

Experimental Methods for the Analysis of Optimization Algorithms

Thomas Bartz-Beielstein · Marco Chiarandini ·
Luís Paquete · Mike Preuss
Editors

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 Springer

Editors

Prof. Dr. Thomas Bartz-Beielstein
Cologne University of Applied Sciences
Institute of Computer Science
Faculty of Computer and
Engineering Science
Campus Gummersbach
Steinmüllerallee 1
51643 Gummersbach
Germany
thomas.bartz-beielstein@fh-koeln.de

Dr. Marco Chiarandini
University of Southern Denmark
Department of Mathematics and
Computer Science
Campusvej 55
5230 Odense
Denmark
marco@imada.sdu.dk

Dr. rer. nat. Luís Paquete
University of Coimbra
CISUC
Department of Informatics Engineering
Pólo II
3030-290 Coimbra
Portugal
paquete@dei.uc.pt

Mike Preuss
TU Dortmund
Department of Computer Science
Algorithm Engineering
Otto-Hahn-Str. 14
44227 Dortmund
Germany
mike.preuss@tu-dortmund.de

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Foreword

This book belongs on the shelf of anyone interested in carrying out experimental research on algorithms and heuristics for optimization problems.

The editors have brought together expertise from diverse sources to address methodological issues arising in this field. The presentation is wide-ranging, containing “big picture” discussions as well as more focused treatment of specific statistical techniques and their application. The emphasis throughout is on careful process and scientific rigor; the discussion is illuminated with many case studies, small tutorials, and references to the literature on optimization.

Don’t keep this book on the shelf: read it, and apply the techniques and tools contained herein to your own algorithmic research project. Your experiments will become more efficient and more trustworthy, and your experimental data will lead to clearer and deeper insights about performance.

Amherst, Massachusetts, February 2010

Catherine C. McGeoch

Foreword

Once upon a time, more exactly nearly half a century ago, when the first cybernetic machines, henceforth called computers, became available to academic institutions, a few people seemed to have waited for their iterative power to perform otherwise boring procedures like solving sets of linear equations, etc. Among other ideas to make use of their tireless working through loops of instructions was the simulation of organic evolution, the main subroutines of which are mutation, recombination, and natural selection. It was only a small step to imagine that by means of the same principles the design of technical devices, managerial tasks and other systems could be stepwise improved, if not even optimized. Competing methods from numerical mathematics were known, of course, but also their limitations to linear and quadratic dependencies between decision variables and objectives. In so-called black box situations where much more complex dependencies prevail and nonlinear constraints, stochastic disturbances, and the like hamper the search for optima, using evolutionary variation and evaluation processes showed up their capacities. Evolutionary algorithms thus were born during the 1960s, and they have matured ever since to a powerful and broadly accepted tool within many disciplines. Together with two other modern streams, artificial *neural networks* (NN) and *fuzzy systems* (FS), they have been subsumed into the so-called *computational intelligence* (CI) field, at least since 1994, when the first world congress on CI took place with its three subbranches NN, FS, and EC (evolutionary computation).

In the beginning of EC one had to be happy if one could rerun a numerical experiment a few times, for example with different seeds of the pseudo random generator or different start positions in the search space. Gathering a whole set of statistical data was unimaginable then, so that many open questions remained about the performance of the algorithms. What are those questions? It's not only an average value and its variance and skewness, or the best result out of a few runs that are interesting. One wants to know whether the ultimate result, i.e. using the algorithm specific stopping criterion, is always the same, whether and how it depends on the random numbers and starting points used. Further it may happen or not that fatal execution errors occur, like division by zero or extracting the square root of a negative number, or that the stopping criterion does not work properly – even if the optimum was

found exactly. And what exactly does it mean to talk of four or eight precise digits or even more (which may depend on the hardware and on the system software handling real numbers, their mantissae and exponents)? Introducing common stopping criteria to compare different methods can easily deliver controversial results depending on the slopes of best (or average) intermediate results over the number of objective function values. Such slopes can not only have one crossing, but even two or more. Then the result depends heavily upon the number of admitted iterations, one method being quicker at the beginning while finally delivering mediocre final results, or the other way round, or even more complicated.

If you are interested in such questions, THIS is the book to look into. Here you will find even more aspects that are treated scientifically by the experts in that exciting domain offering their up-to-date know-how and even leading into philosophical domains.

