
Preface

This book presents a very first comprehensive collection of works on multi-objective Memetic algorithm (MOMAs). The application of sophisticated evolutionary computing approaches for solving complex problems with multiple conflicting objectives in science and engineering have increased steadily in the recent years. Within this growing trend, Memetic algorithms (MAs) are, perhaps, one of the most successful stories, having demonstrated better efficacy in dealing with multi-objective (MO) problems as compared to its conventional counterparts. MAs are population-based metaheuristic search methods that are inspired by Darwinian principles of natural selection and Dawkins notion of a meme defined as a unit of cultural evolution that is capable of local refinements. In diverse contexts, memetic algorithms have also been used under the name of hybrid evolutionary algorithms, Baldwinian evolutionary algorithms, Lamarckian evolutionary algorithms, or genetic local search.

There is a large volume of works on the application of MAs to real-world problems- a fact that is reflected by the number of special sessions and issues in upcoming conferences and journals. Nonetheless, researchers are only beginning to realize the vast potential of multi-objective MAs and there remain many open topics in its design. This edited book represents the first endeavor to reflect the most recent advances in the field, and to increase the awareness of the computing community at large on this effective technology for MO problems. This edition consists of invited papers written by leading researchers in the field to demonstrate the current state-of-the-art in the theory and practice of MOMAs. The book is organized for a wide readership and can be read by engineers, researchers, senior undergraduates and graduate students who are interested in the field of MAs and MO optimization. The assumed background for the book is some basic knowledge of evolutionary computation.

This book is divided into four parts. Part I contains of two chapters, providing readers with an insight to the challenges of MO optimization and the implementation issues of MOMAs. The opening chapter by Gideon on “Evolutionary Multi-Multi-Objective Optimization - EMMOO” examines the optimization of different MO problems, which are coupled by common components.

This necessitates the consideration of multiple MO problems simultaneously to discover satisfactory designs. The next chapter “Implementation of Multiobjective Memetic Algorithms for Combinatorial Optimization Problems: A Knapsack Problem Case Study” by Ishibuchi *et al* discuss the various implementation issues in MOMAs for combinatorial optimization problems. Extensive studies are made to examine the impact of several factors such as the frequency of local search, the choice of initial solutions for local search and the handling of infeasible solutions.

The classification of subsequent chapters into three parts is based on how information and knowledge of the problem is utilized or exploited in MOEA.

- Knowledge infused in design of problem-specific operators.
- Knowledge propagation through cultural evolution.
- Information exploited for local improvement.

Part II considers how knowledge can be infused into design of problem-specific operators and algorithms. In the first chapter “Solving Time-Tabling Problems using Evolutionary Algorithms and Heuristics Search” by Srinivasan and Zhang, the evolutionary algorithm is combined with heuristics, which ensures that all constraints are satisfied, to solve the real-world time-tabling problem of the Electrical and Computer Engineering Department in the National University of Singapore. The next chapter “An Efficient Genetic Algorithm with Uniform Crossover for the Multi-Objective Airport Gate Assignment Problem” by Hu and Di Paolo, presents a genetic algorithm with a novel encoding scheme which represents the relative positions between aircraft in the queues to gates. The encoding scheme facilitates the design of a new uniform crossover operator that ensures the feasibility of new solutions. Knowledge of how noise affect solution assessment is utilized by Lee *et al* in the next chapter “Application of Evolutionary Algorithms for Solving Multi-objective Simulation Optimization Problems” in the design of a multi-objective optimal computing budget allocation (MOCBA) algorithm. Working within the framework of the MOEA, the MOCBA adapts the number of evaluations necessary based in statistical observations of the noisy solutions. An memetic framework incorporating aspects of wrapper and filter feature selection methods for the optimization of classifiers is presented in “Feature Selection Using Single/Multi-Objective Memetic Frameworks ” by Zhu *et al*. In this chapter, the wrapper method is embodied within the evolutionary process while the filter method is introduced as a local learning procedure. The next two chapters presents a class of evolutionary algorithms that approximates computationally expensive fitness functions with meta-models to reduce computational time. Radial basis functions are used as local metamodels in “Multiobjective Metamodel-Assisted Memetic Algorithms” by Georgopoulou and Giannakoglou for the design of a gas turbine power plant and the aerodynamic design of a cascade airfoil. These local metamodels are also exploited as cost-free evaluation functions for the local search process to accelerate convergence. In the chapter “Multi-Objective Robust Optimization Assisted by Response Surface Approximation and Visual Data-Mining” by Shimoyama *et al*, the MOEA is hybridized with the Kriging model for response

