Sequential Parameter Optimization
An Annotated Bibliography

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Abstract

This report collects more than one hundred publications related to the sequential parameter optimization, which was developed by Thomas Bartz-Beielstein, Christian Lasarczyk, and Mike Preuss over the last years. Sequential parameter optimization can be described as a tuning algorithm with the following properties: (i) Use the available budget (e.g., simulator runs, number of function evaluations) sequentially, i.e., use information from the exploration of the search space to guide the search by building one or several meta models. Choose new design points based on predictions from the meta model(s). Refine the meta model(s)) stepwise to improve knowledge about the search space. (ii) Try to cope with noise by improving confidence. Guarantee comparable confidence for search points. (iii) Collect information to learn from this tuning process, e.g., apply explorative data analysis. (iv) Provide mechanisms both for interactive and automated tuning.

Contents

1 Introduction

Research related to *sequential parameter optimization* was inspired by discussions with students at the chair of systems analysis at Technical University Dortmund in 2000. *Christian Feist* gave inspiration to re-think existing ways of presenting results from experimental studies in *evolutionary computation* (EC). These discussions resulted in first publications which used *design of experiment* (DOE) as standard techniques to compare algorithms. [61]. The open minded atmosphere at the *chair of systems anaylysis* accelerated the development of new approaches. *Hans-Paul Schwefel*'s library was a treasure chest: *Jack Kleijnen*'s famous “Statistics for simulation practitioneers”, which was out of print at this time, could be found there besides many other books on statistics and simulation.
Due to the increased computational power, *computational statistics* gained more and more importance, so it was an obvious step to combine classical DOE methods with modern approaches such as *regression trees* [115].
First practical applications of these methods were done in the field of simulation, especially simulation and optimization of an elevator group control. This work was done together with *Sandor Markon* from Fujitec Ltd. [63] and *Claus-Peter Ewald* from NuTech Solutions. [62]
In 2004, the time was ripe to present a first tutorial on experimental research in evolutionary computation [145]. Positive feedback from this tutorial motivated further research in this area. We thank *Gwenn Volkert*, *Jürgen Branke*, *Mark Wineberg*, and *Steffen Christensen* for promoting the idea of experimental research during the leading conferences in evolutionary computation. Several tutorials and workshops were presented since then, e.g., [146], [147],[148],[149],[150], [152].
Combining DOE with *design and analysis of computer experiments* (DACE), which was devoloped for deterministic procedures, requires special techniques to tackle randomness which occurs in many algorithms from evolutionary computation. First results were published with *Konstantinos E. Parsopoulos* and *Michael N. Vrahatis* [56, 37].
The term “sequential parameter optimization” was born during a discussion with *Mike Preuss* and *Christian Lasarczyk*. The basic ideas of this approach can be described as follows:

1. Use the available budget (e.g., simulator runs, number of function evaluations) sequentially, i.e., use information from the exploration of the search space to guide the search by building one or several meta models. Choose new design points based on predictions from the meta model(s). Refine the meta model(s)) stepwise to improve knowledge about the search space.

2. Try to cope with noise by improving confidence. Guarantee comparable confidence for search points.

3. Collect information to learn from this tuning process, e.g., apply explorative data analysis.

4. Provide mechanisms both for interactive and automated tuning.

The article entitled "sequential parameter optimization" [53] was the first attempt to summarize results from tutorials and make this approach known to and available for a broader audience.
Sequential parameter optimization was not discussed in the computer science community only, there is an interesting link to the philosophy of science community: SPO was presented during the *First Symposium on Philosophy, History, and Methodology of Error* (Experimental Reasoning, Reliability, Objectivity & Rationality: Induction, Statistics, Modelling) [140], which was organized by *Deborah Mayo*.
This article is organized as follows: Section 2 describes practical applications of the sequential parameter optimization. Section 3 mentions applications from theory.
The references collects all kind of publications which mention SPO (both active and passive SPO references), i.e., publications which describe applications and use SPO actively to produce new results—in contrast to publications which mention SPO only (passively).
Note, that we do not claim that SPO is the only suitable way for tuning algorithms. Far from it! We state that SPO presents only one possible way—which is possibly not the best for your specific problem. We highly recommend other approaches in this field, namely F-race [5] and REVAC [14].

