Sequential parameter optimisation of evolutionary algorithms for airfoil design

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ABSTRACT

More and more complex optimisation techniques play an increasing role in todays industry. Different techniques like gradient based methods or evolutionary search techniques are coupled (hybridisation, memetic algorithms [1]), enhanced by methods to fasten objective function evaluations (fitness approximation, metamodel assisted optimisation[2, 3]), or applied to more complex tasks with more than one objective function (multi-objective optimisation [4, 5]). Each of these enhanced techniques is able to improve optimisation results. Utilising not only one of them promises to further meliorate results, what is pushed by industrial needs.

The drawback of such highly sophisticated methods and techniques is the growing number of parameters. Due to possible complex interactions, these parameters must by handled with care. A wrong parameter setting may lead to unwanted and bad optimisation results while the right parameter setting for the same algorithm-application combination may lead to extremely good results. This means, that the setting of parameters plays a major role in design optimisation.

This article describes the sequential parameter optimization (SPO) framework [6, 7]. SPO has been succesfully applied to optimisation problems in the following domains: Machine engineering, Aerospace industry, Elevator group control, Algorithm engineering, Graph drawing, Algorithmic chemistry, Technical Thermodynamics, Agri-environmental policy-switchings, vehicle routing, and bioinformatics.

Experimental setup

The new technique to optimise parameter settings it applied to evolutionary (multi-objective) optimisation algorithms on airfoil design optimisation tasks. First, an older two-dimensional NACA-redesign testcase from some European research project is considered. It is described in more detail by Naujoks et.al. [8]. The hypervolume or $\mathcal{S}$-metric is computed to measure the quality of the received Pareto-fronts. This quality indicator measures the covered space of the Pareto-front related to a reference point that is dominated by all solutions of the computed optimisation runs.

The $\mathcal{S}$-metric was incorporated for selection in recently presented EMO algorithms, e.g., the $\mathcal{S}$-Metric Selection EMOA (SMA-EMOA)[9]. This algorithm features a $(\mu + 1)$-selection scheme, where variation operators generate one new individual and the individual providing the least contribution to the hypervolume of the worst ranked front of the population is discarded in each generation. Obviously, the population size μ the variation operator are crucial parameters of the methods that are analysed here. The variation operators incorporated in the analysis are:

- SBX crossover and polynomial mutation proposed by Deb [4] for multi-objective optimisation tasks (abbreviated “Deb” as well) and
- Discrete and intermediate recombination on object parameters and step sizes, respectively as well as mutation featuring n (number of object parameters) step sizes like commonly used in evolution strategies [10] (abbreviated “ES” accordingly).

For the accomplished analysis, we consider an optimisation run as an experiment. Tools from statistical design and analysis of experiments can be applied to perform and analyse optimisation runs. SPO combines methods from classical Design of Experiments (DOE) and modern approaches such as Classification and Regression Trees (CART) and Design and Analysis of Computer Experiments (DACE). Bartz-Beielstein [7] provides a comprehensive introduction. An SPO-toolbox is freely available (http://ls11-www.cs.uni-dortmund.de/people/tom/ExperimentalResearch.html).

Sequential parameter optimisation tries to discover interesting features in the data. A closer look at the data is already sufficient in many situations, no high-level statistics are necessary if the data are ”well-prepared.” We discuss some ”datascopes” from EDA (explorative data analysis) first. EDA tools are useful to screen out worse configurations. High-level tools, which rely on complex regression models, can be used in the second phase. Here we can mention DACE stochastic process models.

Results

Our example is based on a low-dimensional data set: only 27 data points are available (because the optimisation problem is computationally very demanding). The experimental data for our analysis are a mixture of qualitative and quantitative factors: “ES” and “Deb” are qualitative, whereas the “population size” is qualitative. The algorithm design from table 1 has been used for the first experiments.

In addition to (non)parametric statistical tests that have been used to analyze the effect of various parameter settings, we have chosen trellis plots. Trellis plots depict the relationship between different factors through conditioning. They show how plots of two factors change with variations in a third, the so called conditioning factor. Trellis plots consist of a series of panels where each panel represents a subset of the complete data divided into subintervals of the conditioning variable. The data points have been divided into four intervals I_1–I_4 due to their “population size” values (Fig. 1): $I_1 = [7.5, 12.5]$ with 11 data points, $I_2 = [7.5, 17.5]$ with 16 data points, $I_3 = [12.5, 22.5]$ with 16 data points, and $I_4 = [17.5, 22.5]$ with 11 data points.