surface approximation and the self-organizing map is applied in the final stage for easy visualization of complicated tradeoff information. A convergence accelerator operator comprising of a neural network which learns the inverse mapping between the decision and objective space is presented in “A Convergence Acceleration Technique for Multiobjective Optimisation ” by Adra *et al.* The operator works by first suggesting some desired solutions and then applying the neural network to predict the location of these solutions in the decision variable space.

Knowledge propagation in the form of cultural evolution is considered in Part III. The first article, “Risk and Cost Tradeoff In Economic Dispatch Including Wind Power Penetration Based on Multi-objective Memetic Particle Swarm Optimization” by Lingfeng and Singh, presents a Memetic particle swarm optimization approach to find a reasonable tradeoff between system risk and operational cost for the energy dispatch problem of wind power penetration. In this chapter, different fuzzy membership functions are used to reflect the various desires toward the wind power penetration and a synchronous particle local search is also applied to improve convergence. The agents of the multiagent collaborative search algorithm (MACS) presented in “Hybrid Behavioral-Based Multiobjective Space Trajectory Optimization” by Vasile are similarly endowed with both individualistic and social behaviors. A domain decomposition technique is also incorporated to improve consistency and efficiency of the MACS. In the third chapter, a new algorithm inspired by the physical phenomena of particle mechanics is suggested for high-dimensional problems in “Nature-Inspired Particle Mechanics Algorithm for Multi-objective Optimization” by Feng and Lau.

The exploitation of information for local improvement is considered in Part IV. In “Combination of Genetic Algorithms and Evolution Strategies with Self-Adaptive Switching”, Okabe *et al* suggest combining genetic algorithm (GA) and evolutionary strategies in a common MOMA framework, with GA as the global searcher and ES as the local search operator. Issues such as discretization error, self-adaptation and adaptive switching, arising from the combination of GA and ES are also discussed. The chapter “Comparison between MOEA/D and NSGA-II on the multi-objective travelling salesman problem” by Peng *et al* describes an algorithm that decomposes the MO problem into multiple subproblems using different scalarizing functions. The same functions are used by the 2-opt local search heuristic process. In “Integrating Cross-Dominance Adaptation in Multi-objective Memetic Algorithms” by Caponio and Neri, MO version of simulated annealing and Rosenbrock algorithm are applied as local search operators within the MOEA. The balance between local search and genetic operators are maintained by an adaptive probabilistic scheme. The optimization of dynamic MO landscapes is considered by Ray *et al* in “A Memetic Algorithm for Dynamic Multiobjective Optimization”. In this chapter, the MOMA utilizes an orthogonal epsilon-constrained formulation to deal with multi-objectivity and uses a sequential quadratic programming solver to improve tracking performance. An unique approach of incorporating co-evolution and local search into differential algorithm is described by Soliman *et al* in “A Memetic Coevolutionary Multi-objective Differential Evolution Algorithm”. A multiobjective memetic algorithm

which incorporates a simulated annealing algorithm as the local search operator for aerodynamic shape optimization is described in “Multiobjective Memetic Algorithm and its Application in Robust Airfoil Shape Optimization” by Song. In this chapter, local search is performed on each objective function while treating other objective functions as constraints.

We would like to express our appreciation to everyone who has made the publication of this edited book possible. First of all, we are grateful to all contributors, who are leading experts in the field of evolutionary computation, for their high-quality contributions. We are also grateful to Professor Janusz Kacprzyk for the opportunity to edit this book. We also acknowledge the editorial assistance from Springer during the preparation of the book.

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