SYNERGY

Synergy for Smart Multi-Objective Optimisation

D3.6

Edited book on high-performance optimisation

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CONTENTS

1. Introduction

The edited book on "High-Performance Simulation-Based Optimization" was carried out as an activity of the SYNERGY work package WP3.

It was edited by the three partners of the SYNERGY project: JSI (Slovenia), CUAS (Germany) and USTL (France).

2. Goals

The book is intended to be a state of the art of designing high-performance algorithms that combine machine learning and optimization in solving complex problems. This edited book provides theoretical treatments and real-world insights gained by experience, all contributed by leading researchers. It aims to serve as a comprehensive reference for researchers, practitioners and advanced-level students interested in the theory and practice of using computational intelligence in expensive optimization problems.

Indeed, many single- and multi-objective optimization problems in science and industry involve time-consuming simulations and expensive objective functions. Traditional optimization algorithms cannot be used efficiently to solve such problems. The combination of computational intelligence, machine learning and high-performance computing can be an efficient way to deal with such problems.

3. Results

Many world-wide class researchers involved in the topics of the book have been invited. More than 25 invitations have been given. All chapters have been reviewed by the editors of the book and 12 chapters have been selected for the edited book.

More than 12 SYNERGY meetings between the partners of the project have been held to deal with the edited book project. The main agenda of the various meetings were the invitation of leading researchers, reviewing of the contributions, and preparing book for submission to Springer.

4. Outcome

The book was edited by Thomas Bartz-Beielstein, Bogdan Filipič, Peter Korošec, and El-Ghazali Talbi. The book has been submitted to Springer for publication on 3 December 2018.

The book is composed of three parts and 12 chapters. Part I deals with many-objective optimization problems. Part II deals with surrogate-based optimization. Part III of the book highlights parallel optimization aspects.

Appendix: Front pages of the edited book

The appendix contains the preface, acknowledgement, table of contents and list of contributors of the edited book consisting of all the invited, reviewed and selected chapters.

Preface

Many single- and multi-objective optimization problems in science and industry involve time-consuming simulations and expensive objective functions. Traditional optimization algorithms cannot be used efficiently to solve such problems. The combination of computational intelligence, machine learning and high-performance computing can be an efficient way to deal with such problems. The book is intented to be a state of the art of designing high-performance algorithms that combine machine learning and optimization in solving complex problems. This edited book provides theoretical treatments and real-world insights gained by experience, all contributed by leading researchers. It aims to serve as a comprehensive reference for researchers, practitioners and advanced-level students interested in the theory and practice of using computational intelligence in expensive optimization problems.

The book is composed of three parts. Part I deals with many-objective optimization problems.

Chapter 1 is a tutorial on multi-objective optimization based on evolutionary algorithms. This tutorial presents a review of the most important fundamentals in multi-objective optimization and then introduces representative algorithms, illustrates their working principles, and discusses their application scope. In addition, the tutorial describes statistical performance assessment. Finally, it highlights recent important trends and closely related research fields. The tutorial is intended for readers, who want to acquire basic knowledge on the mathematical foundations of multi-objective optimization and state-of-the-art methods in evolutionary multi-objective optimization. The aim is to provide a starting point for researching in this active area, and it should also help the advanced reader to identify open research topics.

Chapter 2 deals with many-objective optimization with limited computing budget. In this chapter, the authors introduce a surrogate-assisted optimization algorithm for many-objective optimization (SaMaO) which is capable of delivering converged and well distributed set of solutions within a limited computing budget. The proposed algorithm successfully combines features of state-of-the-art many-objective optimization and surrogate-assisted optimization strategies. The algorithm relies on principles of decomposition and adaption of reference vectors for effective search. The flexibility of function representation is offered through the use of multiple types of surrogate models.

In Chapter 3, the authors focus on multi-objective Bayesian optimization for engineering optimization. Bayesian optimization methodologies replace a single optimization of the objective function by a sequence of optimization problems: this makes sense as the acquisition function is cheap-to-evaluate whereas the objective is not. Depending on the goal, different acquisition functions are available: multi-objective acquisition functions are relatively new and this chapter gives a state-of-the-art overview and illustrates some approaches based on hypervolume improvement. It is shown that the quality of the model is crucial for the performance of Bayesian optimization. This is illustrated by using the more flexible Student-t processes as surrogate models.

The interest of Chapter 4 is put on the automatic configuration of multi-objective optimizers and multi-objective configuration. In this chapter, the authors review two main aspects where the research on automatic configuration and multi-objective optimization intersect. The first one is the automatic configuration of multi-objective optimizers, where the authors discuss means and specific approaches. In addition, they detail a case study that shows how these approaches can be used to design new, high-performing multi-objective evolutionary algorithms. The second aspect is the research on multi-objective configuration, that is, the possibility of using multiple performance metrics for the evaluation of algorithm configurations.