2 Practical Applications

2.1 Bioinformatics

2.1.1 Hidden Markov models

Gwenn Volkert (Department of Computer Science, Kent State University) discusses results from a sequential parameter optimization approach for investigating the effectiveness of using EAs for training Hidden Markov models. She conludes that "this approach not only offers the possibility for improving the effectiveness of the EA but will also provide much needed insight into directions for future improvements in the design of EAs for the construction of HMMs in general."[105]
Martina Vaupel [25] applied SPO to an EA, which was used for tuning hidden Markov models.

2.1.2 Structural analysis of biomolecules

Thomas Fober, *Eyke Hüllermeier*, and *Marco Mernberger* (Department of Mathematics and Computer Science, Philipps-Universität Marburg) [38] analyze the concept of multiple graph alignment which has recently been introduced as a novel method for the structural analysis of biomolecules. Using inexact, approximate graph-matching techniques, this method enables the robust identification of approximately conserved patterns in biologically related structures. In particular, multiple graph alignments enable the characterization of functional protein families independent of sequence or fold homology. This paper first recalls the concept of multiple graph alignment and then addresses the problem of computing optimal alignments from an algorithmic point of view. In this regard, a method from the field of evolutionary algorithms is proposed and empirically compared to a hitherto existing greedy strategy. Empirically, it is shown that the former yields significantly better results than the latter, albeit at the cost of an increased runtime. The authors adjusted the following exogenous parameters of an EA using the sequential parameter optimization toolbox (SPOT) in combination with suitable synthetic data: μ, the population size; ν, the selective pressure; ρ, the recombination parameter; τ , the probability to check for dummy columns; selfadaption, which can assume values $\{on, off\}$, and enables or disables the automatic step size control; initial step size, which defines the initial step size for the mutation; if the automatic step size control is disabled, this parameter is ignored and a constant step size of 1 is used for the mutation.

2.2 Ecosystems and Environmental Engineering

2.2.1 Water-ressource management

The aim of a paper by *Wolfgang Konen*, *Tobias Zimmer*, and *Thomas Bartz-Beielstein* [43] (Cologne University of Applied Sciences) is the prediction of fill levels in stormwater tanks based on rain measurements and soil conditions. Different prediction methods are compared. The sequential parameter optimization is used to find in a comparable manner the best parameters for each method. Several standard and CI-based modeling methods show larger prediction errors when trained on rain data with strong intermittent and bursting behaviour. Models developed specific to the problem show a smaller prediction error. Main results of this work are: (i) SPO is applicable to diverse forecasting methods and automates the time-consuming parameter tuning, (ii) the best manual result achieved before was improved with SPO by 30% and (iii) SPO analyses in a consistent manner the parameter influence and allows a purposeful simplification and/or refinement of the model design.

Oliver Flasch, *Thomas Bartz-Beielstein*, *Artur Davtyan*, *Patrick Koch*, *Wolfgang Konen*, *Tosin Daniel Oyetoyan*, and *Michael Tamutan* (Cologne University of Applied Science) [125] compare state-of-the-art CI methods, i.e., neural networks (NN) and genetic programming (GP) with respect to their applicability to the prediction of fill levels in stormwater tanks problem. The performance of both methods crucially depends on their parametrization. They compare different parameter tuning approaches, e.g. neuro-evolution and Sequential Parameter Optimization (SPO). In comparison to NN, GP yields superior results. By optimizing GP parameters, GP runtime can be significantly reduced without degrading result quality. The SPO-based parameter tuning leads to results with significantly lower standard deviation as compared to the GA-based parameter tuning. Their methodology can be transferred to other optimization and simulation problems, where complex models have to be tuned.

