Yoel Tenne and Chi-Keong Goh (Eds.)

Computational Intelligence in Expensive Optimization Problems

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Computational Intelligence in Expensive Optimization Problems

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To our families for their love and support.

Preface

Optimization is an essential part of research, both in science and in engineering. In many cases the research goal is an outcome of an optimization problem, for example, improving a vehicle's aerodynamics or a metal alloy's tensile strength.

Motivated by industrial demands, the process of design in science and engineering has undergone a major transformation. The advances in the fields of intelligent computing paradigm and the introduction of massive computing power have facilitated a move away from paper-based analytical systems towards digital models and computer simulations. Computer-aided design optimization is now involved in a wide range of design applications, ranging from large transatlantic airplanes to micro electro mechanical systems.

With the development of more powerful optimization techniques, the research community is continually seeking new optimization challenges and to solve increasingly more complicated problems. An emerging class of such challenging problems is known as the 'expensive optimization problems'. High computational cost can arise due to:

- Resource-intensive evaluations of the objective function: such problems arise when using 'computer-experiments', i.e., when a computer simulation replaces a real-world laboratory experiment during the optimization process. Such simulations can be prohibitory expensive (require anywhere from minutes to hours of evaluation time for each candidate solution). Also, there is no analytic expression for the objective function or its derivatives, requiring optimization algorithms which are derivative-free. Examples include wing shape optimization and electronic circuit design.
- Very high dimensional problems: in problems with hundreds or thousands of variables the 'curse of dimensionality' implies locating an optimum can be intractable due to the size of the search space. Examples include scheduling problems and image analysis.

On top of these difficulties, real-world optimization problems may exhibit additional challenges such as a complicated and non-smooth landscape, multiple optima and discontinuities. Under these difficulties classical optimization methods may perform poorly or may even fail to obtain a satisfactory solution within the allocated resources (such as computer time). To circumvent this, researchers turn to computational intelligence methods such as agent-based algorithms, fuzzy logic and artificial neural networks. Such methods have shown to perform well in challenging scenarios and they can often handle a wide variety of problems when little or no-apriori knowledge is available. These nature- and biologically-inspired techniques are capable of 'learning' the problem features during the optimization and this can improve their performance and provide a better final solution.

However, the application of computational intelligence methods to expensive optimization problems is not straightforward. Their robustness, also referred to as the 'exploration-exploitation trade-off', implies they do not exploit domain knowledge efficiently and this can impair their convergence. For example, an evolutionary algorithm may require many thousands of function evaluations to obtain a satisfactory solution, which is unacceptable when each function evaluation requires hours of computer run-time. This necessitates the need to explore various methods to bridge the missing gaps before computational intelligence can be applied effectively to expensive problems.

Computational intelligence in Expensive Optimization Problems is a recent and emerging field which has received increasing attention in the last decade. This edited book represents the first endeavor to provide a snapshot of the current state-of-the-art in the field, covering both theory and practice. This edition consists of chapters contributed by leading researchers in the field, demonstrating the different methodology and practice to handle high computational cost of today's applications. This book is intended for wide readership and can be read by engineers, researchers, senior undergraduates and graduates who are interested in the development of computational intelligence techniques for expensive optimization problems.

This book is divided into 3 parts:

I Techniques for resource-intensive problems
II Techniques for high-dimensional problems
III Real-world applications

Part I considers the various methods to reduce the evaluation time, such as using models (also known as surrogate-models or meta-models, which are computationally cheaper approximations of the true expensive function) and parallelization. This section starts with two surveys on the current state-of-the-art. Shi and Rasheed survey a wide range of model-assisted algorithms, including frameworks for model-management in single objective optimization while Santana-Quintero *et al.* survey fitness approximations in multi-objective algorithms. Giannakoglou and Kampolis propose a flexible parallel multilevel evolutionary algorithm (EA) framework where each level can employ a different model, different search algorithm or different parametrization. They describe the performance of their approach with real-world expensive aerodynamic shape optimization problems. Koziel and Bandler describe another approach which uses models of different fidelity, the 'space-mapping' method, to accelerate the optimization search. They apply their method to electronic circuit design. In another related study, Takahama and Sakai propose methods for model management which assesses the model accuracy and decides when a model needs to be improved. They implement their method in a differential evolution framework. Ginsbourger *et al.* parallelize the Efficient Global Optimization (EGO) algorithm which uses Kriging models and the expected improvement criterion. They propose statistical criteria for selecting multiple sites to evaluate for each iteration. Guimarães *et al.* propose a memetic algorithm for expensive design optimization problems. Their algorithm identifies promising regions and candidates from these regions are identified with a higher fidelity model and are given more weight by the algorithm. Ochoa also employs statistical criteria and proposes using Estimation of Distribution Algorithms (EDAs) to reduce the number of function evaluations. The study describes several approaches such as Boltzmann estimation and the Shrinkage EDAs. Also within the evolutionary computing framework, Fonseca *et al.* explore the use of similarity-based models (a nearest-neighbour approach) to extend the number of generations of an evolutionary algorithm in expensive optimization problems. Nakayama *et al.* and Bird and Li address the issues of expensive dynamic optimization problems. Nakayama *et al.* describe a model-predictive control algorithm for dynamic and expensive multiobjective optimization problems where they use a support-vector regression model. On the other hand, Bird and Li suggest a specialized particle swarm optimization (PSO) algorithm with least-squares regressors. The regressors locally approximate the objective function landscape and accelerate the convergence of the PSO to local optima.