Chapter 5 describes optimization and visualization in many-objective space trajectory design. This work optimizes the thrusting profile of a low-thrust spacecraft propelled by an ion engine to raise from Earth's low orbit to the vicinity of the Moon. The optimization problem involves of thirty-two variables. Four objective functions are considered, namely the operation time of the ion engine system, time to reach the Moon, maximum eclipse time, and the initial mass of the spacecraft, subject to various constraints. The authors use the many-objective optimizer named Adaptive ε-Sampling and ε-Hood (AεSεH) to search for non-dominated solutions, analyze the trade-offs between variables and objectives, and use a method called visualization with prosections to gain insights into the problem and to analyze the dynamics of the optimization algorithm

Part II deals with surrogate-based optimization.

In Chapter 6, the author details simulation optimization through regression and Kriging metamodels. This chapter surveys two methods for the optimization of real-world systems that are modelled through simulation. These methods use either linear regression or Kriging (Gaussian processes) metamodels. The metamodel guides the design of the experiment; this design fixes the input combinations of the simulation model. The linear-regression metamodel uses a sequence of local first-order and second-order polynomials—known as response surface methodology (RSM). Kriging models are global, but are re-estimated through sequential designs. Robust optimization may use RSM or Kriging to account for uncertainty in simulation inputs.

Chapter 7 focuses on a better integration of surrogate models and optimization. There are two main approaches to the integration of the surrogate and the optimizer: (1) The Surrogate-assisted evolutionary algorithms (SAEAs) alternates between improving the surrogate model and improving the estimate of the optimum (via an optimizer operating on an acquisition function) and (2) certain parts of the SAEA (e.g., selection in evolutionary algorithms) are enhanced by the knowledge obtained through the surrogate model. In this chapter, the authors focus on the first approache. In the literature, several SAEAs have been proposed for use cases with small evaluation budgets. These algorithms can mainly be distinguished by the infill criterion they use, i.e., their strategy for selecting new sample(s) to update the surrogate model.

Chapter 8 describes surrogate-assisted evolutionary optimization for large problems. This chapter highlights the major challenges in solving problems with a large number of objectives (known as many-objective problems) and a large number of decision variables (large-scale optimization problems). In addition, the authors present two recently proposed algorithms called Kriging-assisted reference vector guided EA (K-RVEA) and surrogate-assisted cooperative swarm optimization algorithm (SA-COSO) in the field of expensive many-objectives and large-scale optimization.

In Chapter 9, the authors give an overview and comparison of Gaussian process-based surrogate models for mixed continuous and discrete variables and their application on aerospace design problems. Surrogate modeling is an increasingly popular tool for engineering design as it enables to model the performance of very complex systems with a limited computational cost. A large number of techniques exist for the surrogate modeling of continuous functions, however, only very few methods for the surrogate modeling of mixed continuous/discrete functions have been developed. In this chapter, existing adaptations and variants of Gaussian process-based surrogate modeling techniques for mixed continuous/discrete variables are described, discussed and compared on several analytical test-cases and aerospace design problems.

In Chapter 10, the last chapter of this part, the authors investigate some open issues in surrogate-assisted optimization. This chapter outlines the existing challenges in this field that include benchmarking, constraint handling, constructing ensembles of surrogates and solving discrete and/or multi-objective optimization problems. The authors discuss shortcomings of existing techniques, propose suggestions for improvements and give an outlook on promising research directions. This is valuable for practitioners and researchers alike, since the increased availability of computational resources on the one hand and the continuous development of new approaches on the other hand raise many intricate new problems in this field.

Part III of the book highlights parallel optimization aspects.

Chapter 11 proposes a parallel island model for hypervolume based many-objective optimization. Parallelism arises as an attractive option when Multi-objective Evolutionary Algorithms (MOEAs) demand an intensive use of CPU or memory. The computational complexity of a MOEA depends on the scalability of its input parameters (i.e., the number of decision variables, the number of objectives, the population size, etc.) and on the computational cost of evaluating the objectives of the problem. Nonetheless, current research efforts have focused only on the second case. Therefore, in this chapter, the authors investigate the performance and behavior of S-PAMICRO, a recently proposed parallelization of SMS-EMOA that inhibits exponential execution time as the number of objectives increases. The idea behind S-PAMICRO is to divide the overall population into several semi-independent subpopulations each of which consists of very few individuals. Each subpopulation evolves a serial SMS-EMOA with an external archive for maintaining diversity.

Chapter 12 describes a many-core branch-and-bound algorithm for GPU accelerators and MIC coprocessors. In this chapter, the authors investigate the offload-based parallel design and implementation of branch-and-bound algorithms for coprocessors addressing these issues. Two major many-core architectures are considered and compared: Nvidia GPU and Intel MIC. The proposed approaches have been experimented using the Flow-Shop scheduling problem and two hardware configurations equivalent in terms of energy consumption: Nvidia Tesla K40 and Intel Xeon Phi 5110P. The reported results show that the GPU-accelerated approach outperforms the MIC offload-based one even in its vectorized version. Moreover, vectorization improves the efficiency of the MIC offload-based approach by a factor of two.

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