Preface

Optimization is an integral part of research in most scientific and engineering problems.

The critical challenge in optimization lies in iteratively finding the best combination of variables which minimize or maximize one or more objective functions by satisfying the variable requirements and restrictions which are largely known as constraints. Most optimization problems involve one or many constraints due to the limitation in the availability of resources, physical viability, or other functional requirements. The existence of constraints in problems in science and engineering is continuously motivating researchers to develop newer and more efficient methods of constraint handling in optimization.

Evolutionary optimization algorithms are population-based metaheuristic techniques to deal with optimization problems. These algorithms have been successively applied to a wide range of optimization problems due to their ability to deal with nonlinear, nonconvex, and discontinuous objective and constraint functions. Originally, evolutionary algorithms (EAs) were developed to solve unconstrained problems. However, as demands for solving practical problems arose, evolutionary algorithm researchers have been regularly devising new and efficient constraint handling techniques. Out of these constraint handling techniques, some are borrowed from the classical literature, while others use different strategies like preference of feasible solutions over infeasible ones, choice of less constraint-violated solutions, separation of objective and constraint functions, special operators, and hybrid classical evolutionary methods, to name a few.

In most top evolutionary computation conferences, a good number of papers are regularly published to discuss various ways of handling constraints using different EAs. Almost all books and journals on evolutionary computation consist one or many topics on constrained optimization. In 2009, Springer Studies in Computational Intelligence came up with a full monograph on EA-based constrained optimization (Constraint-Handling in Evolutionary Optimization by Mezura-Montes; ISBN: 978-3-642-00618-0). This book takes the same direction as that monograph, and presents a more updated view of the subject matter. Moreover, this book aims to serve as a self-contained collection of the current research addressing general constrained optimization. The book can also serve as a textbook for advanced courses and as a guide to the future direction of research in the area. Many constraint handling techniques that exist in bits and pieces are assembled together in the present monograph. Hybrid optimization, which is gaining a lot of popularity today due to its capability of bridging the gap between evolutionary and classical optimization is broadly covered here. These areas will be helpful for researchers, novices and experts alike.

The book consists of ten chapters covering diverse topics of constrained optimization using EAs.

Helio J.C. Barbosa, Afonso C.C. Lemonge, and Heder S. Bernardino review the adaptive penalty techniques in the first chapter that mainly deals with constraints using EAs. The penalty function approach is one of the most popular constraint handling methodologies due to its simple working principle and its ease of integration with any unconstrained technique. The study also indicates the need for implementation of different adaptive penalty methods in a single search engine. It will facilitate better information for the decision maker to choose a particular technique.

The theoretical understanding of constrained optimization is one of the key features to select the best constraint handling mechanism for any problem.

To tackle this issue, Shayan Poursoltan and Frank Neumann have studied the influence of fitness landscape in Chap. 2. The study introduces different methods to quantify the ruggedness of a given constrained optimization problem.

Rommel G. Regis proposes a constraint handling method to solve computationally expensive constrained black-box optimization using surrogate-assisted evolutionary programming (EP) in Chap. 3. The proposed algorithm creates surrogates model for the black-box objective function and inequality constraint functions in every generation of the EP. Furthermore, at the end of each generation a trust-region-like approach is used to refine the best solution. Hard and soft constraints are common in constrained optimization problems.

In Chap. 4, Richard Allmendinger and Joshua Knowles point out a new type of constraint known as ephemeral resource constraints (ERCs). The authors have explained the presence of ERCS in real-world optimization problems.

A combination of multi-membered evolution strategy and an incremental approximation strategy-assisted constraint handling method is proposed by Sanghoun Oh and Yaochu Jin in Chap. 5 to deal with highly constrained, tiny and separated feasible regions in the search space. The proposed approach generates an approximate model for each constraint function with increasing order of accuracy. It starts with a linear model and consecutively reaches to the complexity similar to the original constraint function.

Chapter 6, by Tetsuyuki Takahama and Setsuko Sakai, describes a method combining the e-constrained method and the estimated comparison. In this method, rough approximation is utilized to approximate both the objective function as well as constraint violation. The methodology is integrated with differential evolution (DE) for its simple working principle and robustness.

Jeremy Porter and Dirk V. Arnold carry out a detailed analysis of the behavior of a multi-recombinative evolution strategy that highlights both cumulative step size adaptation and a simple constraint handling technique in Chap. 7. In order to obtain the optimal solution at the cones apex, a linear optimization problem is considered for analysis with a feasible region defined by a right circular cone, which is symmetric about the gradient direction.

A niching technique is explored in conjunction with multimodal optimization by Mohammad Reza Bonyadi and Zbigniew Michalewicz in Chap. 8 to locate feasible regions, instead of searching for different local optima. Since in continuous constrained optimization, feasible search space is more likely to appear with many disjoint regions, the global optimal solution might be located within any one of them. A particle swarm optimization is used as search engine.

In Chap. 9, Rammohan Mallipeddi, Swagatam Das, and Ponnuthurai Nagaratnam Suganthan present an ensemble of constraint handling techniques (ECHT). Due to the nonexistence of a universal constraint handling method, an ensemble method can be a suitable alternative. ECHT is collated with an improved (DE) algorithm and the proposed technique is known as EPSDE.

Rituparna Datta and Kalyanmoy Deb propose an adaptive penalty function method using genetic algorithms (GA) in the concluding chapter (Chap. 10) of this book. The proposed method amalgamates a bi-objective evolutionary approach with the penalty function methodology in order to overcome individual weakness. The bi-objective approach is responsible for the approximation of appropriate penalty parameter and the starting solution for the unconstrained penalized function by a classical method, which is responsible for exact convergence.

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