2.3 Mechanical Engineering

2.3.1 Mold temperature control

Jörn Mehnen, *Thomas Michelitsch*, *Christian Lasarczyk*, (TU Dortmund University) and *Thomas Bartz-Beielstein* [44] (Cologne University of Applied Sciences) apply SPO in mechanical engineering for the design of mold temperature control strategies, which is a challenging multi-objective optimization task. It demands for advanced optimization methods. Evolutionary algorithms (EA) are powerful stochastically driven search techniques. In this paper an EA is applied to a multi-objective problem using aggregation. The performance of the evolutionary search can be improved using systematic parameter adaptation. The DACE technique (design and analysis of computer experiments) is used to find good MOEA (multi-objective evolutionary algorithm) parameter settings to get improved solutions of the MTCS problem. An automatic and integrated software package, which is based on the DACE approach, is applied to find the statistically significant and most promising EA parameters using SPO.

2.3.2 Surface reconstruction

Tobias Wagner, *Thomas Michelitsch*, and *Alexei Sacharow* (Department of Machining Technology(ISF), University of Dortmund) [106] use evolutionary algorithms for surface reconstruction tasks. Three EA runs over 10000 generations with different random seeds have been performed. A low number of parents and offspring $\mu = \lambda = 2$ is chosen because only a single objective is considered and function evaluations have to be sparingly utilised. In this vein, the concept of greedily using information obtained during selection, applied in the SMSEMOA, is transferred to the single-objective case. The authors recommend the using of sequential parameter optimization methods, but state that "More runs and an optimised parameter setting would be desired, but cannot be provided due to running times of several hours per run."[106].

2.4 Optimization of Simulation Models

2.4.1 Elevator group control

Thomas Bartz-Beielstein (Cologne University of Applied Sciences) and *Sandor Markon* (Kobe Institute of Technology) [63] apply DOE methods for the analysis of *threshold selection*. Threshold selection is a selection mechanism for evolutionary algorithms disturbed by noise. Theoretical results are presented and applied to a simple model of stochastic search and to a simplified elevator simulator. Design of experiments methods are used to validate the significance of the results.

A regression tree based approach for tuning search algorithms for real-world applications, e.g., elevator group control, is presented in [54].

2.4.2 Biogas

Jörg Ziegenhirt, *Thomas Bartz-Beielstein*, *Oliver Flasch*, *Wolfgang Konen*, and *Martin Zaefferer* (Cologne University of Applied Sciences) use SPOT to optimize the simulation of biogas plants [138]. Biogas plants are reliable sources of energy based on renewable materials including organic waste. There is a high demand from industry to run these plants efficiently, which leads to a highly complex simulation and optimization problem. A comparison of several algorithms from computational intelligence to solve this problem is presented in their study. The sequential parameter optimization was used to determine improved parameter settings for these algorithms in an automated manner. They demonstrate that genetic algorithm and particle swarm optimization based approaches were outperformed by differential evolution and covariance matrix adaptation evolution strategy. Compared to previously presented results, their approach required only one tenth of the number of function evaluations.

2.5 Aerospace and Shipbuilding Industry

2.5.1 Airfoil design optimization

Boris Naujoks (TU Dortmund University), *Domenico Quagliarella* (Centro Italiano Ricerche Aerospaziali (CIRA), Capua), and *Thomas Bartz-Beielstein* (Cologen University of Applied Sciences) [97] describe the sequential parameter optimisation of evolutionary algorithms for airfoil design. They demonstrate the high potential of the SPO aproach. DOE and EDA methods are use to screen out wrong factor settings. They state: "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."

