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Shengxiang Yang · Xin Yao  
Editors

# Evolutionary Computation for Dynamic Optimization Problems

 Springer

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To our families

# Preface

Evolutionary computation (EC) represents a class of optimization methodologies inspired by natural evolution. During the past several decades, evolutionary algorithms (EAs) have been extensively studied by the computer science and artificial intelligence communities. As a class of stochastic optimization techniques, EAs can often outperform classical optimization techniques for difficult real-world problems.

Due to the properties of ease-to-use and robustness, EAs have been applied to a wide variety of optimization problems. Most of these optimization problems tackled are stationary and deterministic. However, many real-world optimization problems are subjected to dynamic environments that are often impossible to avoid in practice. For example, the objective function, the constraints, and/or environmental conditions may change over time due to many reasons. For these dynamic optimization problems (DOPs), the objective of an EA is no longer to simply locate the global optimal solution, but to continuously track the optimum in dynamic environments. This poses serious challenges to classical optimization techniques as well as conventional EAs. However, conventional EAs with proper enhancements are still good choices for DOPs. This is because EAs are inspired by principles of natural evolution, which takes place in the ever-changing dynamic environment in nature.

Addressing DOPs has been a topic since the early days of EC and has only received increasing research interests over the last two decades due to its challenge and its importance in practice. A number of events, e.g., edited books, journal special issues, symposia, workshops and conference special sessions, have taken place, which are relevant to the field of EC for DOPs. A variety of EC methods for DOPs have been reported across a range of application backgrounds in recent years. This motivated the edition of this book. This book aims to timely reflect the most recent advances, including benchmark test problems, methodologies, theoretical analysis, and relevant real-world applications, and explore future research directions in the field.

We have a total of 17 chapters in this book, which cover a broad range of topics relevant to EC in dynamic environments. The chapters in this book are organized into the following four categories:

- Part I: Fundamentals
- Part II: Algorithm Design
- Part III: Theoretical Analysis
- Part IV: Applications

## **Part I: Fundamentals**

During the last two decades, researchers from the EC community have developed a variety of EC approaches to address DOPs and evaluated them on many benchmark and real-world DOPs under different performance measures. Part I of the book consists of four chapters, which review the developments in terms of test and evaluation environments, methodologies, and challenges, and lay the foundations for the research field of EC for DOPs.

Chapter 1, contributed by Yang *et al.*, first introduces the concept of DOPs and reviews existing dynamic test problems (including both benchmark and real-world DOPs) that are commonly used in the literature with discussions regarding their major features. Then, this chapter reviews and discusses the performance measures that are widely used to evaluate and compare EC approaches for DOPs, followed by suggestions for future improvement regarding dynamic test and evaluation environments. Finally, this chapter describes in detail a generalized dynamic benchmark generator (GDBG), which has been recently developed and used in the 2009 and 2012 IEEE Competitions on EC for DOPs.

Chapter 2, contributed by Nguyen *et al.*, summarizes main EC methodologies that have been developed over the years for solving DOPs with discussions on the strength and weakness of each approach and their suitability for different types of DOPs. Current gaps, challenging issues and future directions regarding EC methodologies for DOPs are also presented in this chapter.

In Chapter 3, Rohlfschagen and Yao discuss challenges and perspectives on EC for DOPs regarding several key issues, including different problem definitions that have been proposed, the modelling of DOPs in terms of benchmark suites, and the way the performance of an algorithm is assessed. This chapter critically reviews the work done in each of these aspects, points out many gaps and vagueness in the current research, and identifies some promising research directions for the future of the field.

As well as addressing single-objective DOPs, researchers from the EC community have also investigated dynamic multi-objective optimization problems (DMOPs) in recent years. In the last chapter of Part I (Chapter 4), Raquel and Yao provide a survey of EC for DMOPs with regards to the definition and classification of DMOPs, test problems, performance measures and optimization approaches, and identify gaps, challenges and future directions in the domain of EC for DMOPs.

## Part II: Algorithm Design

As mentioned before, many EC methodologies have been developed to address DOPs during the last two decades. Part II of the book includes four chapters on the design of different EC methods for solving DOPs with experimental studies.