Dortmund, February 2010

Hans-Paul Schwefel

Preface

Optimization algorithms are used to solve problems that arise in relevant research and application areas such as operations research, computer science, and engineering. During recent decades the experimental approach has been recognized and accepted in the analysis of these algorithms and a considerable body of research has been devoted to the development and establishment of an adequate scientific methodology for pursuing this kind of analysis. Statistical tools have become more and more popular. This book is written for researchers and practitioners of operations research and computer science who wish to improve the experimental assessment of their optimization algorithms with the final goal of improving their design. It collects prominent methodological works on different scenarios of experimental analysis.

The book consists of an introduction and 4 chapters written by the editors plus 11 chapters (including an appendix) written by *invited* contributors. All together the project involved 30 authors of 16 world-wide academic institutions.

The first part of the book lays the basis giving an all-round view of the issues involved in the experimental analysis of algorithms. The second part treats the characterization by means of statistical distributions of the algorithm performance in terms of solution quality, run-time, and other measures. The third part collects advanced methods from experimental design for configuring and tuning algorithms on a specific class of instances with the goal of using the least amount of experimentation and attaining sound conclusions. Several chapters are enriched with case studies.

Acknowledgments

We are indebted to many people, especially to the contributors of this volume.

The book is the result of an inspiring and fruitful cooperation among the editors. First contacts were established during the Metaheuristic International Conference in Vienna in 2005 — followed by research visits and meetings during conferences.

We realized that problems that we had been trying to solve are of interest for a broader audience and not restricted to our own research areas (computational intelligence, operations research, mathematical optimization). Certainly, a milestone in the pathway to this book was the Workshop on Empirical Methods for the Analysis of Algorithms held in Reykjavik in 2006. We are thankful to all the participants of that workshop, many of whom became authors in this book and contributed to define its scope. Among them, a special mention goes to Catherine McGeoch whose perspective in the experimental analysis of algorithms highly influenced our views.

On an individual basis, Bartz-Beielstein gratefully acknowledges the support of colleagues at Cologne University of Applied Sciences: Wolfgang Konen for the inspiring intellectual exchange and Michael Bongards for providing valuable input for real-world applications. Some of Thomas Bartz-Beielstein's work was conducted under a Bundesministerium für Forschung und Bildung (BMBF) grant (FIWA, AIF FKZ 17N2309) and under a Cologne University of Applied Sciences grant (COSA). Thomas Bartz-Beielstein would like to thank Deborah Mayo for exchanging ideas about error and inference. Many thanks go to Jack P.C. Kleijnen, Ekaterina Vladislavleva, and Dick den Hertog for invitations to the wonderful mini-symposia at Tilburg University. Thomas Bartz-Beielstein and Mike Preuss are grateful to Hans-Paul Schwefel and Günter Rudolph for detailed comments, valuable suggestions and inspiring advice over many years. 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. Ruxandra and Catalin Stoean also deserve thanks for the open-mindedness to jointly investigate every possible algorithmic variation. This also applies to the colleagues at RWTH Aachen, Christoph Kausch, Frank Henrich and Claude Bouvy, who added valuable insight into industrial optimization problems in work conducted together under DFG project grant 252441. Marco Chiarandini is thankful to Yuri Goegebeur for his advice on statistical issues during the reviewing process of the chapters. Luís Paquete is grateful to Carlos Fonseca and Thomas Stützle for the encouraging advice and stimulating exchange of ideas about the main topic of this book. He also acknowledges his colleagues at University of Coimbra, mainly Ernesto Costa and Alberto Moraglio, for the enlightening discussions on design and analysis of stochastic algorithms for optimization.

Finally, we all would like to thank Ronan Nugent of Springer, who provided great support during all production stages of this book.

Gummersbach, Odense, Coimbra, Dortmund,
February 2010

Thomas Bartz-Beielstein
Marco Chiarandini
Luís Paquete
Mike Preuss

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List of Contributors

Prasanna Balaprakash
IRIDIA, CoDE, Université Libre de Bruxelles,
Brussels, Belgium
e-mail: pbalapra@ulb.ac.be

Thomas Bartz-Beielstein
Institute of Computer Science, Cologne University of Applied Sciences
Gummersbach, Germany
e-mail: thomas.bartz-beielstein@fh-koeln.de

Dario Basso
Department of Statistics, University of Padua
Padua, Italy
e-mail: dario@stat.unipd.it

Mauro Birattari
IRIDIA, CoDE, Université Libre de Bruxelles
Brussels, Belgium
e-mail: mbiro@ulb.ac.be