2.5.2 Linearjet propulsion system

Günter Rudolph, *Mike Preuss*, and *Jan Quadflieg* (TU University Dortmund) [133] discuss the optimization of a relatively new ship propulsion system (a linearjet) which possesses 15 design variables. It consists of a tube with a rotor and a stator, and several lengths, angles, and thicknesses can be variated. The objective function is a very basic fluid dynamic simulation of a linearjet that takes about 3 minutes to compute, and the task is to reduce cavitation at a predefined efficiency. Cavitation (the emergence of vacuum bubbles in case of extreme pressure differences due to very high accelerations of the water) damages the propulsion system and also leads to high noise levels. For bringing down the simulation time to minutes, many simplifications are in effect, so that the obtained result is not very accurate. A full simulation would take about 8 hours, employing parallel computation, which is by far too much to serve as test problem. However, the simplified simulation is still accurate enough to detect good design points that can afterwards validated by the full simulation.

The authors conclude: “The validation experiment is successful, as the SPO-tuned parameter values lead to a significant performance increase. The different distributions of the validation runs probably stem from the type of algorithm chosen. The tuned MAES resembles a model-enhanced (4,11)- ES with $\kappa = 20$ and so may profit from a more globally oriented behavior than the standard parameter setting with a population size of one.”[133]

2.6 Graph drawing

2.6.1 Crossing minimization in graph drawing with genetic algorithms

Marco Tosic (Algorithm Engineering, TU Dortmund University) [24] applies sequential parameter optimzation to crossing minimization in graph drawing using genetic algorithms.

2.6.2 Solving the k-page Book Crossing Number Problem with Ant Colony Optimization

Niels Hendrik Pothmann (TU Dortmund University) [22] applies SPO in order to optimize an ant colony optimization for graph drawing with ten parameters.

2.7 Chemical Engineering

2.7.1 Distillation sequence synthesis

Frank Henrich, *Claude Bouvy*, *Christoph Kausch*, *Klaus Lucas* and *Peter Roosen* (Lehrstuhl für Technische Thermodynamik, RWTH-Aachen) and *Mike Preuss*, *Günter Rudolph*, (Computational Intelligence Research Group, Chair of Algorithm Engineering, TU Dortmund University) [40] address the *general distillation sequence synthesis problem* featuring the separation of multicomponent feed streams into multicomponent products. Potential flowsheets include stream bypassing and mixing and use sharp separations as well as non-sharp splits where key component distribution is allowed. Compared to conventional sharp distillation sequence synthesis, this leads to a mixed-integer non-linear programming problem of increased complexity, including non-convexities as well as multimodalities. Product specifications create additional constraints while simultaneously call for a rigorous modeling of the non-key distribution. A synthesis method is proposed that models the various flowsheet configurations with a new and flexible superstructure concept and connects the gradient-free optimization technique of application-orientedly developed Evolutionary Algorithms (EAs) to the rigorous modeling capabilities of a commercial simulation system, thus enabling realistic process design and cost objective function calculation. *Mike Preuss* presents *general distillation sequence synthesis problem* in the sequential parameter optimization context [53].

2.8 General Recommendations

2.8.1 Learning from errors

Jörn Mehnen (Decision Engineering Centre, Cranfield University) [91] claims that since the early beginnings of EA, a continuous "horse race" between different methods can be observed—with (in his opinion) more or less trustworthy or useful results. He refers to the approach presented in [1], stating "Whenever a comparison of EC algorithms is performed, it needs a fair systematic statistical parameter analysis—which causes an optimisation problem in itself." The author opens this article with the statement that everybody makes mistakes—we all make one eventually if we just work hard enough! This is considered good news and bad news. We learn from mistakes but mistakes are also painful and could turn out to be costly in terms of money, reputation and credibility. One is prone to make mistakes particularly with new and complex techniques with unknown or not exactly known properties. This paper talks about some of my more unfortunate experiences with evolutionary computation. The paper covers design and application mistakes as well as misperceptions in academia and industry. You can make a lot of technical mistakes in evolutionary computation. However, technical errors can be detected and rectified. Algorithms are implemented, presented and analysed by humans who also discuss and measure the impact of algorithms from their very individual perspectives. A lot of "bugs" are actually not of a technical nature, but are human flaws. The author tries also to touch on these "soft" aspects of evolutionary computing.

