

Preface

Multiobjective optimization has been available for about two decades, and its application in real world problems is continuously increasing. An important task in multiobjective optimization is to identify the set of Pareto-optimal solutions. An evolutionary algorithm is characterized by a population of solution candidates and the reproduction operator enables the process to combine existing solutions to generate new solutions. As a result, the computation finds several members of the Pareto-optimal set in a single run instead of performing a series of separate runs, which is the case for some of the conventional stochastic processes. The main challenge in a multiobjective optimization environment is to minimize the distance of the generated solutions to the Pareto set and to maximize the diversity of the developed Pareto set. A good Pareto set may be obtained by appropriate guiding of the search process through careful design of reproduction operators and fitness assignment strategies. To obtain diversification special care has to be taken in the selection process. Special care is also to be taken to prevent non-dominated solutions from being lost.

Addressing the various issues of evolutionary multiobjective optimization problems and the various design challenges using different intelligent approaches is the novelty of this edited volume. This volume comprises 12 chapters' including two introductory chapters giving the fundamental definitions and some important research challenges. Several complex test functions and a practical problem involving the multiobjective optimization of space structures under static and seismic loading conditions used to illustrate the importance of the evolutionary algorithm approach.

First, we would like to thank Lance Chambers (Australia) for initiating this book project in 2001. We are very much grateful to the authors of this volume and to the reviewers for their tremendous service by critically reviewing the chapters. The editors would like to thank Beverly Ford and Catherine Drury of Springer Verlag, London office and Jenny Wolkowicki of Springer Verlag, New York Office for the editorial assistance and excellent cooperative collaboration to produce this important scientific work. We are also indebted to Berend Jan van der Zwaag (University of Twente, The Netherlands) for the tremendous help during the preparation of the manuscript. We hope that the reader will share our excitement to present this volume on 'Evolutionary Multiobjective Optimization: Theoretical Advances and Applications' and will find it useful.

Oklahoma State University, USA
University of South Australia, Australia
Queens College, USA

Ajith Abraham
Lakhmi Jain
Robert Goldberg
(Editors)

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Ajith Abraham and Lakhmi Jain

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