Chi-Keong Goh and Kay Chen Tan

Evolutionary Multi-objective Optimization in Uncertain Environments

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Editor-in-Chief
Prof. Janusz Kacprzyk
Systems Research Institute
Polish Academy of Sciences
ul. Newelska 6
01-447 Warsaw
Poland
E-mail: kacprzyk@ibspan.waw.pl

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Chi-Keong Goh
Kay Chen Tan

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Dr. Chi-Keong Goh
Data Storage Institute,
Agency for Science, Technology and Research
5 Engineering Drive 1
Singapore 117608
Email: Goh_Chi_Keong@dsi.a-star.edu.sg

Dr. Kay Chen Tan
Department of Electrical and Computer Engineering
National University of Singapore
4 Engineering Drive 3
Singapore 117576
E-mail: eletankc@nus.edu.sg

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Preface

Many real-world problems involve the simultaneous optimization of several competing objectives and constraints that are difficult, if not impossible, to solve without the aid of powerful optimization algorithms. What makes multi-objective optimization so challenging is that, in the presence of conflicting specifications, no one solution is optimal to all objectives and optimization algorithms must be capable of finding a number of alternative solutions representing the tradeoffs. However, multi-objectivity is just one facet of real-world applications. Most optimization problems are also characterized by various forms of uncertainties stemming from factors such as data incompleteness and uncertainties, environmental conditions uncertainties, and solutions that cannot be implemented exactly.

Evolutionary algorithms are a class of stochastic search methods that have been found to be very efficient and effective in solving sophisticated multi-objective problems where conventional optimization tools fail to work well. Evolutionary algorithms' advantage can be attributed to it's capability of sampling multiple candidate solutions simultaneously, a task that most classical multi-objective optimization techniques are found to be wanting. Much work has been done to the development of these algorithms in the past decade and it is finding increasingly application to the fields of bioinformatics, logical circuit design, control engineering and resource allocation. Interestingly, many researchers in the field of evolutionary multi-objective optimization assume that the optimization problems are deterministic, and uncertainties are rarely examined. While multi-objective evolutionary algorithms draw its inspiration from nature where uncertainty is a common phenomenon, it cannot be taken for granted that these algorithms will hence be inherently robust to uncertainties without any further investigation.

The primary motivation of this work is to provide a comprehensive treatment on the design and application of multi-objective evolutionary algorithms for multi-objective optimization in the presence of uncertainties. Chapter 1 provides the necessary background information required to appreciate this work, covering key concepts and definitions of multi-objective optimization as well as a survey of the state-of-the-arts which highlights the major design issues of multi-objective evolutionary techniques.

The rest of this work is divided into three parts, which each part considering a different form of uncertainties: 1) noisy fitness functions, 2) dynamic fitness functions, and 3) robust optimization. The first part comprises of Chapters 2-4 and addresses the issues of noisy fitness functions. Chapter 2 investigates the effect of noise on multi-objective evolutionary algorithms and Chapter 3 provides a comprehensive survey of noisy evolutionary multi-objective optimization literature and presents a comparative study between existing algorithms for noisy multi-objective optimization. As a specific instance of a noisy multi-objective problem, Chapter 4 presents a hybrid multi-objective evolutionary algorithm for the evolution of artificial neural network classifiers.

Part II is concerned with dynamic multi-objective optimization and comprises of Chapters 5 and 6. Chapter 5 provides a survey of dynamic evolutionary multi-objective optimization literature as well as a discussion on the different types of dynamic multi-objective test functions and performance indicators. Chapter 6 extends the notion of coevolution to track the Pareto front in a dynamic environment. Since problem characteristics may change with time, it is not possible to determine one best approach to problem decomposition. Therefore, this chapter introduces a new coevolutionary paradigm that incorporates both competitive and cooperative mechanisms observed in nature to facilitate the adaptation and emergence of the decomposition process with time.

The final part of this work addresses the issues of robust multi-objective optimization where the optimality of the solutions is sensitive to parameter variations. Analyzing the existing benchmarks applied in the literature reveals that the current corpus has severe limitations. Therefore, Chapter 7 presents a robust multi-objective test suite with noise-induced solution space, fitness landscape and decision space variation. In addition, the vehicle routing problem with stochastic demand (VRPSD) is presented a practical example of robust combinatorial multi-objective optimization problems. A survey of existing robust multi-objective evolutionary techniques are presented in Chapter 8 and simulations are conducted to solve the test suite suggested in Chapter 7. In Chapter 9, a hybrid MOEA is developed to optimize robust route schedules for the VRPSD problem.

Data Storage Institute, Chi-Keong Goh
National University of Singapore, Kay Chen Tan

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