3 Applications in Theory

3.1 Philosophy of science

3.1.1 New experimentalism

Thomas Bartz-Beielstein (Cologne University of Applied Science) [1] describes how concepts from the *new experimentalism* can be applied in computer science.

3.1.2 Mayo's learning model

Thomas Bartz-Beielstein (Cologne University of Applied Science) [36] claims that learning from errors is an important strategy for the experimental analysis of algorithms. Although theoretical results for several algorithms in many application domains were presented during the last decades, not all algorithms can be analyzed fully theoretically. Experimentation is necessary. The analysis of algorithms should follow the same principles and standards of other empirical sciences. The focus in this article lies on stochastic search algorithms, such as evolutionary algorithms or particle swarm optimization. Stochastic search algorithms tackle hard real-world optimization problems, e.g., problems from chemical engineering, airfoil optimization, or bioinformatics, where classical methods from mathematical optimization fail. Nowadays statistical tools for the analysis of algorithms, which are able to cope with problems like small sample sizes, non-normal distributions, noisy results, etc. are developed. They are adequate tools to discuss the statistical significance of experimental data. However, statistical significance is not scientifically meaningful per se. It is necessary to bridge the gap between the statistical significance of an experimental result and its scientific meaning. Based on Deborah Mayo's *learning model* (NPT^*), some ideas how to accomplish this task are proposed.

3.2 Tuning and Comparison of Computer Algorithms

3.2.1 Automated tuning approaches

Frank Hutter (University of British Columbia) [32] introduces a general framework for sequential model-based Optimization. He describes and experimentally compared two existing instantiations of this general framework from the literature, sequential kriging optimization (SKO) and SPO. He concludes:" In this comparison, SPO performed much more robustly 'out-of-the-box', whereas SKO became very competitive when using a log transformation of the response values."
Frank Hutter, *Holger H. Hoos*, *Kevin Leyton-Brown*, and *Kevin Murphy* (University of British Columbia) [83] show how to extend the Sequential Parameter Optimization framework to operate effectively under time bounds. They state that the optimization of algorithm performance by automatically identifying good parameter settings is an important problem that has recently attracted much attention in the discrete optimization community. One promising approach constructs predictive performance models and uses them to focus attention on promising regions of a design space. Such methods have become quite sophisticated and have achieved significant successes on other problems, particularly in experimental design applications. However, they have typically been designed to achieve good performance only under a budget expressed as a number of function evaluations (e.g., target algorithm runs). The authors take into account both the varying amount of time required for different algorithm runs and the complexity of model building and evaluation. Specifically, they introduce a novel intensification mechanism, and show how to reduce the overhead incurred by constructing and using models. Overall, they show that their method represents a new state of the art in model-based optimization of algorithms with continuous parameters on single problem instances.

3.2.2 Evolutionary algorithms

Thomas Fober (Philipps-Universität Marburg) [20] presents an extensive comparison of evolutionary algorithms which is based on a CEC'05 test function set.
Selmar Smit and *Gusz Eiben* (Vrije Universiteit Amsterdam, The Netherlands) [103] compare parameter tuning methods for EAs. Their article is meant to be stepping stone towards a better practice by discussing the most important

issues related to tuning EA parameters, describing a number of existing tuning methods, and presenting a modest experimental comparison among them. They summarize the comparison of three tuners, namely