In Part II, researchers explore sophisticated operators, such as those utilizing domain knowledge or which self-adapt during the search to combat the 'curse of dimensionality'. Caponio *et al.* implement a memetic algorithm which combines differential evolution (DE) with an adaptive local search which scales the DE vector, along with other algorithmic enhancements. Carvalho and Ferreira tackle the electric network distribution problem, which is a large scale combinatorial problem. They propose several hybrid Lamarckian evolutionary algorithms with specialized operators. dos Santos *et al.* tackle the traveling salesman problem (TSP) and propose a reinforcement learning metaheuristic for a specialized parallel hybrid EA. They show performance can be improved by using multiple search trajectories. Süral *et al.* also focus on the TSP and the TSP with back hauls problem and propose several evolutionary algorithms with specialized crossover and mutation and operators. They show that utilizing domain knowledge improves the algorithms performance. Cococcioni *et al.* study multiobjective genetic Takagi-Sugeno fuzzy systems in high-dimensional problems, which pose a challenge to such multiobjective EAs. They propose two enhancements to the multiobjective EA to accelerate the search. Davis-Moradkhan and Browne propose a specialized evolutionary algorithm to tackle the multicriterion minimum spanning tree problem, a challenging combinatorial problem. They suggest several specialized operators as well as several algorithm variants to improve the spread of solutions along the Pareto front. Lastly, Shilane *et al.* present a specialized evolutionary algorithm to tackle the problem of risk-minimization in statistical parameter estimation, a multimodal high-dimensional problem. They demonstrate that their algorithm compares well with existing parameter-estimation methods while having the advantage that it can run in parallel.

Part III focuses on real-world applications. Successful application of computational intelligence methods to real-world problems is non-trivial and there are important insights and lessons to be learned from researchers' experience. Chen *et al.* use a particle swarm optimization algorithm for an expensive optimization problem of a transceiver design. They study a semi-blind joint maximum likelihood channel estimation and data detection for a receiver and the minimum bit-error-rate multiuser transmission. Results show their algorithm outperforms existing approaches. Donateo describes a multiobjective optimization of a diesel engine piston. The study used a multiobjective evolutionary algorithm which is parallelized over a cluster to reduce evaluation time. They obtained a more efficient engine with lower pollution level. Vasile and Croisard study the robust planning of a space mission, where the computational time grows exponentially with the number of uncertain variables. They use a multiobjective EA and apply the Evidence theory and an indirect approach to estimate the belief and plausibility functions. Kumar and Bauer propose a methodology to manage an expensive design process from the conceptual stage to a final design. They apply the methodology to the design of electrical drives and electrical circuits. Won *et al.* consider the problem of reliable network design and proposed a hybrid EA-ant colony system algorithm. They propose a multiring encoding scheme to combine the two and apply their algorithm to a variety of network design problems. Yamada and Berger describe the optimization of neural network for speech recognition using an EA. The structure of the EA changes from a random search to a steady state EA and finally to an elitist EA during the optimization. The algorithm reduces the high computational cost of the optimization by identifying a promising subset of variables and concentrating on it. Guichón and Castro tackle the expensive optimization problem of automatic image registration optimization by using a parallel evolutionary algorithm. The study describes an implementation of a fast and robust Internet subtraction service using a distributed evolutionary algorithm and a service-oriented architecture. Finally, Pilato *et al.* describe an expensive multiobjective optimization digital circuits, where the proposed algorithm uses fitness inheritance and approximation models to reduce the number of calls to the expensive simulation.

Overall, the chapters in this volume discuss a wide range of topics which reflect the broad spectrum of computational intelligence in expensive optimization problems. The chapters highlight both the current achievements and challenges and point to promising future research venues in this exciting field.

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Yoel Tenne
Chi-Keong Goh

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