Particle swarm optimization (PSO) has been widely applied to solve DOPs due to its efficiency of locating optima. In Chapter 5, Li and Yang review PSO with variant enhancements, e.g., diversity, memory, multi-population, adaptive, and hybrid schemes, for solving DOPs, and discuss the weaknesses and strengths of those approaches. A set of typical PSO approaches to solving DOPs are chosen to experimentally compare their performance on the moving peaks problem. Based on the experimental results and relevant analyses, suggestions are given regarding algorithm design of PSO for DOPs in this chapter.

Memetic algorithms, as a class of hybrid EC methods, have also been studied for solving DOPs in recent years in the literature. Chapter 6, contributed by Wang and Yang, investigates the application of memetic algorithms to solving DOPs. A memetic algorithm that integrates a new adaptive hill climbing method as the local search technique is proposed for solving DOPs. In order to address the convergence problem, an adaptive elitism-based immigrants scheme is introduced into the proposed memetic algorithm. Experiments were conducted to investigate the performance of the proposed memetic algorithm in comparison with some other algorithms. The experimental results have showed the efficiency of the proposed memetic algorithm for solving the tested DOPs.

Hybridizing different enhancement approaches (with proper choices) into EAs has been shown beneficial and is becoming a trend in solving DOPs due to the ability of combining different advantages of different enhancement approaches. In Chapter 7, Alba *et al.* propose a new EA that is augmented by the memory, bi-population, local search, and immigrants schemes to solve the dynamic knapsack problem. The two populations inside the algorithm are used to search in different directions in the search space: the first one takes charge of exploration while the second is responsible for exploitation. According to the experimental results, the proposed algorithm is very competitive in comparison with a few existing EAs taken from the literature for solving the dynamic knapsack problems.

Dynamic constrained optimization problems (DCOPs) are a class of challenging DOPs, where constraints are integrated and may also change over time. DCOPs have recently been investigated by the EC community and are in great need of much more research. In Chapter 8, Nguyen and Yao investigate EC for continuous DCOPs. They first present some studies on the characteristics that can make DCOPs difficult to solve by some existing EAs designed for general DOPs, and then introduce a set of benchmark problems with these characteristics and experimentally test several representative EAs on these problems. The experimental results confirm that DCOPs do have special characteristics that can significantly affect the performance of algorithms. Based on the experimental results and analyses, they suggest a list of potential requirements for an algorithm to solve DCOPs effectively.

### Part III: Theoretical Analysis

In comparison with the developments of benchmark and test problems and methodologies on EC for DOPs, theoretical analysis of EC for DOPs has been significantly lagged behind with very limited results. This is mainly because it is very challenging and difficult to theoretically analyze EC methods, even for stationary optimization problems, let alone for much more challenging DOPs. Although challenging and difficult, theoretical analysis is very important for the field of EC for DOPs since the relative lack of theoretical analysis makes it difficult to fully justify the strengths and weaknesses of EC methods for DOPs. In recent years, it is great to see that some researchers have started to address this challenging issue – formally analyzing EC methods for DOPs. Part III of the book includes four chapters and serves as a review as well as an introduction to some recent research in this important area.

Chapter 9, contributed by Rohlfschagen *et al.*, provides a review of theoretical advances in the field of EC for DOPs. In particular, the authors argue the importance of theoretical results, highlight the challenges faced by theoretical researchers, and summarise the work that has been done so far in the area. They subsequently identify relevant directions for future research regarding theoretical analysis of EC for DOPs.

In Chapter 10, Tinós and Yang apply the dynamical systems approach to describe the conventional genetic algorithm as a discrete dynamical system for solving DOPs. Based on this dynamical system model, they define some properties and classes of DOPs and analyze some DOPs used by researchers in the field of EC for DOPs. The analysis of DOPs via the dynamical systems approach allows explaining some behaviors of algorithms observed in the results of the experiments conducted in the chapter and, hence, is important to understand the experimental results and to analyze the similarity of such problems to other DOPs.

In Chapter 11, Richter takes a different viewpoint of solving DOPs by EC methods, i.e., grounding it on the theoretical framework of dynamic fitness landscapes. The author defines such dynamic fitness landscapes, discusses their properties, and studies the analytical tools for measuring topological and dynamical landscape properties. Based on these landscape measures, an approach for drawing conclusion regarding characteristic features of a given optimization problem is obtained, which may allow us to address the question of how difficult the problem is for an EC approach, and what type of algorithm is most likely to solve it successfully. The proposed methodology is further experimentally illustrated using the moving peaks problem in this chapter.