1. Relevance estimation and value calibration of parameters (REVAC),
2. SPOT, and
3. CMA-ES (used as a tuner)

as follows: "Our results also support preferences regarding the tuning algorithms to be used. For a careful advise, we need to distinguish two functionalities tuners can offer. First and foremost, they can optimize EA parameters, second they can provide insights into the (combined) effects of parameters on EA performance. Regarding the insights offered the three methods we tested are quite different. On the low end of this scale we have the CMA-ES that is a highly specialized optimizer building no model of the utility landscape. REVAC, and meta-EDAs in general, does create a model, the marginal distributions over the ranges of each parameter. The fact that these distributions only take one parameter into account means that the model is simple, it is blind to parameter interactions. On the other hand, REVAC is able to provide information about the entropy associated with the parameters, hence showing the amount of tuning each parameter requires. SPO is situated on the high end of the insights scale, since it is inherently based on a model of the utility landscape. In principle, this model is not restricted to a specific form or structure, offering the most flexibility and insights, including information on parameter interactions. Based on these considerations and the outcomes of our experiments our preferred method is the CMA-ES if a very good parameter vector is the most important objective, and SPO if one is also interested in detailed information over the EA parameters."
Thomas Bartz-Beielstein (Cologne University of Applied Sciences) [117] applies DOE for the experimental analysis of evolution strategies.
Oliver Kramer (TU Dortmund University), *Bartek Gloger*, and *Andreas Goebels* (University of Paderborn) [88] compare evolution strategies and particle swarm optimization based on design of experiment (DoE) techniques. They report that "reasonable improvements have been observed."

3.2.3 Particle swarm optimization

Thomas Bartz-Beielstein (Cologne University of Applied Sciences), *Konstantinos E. Parsopoulos* and *Michael N. Vrahatis* (University of Patras Artificial Intelligence Research Center) [56, 37] propose a new methodology for the experimental analysis of evolutionary optimization algorithms. The proposed technique employs computational statistic methods to investigate the interactions among optimization problems, algorithms, and environments. The technique is applied for the parameterization of the *particle swarm optimization* algorithm. An elevator supervisory group control system is introduced as a test case to provide intuition regarding the performance of the proposed approach in highly complex real-world problems.

3.2.4 Genetic programming

Christian Lasarczyk (Department of Computer Science, TU Dortmund University) and *Wolfgang Banzhaf* (Department of Computer Science, Memorial University of Newfoundland) present a new algorithm to execute algorithmic chemistries during evolution. Algorithmic chemistries are artificial chemistries that aim at algorithms. They ensure synthesizes of the whole program and cut off execution of unneeded instructions without restricting the stochastic way of execution. The authors demonstrate benefits of the new algorithm for evolution of algorithmic chemistries and discuss the relation of algorithmic chemistries with estimation of distribution algorithms. They perform parameter optimization using [56, 37]. First, the success rate is estimated after 10^8 instructions have been executed based on 10 runs at 200 points within our parameter space, chosen by an initial Latin Hypercube Sampling. The success rate corresponds to the proportion of runs that evolve an individual which computes the correct parity for all fitness cases of the test set. Success rates are used to model the response of the system. A quadratic regression model and a model for its prediction error using kriging interpolation can be employed. Using this composed model success rates of 2000 points from an Latin Hypercube Sampling can be predicted and the most promising settings by running real experiments. The sample size is doubled at the best (two) points known so far and for new settings we run the same number of experiments. After this verification step a new model is created, including the newly evaluated points. Again we predict success rates at points of a new Latin hypercube design and verify the most promising settings. [89].

3.3 Multicriteria Optimization

3.3.1 Evolutionary multi-objective optimization

Thomas Bartz-Beielstein (Cologne University of Applied Sciences), *Boris Naujoks*, *Tobias Wagner*, and *Simon Wessing* (TU Dortmund University) [55] illustrate the possible transfer of SPO to evolutionary multi-objective optimisation algorithms (EMOA). The application of sequential parameter optimisation (SPO) bears a new quality for the parametrisation of heuristic search methods. It allows for a deep analysis of parameter interactions resulting in close to optimal parameter settings for a given algorithm-application combination. The algorithm considered is SMS-EMOA, a state-of-the-art EMOA featuring indicator based selection. In this EMOA, the hypervolume indicator is employed. Such indicators can also be involved in SPO for quality assessment of the current experiment, i.e., one EMOA run on the considered test case. For the parametrisation of SMS-EMOA, the population size within its $(m + 1)$ approach suggests itself for investigation. Next to this, parameters of different variation operators are considered, e.g., their application probability and distribution indices, resulting in a meaningful investigation of parameter influence for the given combinations. The test cases involved stem from a test case collection considered for a competition at some recent conference, i.e., the IEEE Congress on Evolutionary Computation 2007 in Singapore. For this work, R_{ZDT4} (two objectives, multi-modal), R_{DTLZ2} (three objectives, uni-modal) of the above collection were utilized.

