure distributions on upper an lower surface from the airfoil design in figure 2 (lines) and two target airfoils (dots)

In addition to the Pareto-front, conclusions can be drawn from the typical fitness over generations plots. Different curves can be investigated like the fitness of each objective against the generation number or the sum of both objectives against the generation number. But this will not be done here. Instead, the path of the parent individual in the fitness function space is observed as another method for comparison.

5.1 DIFFERENT SELECTION SCHEMES

Comparing the different selection schemes presented in this paper, the Pareto-fronts show the most obvious and remarkable results. A typical Pareto-front obtained by selection scheme 1 is presented in figure 4. Here, as well as in the following figures of the same type all 1000 individuals of one optimization run are presented and the Pareto-front members are marked more dark. The search focuses on the path to the origin of the fitness function space. This behavior can also be observed in the way of the parent individual in the fitness function space drawn in figure 5. It is expected that this behavior originates from the third selection step, taking this distance to the origin of the fitness function space into consideration.

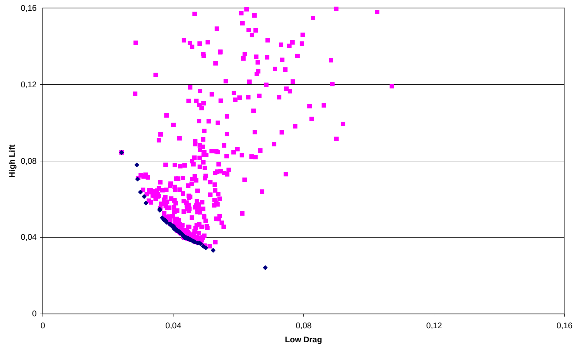

Figure 4: Pareto-front, selection scheme 1

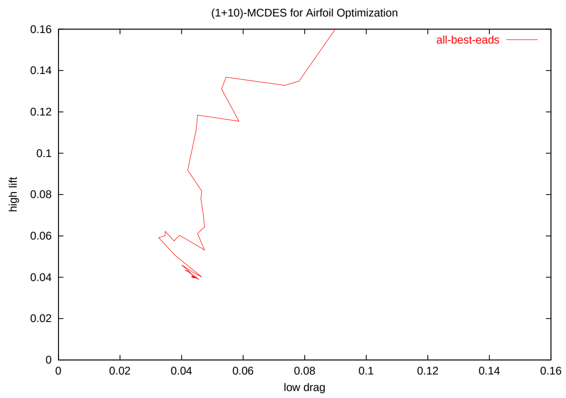

Figure 5: Path of parent individual, selection scheme 1

Surprisingly, the behavior does not change significantly, if the third selection step is changed. In figure 6 the Pareto-front obtained by a typical run using selection scheme 2 is shown. The same behavior like before, the focus of the search towards the origin of the fitness function space, can be observed. This behavior changes not until the second selection step, selection considering the number of dominated solutions, is omitted from the selection procedure.

5.2 SELECTION SCHEME 3

Figure 7 presents a typical Pareto-front from a run using selection scheme 3. The Pareto-front is covered satisfactorily, showing a wide range of different alternative solutions. This gives the user the possibility to compare many alternative solutions featuring different

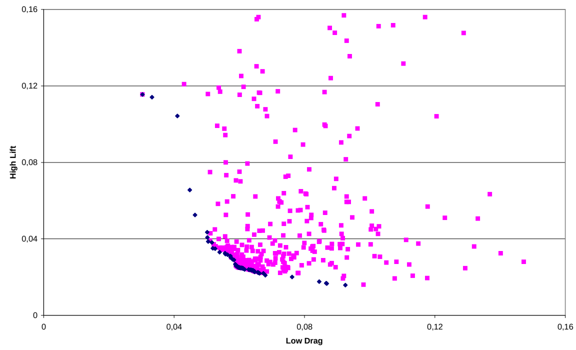

Figure 6: Pareto-front, selection scheme 2

design aspects.

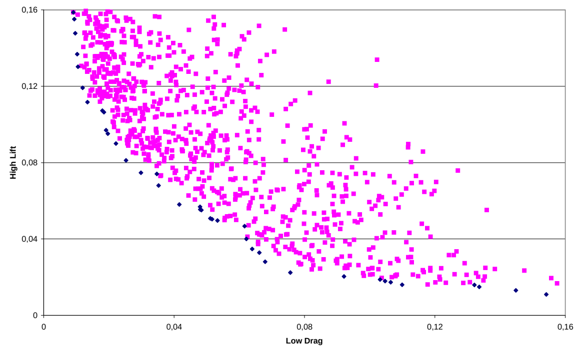

Figure 7: Pareto-front, selection scheme 3

Furthermore, even the extreme specifications of the fitness function space are explored, where the solutions focus on only one objective. This behavior may be of special interest, if one objective plays an accentuated role among the others.

