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Editorial: Evolutionary Multiobjective Optimization

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Multiobjective optimization is about finding solutions to problems with respect to multiple, often conflicting, decision criteria. Also termed multicriteria optimization or vector optimization, this area has been strongly developed in the 1970s within operations research, decision theory [1], and engineering [17]. Typical application examples range from expected profit versus risk in portfolio theory over model size versus predictive accuracy in statistical machine learning to cost versus power versus energy consumption in many engineering design problems.

Optimal solutions of a multiobjective problem are minimal elements with respect to the quasi-order (dominance relation) given by the intersection of the linear orders due to the different decision criteria. It has hence become customary to distinguish two steps: an *objective* one, where minimal elements (nondominated or Pareto-optimal solutions) are sought, and a *subjective* one, which makes use of preference information for weighing or prioritizing the different criteria to impose a linear preference order and arrive at a single final solution. Different solution approaches are thus often classified according to when and how the subjective information enters the search process [10].

Facing the traditional approaches that were almost entirely based on transforming the multiobjective problem into a single-objective surrogate problem, the evolutionary computation community realized the potential of a different approach, namely to exploit the concept of a *population* within evolutionary algorithms to search for a set of different solutions concurrently in a single run. Early studies [19, 7, 11] used the different criteria to affect the selection of different parts of the population. During the mid-1990s, scalarization was replaced entirely by the proposal to rank solutions directly by the quasi-order of comparing all criteria simultaneously. This mindset has given rise to a large research effort in the area of *evolutionary multiobjective optimization* including a dedicated bi-annual conference series [20, 6, 3], two textbooks [5, 2] and more than 130 PhD theses [4].

This special issue presents recent results of leading researchers in the area of evolutionary multiobjective optimization. The type of results are mainly methodological and algorithmic issues, some including example applications, but each with a certain tutorial aspect, which makes them useful also for novices to the field. The paper by *Handl and Knowles* addresses the problem of feature selection in unsupervised learning, which by itself is an interesting problem in the area of computational intelligence. On the methodological side, the article shows the benefits of using a secondary, structural objective function to explicitly acknowledge that different solutions are not entirely comparable by the primary objective as this involves a bias depending on certain structural properties of the potential solutions. *Haubelt, Schlichter and Teich* also present a challenging application, the design space exploration problem in computer engineering. The authors suggest a hierarchical approach: By fixing certain decision variables, the objective values are determined, but choosing feasible values for the remaining variables is an NP-complete subproblem that can be reduced to the satisfiability (SAT) problem. It is demonstrated how domain-specific tools such as decision diagrams and heuristic SAT solvers can be integrated into multiobjective evolutionary algorithms (MOEAs)for solving difficult subproblems, especially to quickly determine feasibility of the subspaces sampled by the MOEA. The paper by *Basseur and Zitzler* considers selection under uncertainty, i.e., which of the generated potential solutions to retain during the run of a MOEA when their objective values are only given as samples from an unknown random variable instead of deterministic values. The authors show how the concept of performance indicators, originally introduced for the empiricical assessment of MOEAs [21], can be used to estimate the expected contribution of each solution to the quality of the whole solution set. As computing these estimators exactly is exponential in the sample size, the paper presents and compares various approximative estimators of lower complexity. A link to the aforementioned traditional approaches to multiobjective optimization is provided by *Deb, Sundar, Rao Namagiri, and Chaudhuri*. They suggest a way to effectively incorporate preference information into the evolutionary search process in terms of reference points representing areas of interest to the decision maker. Their simulation results show that this reference-point based MOEA is still able to find a set of different compromise solutions, but in this case focused on the desired regions. Finally, the paper by *Reyes-Sierra and Coello Coello* leaves the realm of evolutionary algorirthms in the narrow sense and gives an introduction to a related family of metaheurstic techniques called multiobjective particle swarm optimization (MOPSO). The authors highlight the conceptual and differences between MOPSO and EMO, but also show how certain important algorithmic aspects, especially with respect to the evaluation and selection of solution under multiple objectives, are in fact very similar for both techniques, which probably holds for any randomized search heuristic in a multiobjective setting.

Not covered in this issue are theoretical studies concerning the convergence and running time analysis of MOEAs for certain problems or problem classes. Although the first attempts have been made and rigorous results are available for, e.g., the asymptotic behaviour in the limit $t \to \infty$ [18, 12] as well as for the expected optimization time on simple pseudo-Boolean functions [13, 8, 9] and easy combinatorial problems [14, 15, 16], more effort is certainly needed to broaden the theoretical basis of the field and extend our understanding of the methods beyond purely empricial validation.

Although it was not explicitly planned for, all contributions involved young researchers in or just after their PhD studies. This is yet another indication of the liveliness and potential of the field and generates prospects of interesting results to be produced in the future.

Acknowledgments

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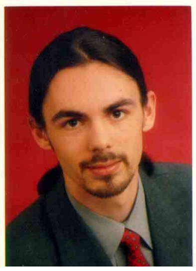
Editor Biographies



Marco Laumanns received the Diploma degree in computer science from the University of Dortmund, Germany, in 1999 and the Ph.D. (doctor of science) from the ETH Zurich, Switzerland, in 2003. He is currently with Institute for Operations Research at ETH Zurich as senior research assistant where his work focuses on the analysis and control of dynamic processes in material and information flow networks. In multiobjective optimization, his research interests are the theoretical understanding of evolutionary algorithms for multiobjective problems and their application in engineering design.

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Günter Rudolph received the Diploma degree in computer science and the Ph.D. (doctor of natural sciences) from the University of Dortmund, Germany, in 1991 and 1996, respectively. Since then he held research positions at the University of Dortmund and the Informatics Centre Dortmund (ICD). After four years of employment in industry at Parsytec AG, Aachen, he became professor of computer science at the University of Dortmund in April 2005. His research interests regarding multiobjective optimization now centers on interactive multiobjective evolutionary algorithms and on generalizations of multiobjective search toward more abstract problem classes.

Jürgen Teich received his masters degree (Dipl.-Ing.) in 1989 from the University of Kaiserslautern (with honours). From 1989 to 1993, he was PhD student at the University of Saarland, Saarbrücken, Germany from where he received his PhD degree (summa cum laude). His PhD thesis summarizes his work on extending techniques for mapping computation intensive algorithms onto dedicated VLSI processor arrays. In 1994, Dr. Teich joined the DSP design group in the Department of Electrical Engineering and Computer Sciences (EECS) at UC Berkeley where he was working in the Ptolemy project (PostDoc).

From 1998 to 2002, he was full professor in the Electrical Engineering and Information Technology department of the University of Paderborn, holding a chair in Computer Engineering. Since 2003, he is appointed full professor in the Computer Science Institute of the Friedrich-Alexander University Erlangen-Nuremberg holding a chair in Hardware-Software-Co-Design. He is member of the IEEE and author of a textbook on Co-Design edited by Springer in 1997. His research interests are massive parallelism, embedded systems, Co-Design, and computer architecture.