3.3.2 Statistical analysis

Christian Lasarczyk (Department of Computer Science, TU Dortmund University) [13] integrates *optimal computational budget allocation* into SPO.

Heike Trautmann (TU Dortmund University, Department of Computational Statistics) and *Jörn Mehnen* (Decision Engineering Centre, Cranfield University) [46] give practical examples of the benefits of applied statistical consultancy in mechanical engineering. Statistics provide highly efficient tools for approaching real-world problems systematically. Engineering problems can be extremely difficult. They become even more challenging if solutions for many objectives have to be found. In complex environments with high dimensional search spaces and multiple objectives, evolutionary algorithms prove to be a good approach for solving artificial as well as real-world problems. It can be very helpful for the optimisation process if some expert knowledge can be introduced into the search process. Statistics improve the practical optimisation task in terms of problem modelling, guiding the search process during the evolutionary run or even finding good parameter adjustments for the optimisation algorithms. the authors introduce two real-world engineering problems, namely mould temperature control design and machining of gradient material. Desirability functions are used to introduce expert knowledge into the evolutionary search process. DACE/SPO (Design and Analysis of Computer Experiments / Sequential Parameter optimisation) serves the purpose of Multiobjective Evolutionary Algorithm parameter tuning. The problem of multivariate DACE/SPO modelling of machining processes is discussed.

3.3.3 Multimodal optimization

Mike Preuss, *Günter Rudolph*, and *Feelly Tumakaka* (TU University Dortmund) [100] analyze a new approach for *multimodal optimization problems*. For solving multimodal problems by means of evolutionary algorithms, one often resorts to multistarts or niching methods. The latter approach the question: "What is else- where?" by an implicit second criterion in order to keep populations distributed over the search space. Induced by a practical problem that appears to be simple but is not easily solved, a multiobjective algorithm is proposed for solving multimodal problems. It employs an explicit diversity criterion as second objective. Experimental comparison with standard methods suggests that the multiobjective algorithm is fast and reliable and that coupling it with a local search technique is straightforward and leads to enormous quality gain. The combined algorithm is still fast and may be especially valuable for practical problems with costly target function evaluations.

3.4 Fuzzy Logic

3.4.1 Fuzzy operator trees

Yu Yi (Fachbereich Mathematik und Informatik, Philipps-Universität Marburg) [17] proposes a method for modeling utility (rating) functions based on a novel concept called Fuzzy Operator Tree (FOT). As the notion suggests, this method makes use of techniques from fuzzy set theory and implements a fuzzy rating function, that is, a utility function that maps to the unit interval, where 0 corresponds to the lowest and 1 to the highest evaluation. Even though the original motivation comes from quality control, FOTs are completely general and widely applicable. *Yu Yi* reports that "several works have shown that SPO outperforms other alternatives, especially for evolution strategies, we shall apply SPO to determine the parameters of ES in this section. Sequential sampling approaches with adaptation have been proposed for DACE, here let us review the basic idea of Thomas Bartz-Beielstein, which is also used in this section to determine the parameters of ES."

4 Summary and Outlook

We are happy to include your publication in this list. Please send an e-mail to: `thomas.bartz-beielstein@fh-koeln.de`. Note, the following bibliography reports publications with references to SPO, even if they do not apply SPO actively.

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