Marco Chiarandini
Department of Mathematics and Computer Science, University of Southern
Denmark
Odense, Denmark
e-mail: marco@imada.sdu.dk

Markus Chimani
Algorithm Engineering, TU Dortmund
Dortmund, Germany
e-mail: markus.chimani@tu-dortmund.de

Agoston E. Eiben
Vrije Universiteit
Amsterdam, The Netherlands
e-mail: gusz@cs.vu.nl

Viviane Grunert da Fonseca
CEG-IST – Centre for Management Studies, Instituto Superior Técnico
Lisbon, Portugal
INUAF – Instituto Superior D. Afonso III
Loulé, Portugal
e-mail: viviane.grunert@vodafone.pt

Carlos M. Fonseca
CEG-IST – Centre for Management Studies, Instituto Superior Técnico
Lisbon, Portugal
Department of Electronic Engineering and Informatics, Faculty of Science and
Technology, Universidade do Algarve
Faro, Portugal
e-mail: cmfonsec@ualg.pt

Matteo Gagliolo
IRIDIA, CoDE, Université Libre de Bruxelles
Brussels, Belgium
Faculty of Informatics, University of Lugano
Lugano, Switzerland
e-mail: mgagliolo@iridia.ulb.ac.be

Yuri Goegebeur
Department of Mathematics and Computer Science, University of Southern
Denmark
Odense, Denmark
Research Group Quantitative Psychology and Individual Differences, K.U.Leuven
Leuven, Belgium
e-mail: yuri.goegebeur@stat.sdu.dk

Nicholas G. Hall
Department of Management Sciences, The Ohio State University
Columbus, Ohio, USA
e-mail: hall_33@fisher.osu.edu

Holger H. Hoos
Department of Computer Science, University of British Columbia
Vancouver, Canada
e-mail: hoos@cs.ubc.ca

Jürg Hüsler
Department of Mathematical Statistics, University of Bern
Bern, Switzerland
e-mail: juerg.huesler@stat.unibe.ch

Frank Hutter

Department of Computer Science, University of British Columbia
Vancouver, Canada
e-mail: hutter@cs.ubc.ca

Jack P.C. Kleijnen

Department of Information Management / CentER, Tilburg University
Tilburg, The Netherlands
e-mail: kleijnen@uvt.nl

Karsten Klein

Algorithm Engineering, TU Dortmund
Dortmund, Germany
e-mail: karsten.klein@tu-dortmund.de

Daniel Kudenko

Department of Computer Science, The University of York
York, UK
e-mail: Kudenko@cs.york.ac.uk

Christian Lasarczyk

Algorithm Engineering, TU Dortmund
Dortmund, Germany
e-mail: Christian.Lasarczyk@udo.edu

Catherine Legrand

Institut de statistique, Université catholique de Louvain
Louvain-la-Neuve, Belgium
e-mail: catherine.legrand@uclouvain.be

Kevin Leyton-Brown

Department of Computer Science, University of British Columbia
Vancouver, Canada
e-mail: kevinlb@cs.ubc.ca

Manuel López-Ibáñez

IRIDIA, CoDE, Université Libre de Bruxelles
Brussels, Belgium
e-mail: manuel.lopez-ibanez@ulb.ac.be

Kevin P. Murphy

Department of Computer Science, University of British Columbia
Vancouver, Canada
e-mail: murphyk@cs.ubc.ca

Luís Paquete

CISUC, Department of Informatics Engineering, University of Coimbra
Coimbra, Portugal
e-mail: paquete@dei.uc.pt

Marc E. Posner
Department of Integrated Systems Engineering, The Ohio State University
Columbus, Ohio, USA
e-mail: posner.1@osu.edu

Mike Preuss
Algorithm Engineering, TU Dortmund
Dortmund, Germany
e-mail: mike.preuss@tu-dortmund.de

Enda Ridge
Forensic Technology and Discovery Services, Ernst and Young
London, UK
e-mail: enda.ridge@gmail.com

Selmar K. Smit
Vrije Universiteit
Amsterdam, The Netherlands
e-mail: sksmit@cs.vu.nl

Thomas Stütze
IRIDIA, CoDE, Université Libre de Bruxelles
Brussels, Belgium
e-mail: stuetzle@ulb.ac.be

Zhi Yuan
IRIDIA, CoDE, Université Libre de Bruxelles
Brussels, Belgium
e-mail: zyuan@ulb.ac.be