Fig. 1 indicates that ES performs significantly better than Deb. The trellis plots show that this effect occurs independently from the settings of the “population size”, i.e., there is no interaction between these factors.

The second step of our analysis considers the ES operator only. We are interested in the influence of the population size on the performance, i.e., “Are larger population sizes better?” A stochastic process model was used to generate data shown in Fig. 2.

Summarizing, the experiments indicate that ES variation and relatively small population sizes are beneficial for this problem instance. However, further analyses are necessary, e.g., to verify that these results occur independently from the chosen performance measure.

Design	Popsize	Variation
d1	{10,15,20}	{Deb, ES}

Table 1: *EA algorithm designs to optimise the NACA-redesign testcase.*

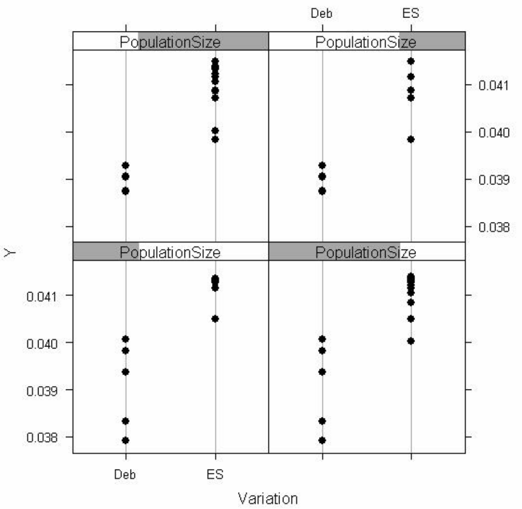

Figure 1: *Trellis plots. Algorithm's performance measured as hypervolume Y. These figures support the assumption that ES outperforms Deb variation significantly. Note, larger hypervolume values (Y)are better in this graph*

Discussion

This small example demonstrates the high potential of the SPO aproach. Classical and modern tools from statistic are to be combined. DOE and EDA methods are useful to screen out wrong factor settings. They can handle qualitative and quantitative factors. The DACE approach is useful for relatively few quantitative factors and should be used in a second step. SPO includes tools to predict promising design points for further experiments, so that the algorithms can be tuned sequentially (to keep the number of algorithms runs low).

From our experience it is beneficial to tune algorithms before the experiments are performed. We observed a reduction in the number of function evaluations with SPO by a factor of ten or more in many situations. That is, the same result could be obtained with, e.g. 1000 instead of 10,000 function evaluations.

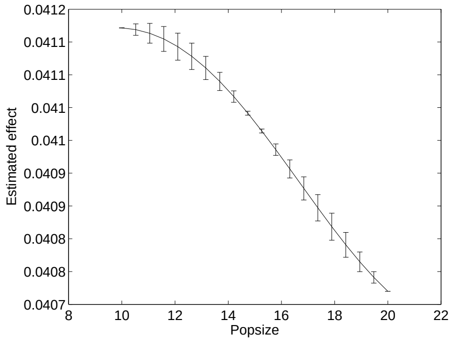

Figure 2: *Effects in the DACE stochastic process model. This graph depicts the effect of the population size on the performance of the algorithm (hypervolume) with confidence intervals. Only results from the ES variant are shown, because the screening procedure showed that it outperforms the Deb operator significantly. The results indicate that smaller population sizes are advantageous*

Outlook

The full paper will provide the aforementioned analysis with high-level DACE tools next to more studies in airfoil design applications. Here, a different application will be presented that is solved using two modelling techniques. A rather coarse technique using xfoil will be compared with a more precise one using a Navier-Stokes solver. This will lead to preliminary results indicating whether optimisation parameters have to be changed, if the modelling technique on a design optimisation task is changed or a more precise modelling technique is worth the more expense with respect to calculation power.

Moreover, all techniques that are only described roughly here, are explained in more detail. This implies evolutionary optimisation techniques as well as the sequential parameter optimisation methods.

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