Chapter 12, contributed by Comsa *et al.*, is devoted to the field of analyzing EC for DMOPs. The authors briefly review some recent work in this field and present the analysis of a multi-objective genetic algorithm with an external archive and a combination of Pareto dominance and aggregated fitness function on dynamic multi-objective subset sum problems.

## Part IV: Applications

In recent years, some researchers from the EC community have started to address real-world DOPs since many real-world optimization problems are DOPs. Part IV of the book consists of five chapters that are devoted to apply EC methods to solve real-world DOPs.

Ant colony optimization (ACO) algorithms, as a class of EC methods, have proved to be powerful methods to address DOPs, especially dynamic travelling salesman problems (DTSPs). In Chapter 13, Mavrovouniotis and Yang investigate ACO algorithms with different immigrants schemes, which help to maintain the diversity of the population via transferring knowledge from previous environments to the pheromone trails, to solve DTSPs with traffic factors. The experimental results based on different DTSP test cases show that the proposed ACO algorithms outperform other peer ACO algorithms and that different immigrants schemes are beneficial on different environmental cases.

Nowadays, with the advancement in wireless communications, more and more mobile ad hoc networks (MANETs) appear in different fields in the real world. For MANETs, one of the most important characteristics is the topology dynamics, i.e., the network topology changes over time due to energy conservation or node mobility. This topology dynamics poses big challenges to solve routing problems, which play an important role in MANETs. In Chapter 14, Cheng and Yang investigate the application of several genetic algorithms with appropriate enhancements to solve two typical dynamic routing problems, i.e., the dynamic shortest path routing problem and the dynamic multicast routing problem, in MANETs. The experimental results show that these specifically designed genetic algorithms can quickly adapt to the network topology changes and produce high quality solutions after each change.

The capacitated arc routing problem (CARP) is a classic combinatorial optimization problem that has many applications in the real world. In Chapter 15, Mei *et al.* investigate two EC methods, a repair-based tabu search and a memetic algorithm with extended neighborhood search, to solve a new dynamic CARP, where stochastic factors are included in the CARP. The objective of the dynamic CARP is to find a robust solution that shows good performance in uncertain environments. For the dynamic CARP, the authors define a robustness measure and design the corresponding repair operator according to the real-world considerations, which is used in the EC methods. Experiments are conducted based on some benchmark instances of the dynamic CARP generated in this chapter, and the preliminary analysis for the fitness landscape of the dynamic CARP is provided.

In Chapter 16, Peng *et al.* apply EAs to solve the online path planning (OPP) and dynamic weapon target assignment (WTA) problems for the multiple unmanned aerial combat vehicles anti-ground attack task. A dynamic multi-objective EA with historical Pareto set linkage and prediction, denoted LP-DMOEA, is proposed to solve the OPP problem. In the LP-DMOEA, a Bayesian network and fuzzy logic are used to quantify the bias value to each optimization objective in order to intelligently select an executive solution from the Pareto set. For the dynamic WTA problem, an estimation of distribution algorithm with an environment identification based

memory scheme, denoted EI-MEDA, is proposed as the optimizer. The proposed approaches are validated via simulation. The results show that LP-DMOEA and EI-MEDA can efficiently solve the OPP and dynamic WTA problems respectively.

Finally, the last chapter in Part IV (Chapter 17), contributed by Ibrahimov *et al.*, presents detailed insights into a project for transitioning a wine manufacturing company from a mostly spreadsheet driven business with isolated silo-operated planning units into one that makes use of integrated and optimised decision making through the use of modern heuristics. The authors present the modelling of business entities and their silo operation and optimization, and pave the path for a further holistic integration to obtain company-wide globally optimised decisions. They argue that the use of computational intelligence methods, including EC methods, is essential in dealing with dynamic and non-linear constraints and solving today's real-world problems as exemplified by the given wine supply chain.

In summary, this book fulfils the original aims well. The four parts of the book represent a variety of work in the area of EC for DOPs. We hope that the publication of this book will further promote this emerging and important research field.

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