It should be emphasized again, that all results have been obtained within the small number of 1000 fitness function evaluations. This is small in comparison to other MOEAs on similar problems (compare to Obayashi [9] or Quagliarella et al. [10]) and especially compared to authors working on theoretical test function, usually using more than 10000 fitness function evaluations [11, 12].

In the following, the Pareto-front from figure 7 is compared to another one obtained using selection scheme 3. This one is presented in figure 8. Here, a focus towards the low-drag area of the fitness function space can be observed next to yielding a similar distributed Pareto-front. In contrast to this run focusing more on the low-drag area, an emphasis on the high-lift area can be detected in figure 7.

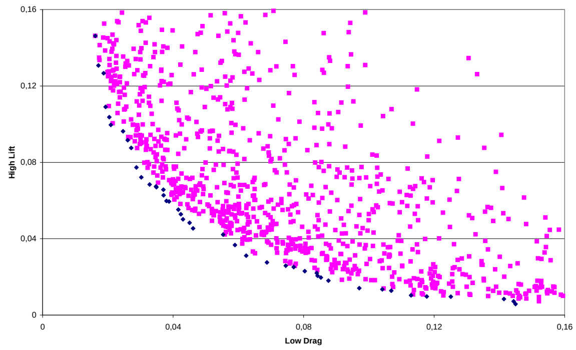

Figure 8: Pareto-front, selection scheme 3, further run

For further investigations, the path of the parent individual in the fitness function space is considered. The path of the parent individual from the run presented in figure 7 using selection scheme 3 is presented in figure 9. It can be directly compared to the path of the parent individual obtained using selection scheme 1 from figure 5. It can be observed, that the path of the parent individual in figure 9 is much more distributed in the fitness function space. In conjunction with the selection pressure this distribution is moved towards the Pareto-front. The result is, that a much larger part of the Pareto-front is covered here.

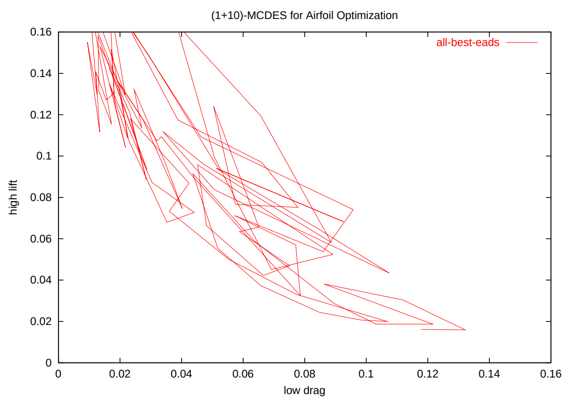

Figure 9: Path of parent individual, selection scheme 3

In figure 10 the path of the parent individual from the run presented in figure 8 is shown. The distribution of the Pareto-front is as wide as in figure 9 sharing the same selection scheme. This shows the reliability of the method used. Otherwise, some differences between the runs can be observed again. This kind of plots emphasizes the preferred search direction. While figure 9 focuses much more on the high-lift quality of the airfoil, figure 10 more tends towards the low-drag part. It can be observed, that this preferred search directions are more driven towards the absolute minimum, the target airfoil respectively. This results in a shorter distance to the corresponding axes. Based on this results, it can be assumed, that more fitness function evaluations would lead to better results, driving both qualities of the airfoil to much better solutions.

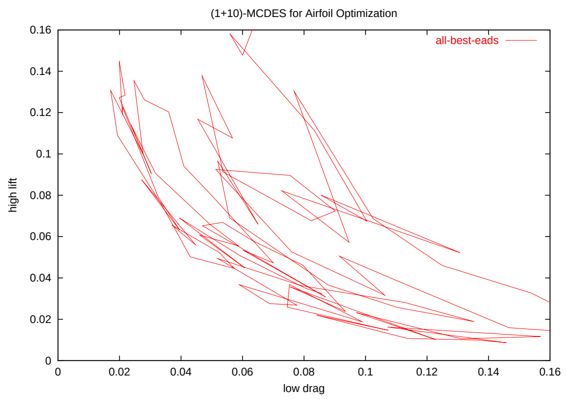

Figure 10: Path of parent individual, selection scheme 3, further run

6 CONCLUSIONS

Three different selections schemes have been presented, each able to select exactly one individual from a set of candidates using a multi objective fitness function. This was necessary for carrying the derandomized step size control mechanism from single point airfoil design, where it was applied very successfully, to multi point the design case.

Two of the presented selection schemes lead to insufficient results, not yielding Pareto-fronts of an expected quality, e.g. distribution over the fitness function space. This was due to considering the number of individuals dominated for the selection scheme and therefore focusing too much on Pareto techniques instead of the diversity of individuals.

Much better results could be obtained by focusing more on the distribution of individuals in the selection scheme, omitting the part considering dominated individuals in between. Using the new selection scheme 3 different results of comparable qualities can be obtained focusing on different regions of the fitness function space. The high quality Pareto-fronts have been computed within the very small number of 1000 fitness function evaluations and much better solutions, focusing on more regions of the fitness function space can be assumed from more fitness function evaluations.

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