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BOOK REVIEW

INTELLIGENT OPTIMIZATION TECHNIQUES, GENETIC ALGORITHMS, TABU SEARCH, SIMULATED ANNEALING, AND NEURAL NETWORKS, D. T. Pham and D. Karaboga, Springer: Berlin, Heidelberg, New York; Springer London: London, 2000, 302pp, ISBN 1-85233-028-7

Optimization has been used in all areas of engineering for the purpose of enhancing performance, durability, productivity, and efficiency among other agendas. Optimization originated in the applied mathematics arena, where the well-known derivative-based methodologies was established. For constraint optimization, a traditional derivative-based optimization algorithm may include the use of Lagrange multipliers and the necessary Kuhn–Tucker conditions to define local minimum points in the search space [1]. The primary drawback of these commonly used derivative-based algorithms is that in general no guarantee of global optimal point can be attached to a solution. In addition, highly constraint—or interconnected—problems tend to become cumbersome if not impossible to solve. This complexity, or epistasis, turns out to be an advantage for some of the evolutionary-based optimization algorithms.

Genetic algorithms [2] (GA) are evolutionary-based algorithms that simulate Darwin's survival of the fittest principle. An initial population of candidate solutions is randomly generated and represented as chromosomes in the form of genes, where the genes represent the parameter space and each chromosome is a potential solution to the problem. These chromosomes are evaluated based on an objective function—or also referred to a fitness function—and ranked in terms of its fitness. A subset of the next generation of candidate solutions is selected based on their performance with the objective function. The remaining set of the new generation is generated by a mating process. In many implementations of GAs, the best performing candidate solution set has a high likelihood of being selected to the subset of the parents. In addition to the mating process, a mutation rate is also imbedded in the generation of the new population. The mutation enables the search for the optimum solution. It provides for a way to overcome local minimums or bounded constraints, which scatter the feasibility region and therefore enable to locate the global optimum. This process of selection, mating, and mutation is repeated a number of times until the best performing candidate solution converges to some stationary value. Besides of the capability of overcoming local optimum points, some additional advantages of a GA are the ease with which large numbers of parameters can be handled, the fact that they do not require the traditional approach of taking derivatives, the fact that they result in a set of optimum candidate solutions rather than a single candidate solution, and that they work well with experimental data as well as simulated data.

The tabu search (TS) algorithm, which was originally introduced by Glover [3] in 1986, is another iterative-based algorithm that has the potential to find the global optimal point. The algorithm is based on a heuristic method, which guides a local search procedure to explore the search space in such a way that entrapment in local minima is avoided. The tabu list is a set of prior solution obtained during the iteration process of the algorithm, which is the key to this algorithm and its origin can be linked to artificial intelligence (AI) concepts. The TS pursues a local search whenever it encounters a local optimum by allowing non-improving moves. The tabu list is used to prevent the appearance of previously visited solutions. The TS often evolves from the present solution to one, which is worse, with the hope that this iteration will ultimately progress to an even better solution.

The simulated annealing (SA) algorithm was—as GAs—inspired by natural phenomena. This optimization algorithm was introduced by Kirkpatrick *et al.* [4] in 1983. The concept studied and used as a basis for the algorithm is the annealing process. Annealing results—if done carefully—into a perfect allocation of atoms of a particular substance. In nature, the substance is first heated above its melting temperature and then cooled to allow for the crystal to arrange them perfectly. The algorithm uses the temperature as a control parameter, which gives the speed of progression to the optimum value of the cost function. For the algorithm, the cost function is analogous to the energy level of the substance and the optimization parameters represent the atoms.

In accordance to the GA and the SA algorithm, neural networks (NN) are also the result of successfully adapting natural processes to solve optimization problems. NN are also used for modelling purposes and controls. NNs are basically massively connected networks that are trained based on observed data [5]. Since its wide application to controls and modelling, there have been proposed a fast amount of different NNs that all have different advantages and applications, distinguishing themselves through their architecture and the learning processes. For optimization purposes, the NNs are constructed to minimize energy functions, which represent the cost function of the optimization process.

None of the above-listed algorithms do require taking derivatives to find a search direction (though it might be beneficial in some circumstances to include this information in a GA). This and the ease of using these algorithms make the non-derivative-based algorithm so appealing to be used in optimization problems. In addition, GAs also provide for a number of solutions, rather than one, and are very suitable for parallel processing applications and multi-objective optimization problems.

The book by Pham and Karaboga sets out to give an introduction to the four above-listed intelligent optimization techniques to engineers without background or prior exposure to these algorithms. The establishment of the background material for the four different optimization algorithms is presented in Chapter 1. GAs are explained using the binary GA version, which complements the explanation of mating and mutation well. The TS and SA algorithms are described briefly and many details are left out, which is not compensated in the later chapters of the book. In contrast, the NN algorithm for optimization has more substance in description for the designed audience. At the end of this chapter the authors effectively demonstrate the performance of these optimization algorithms using typical 'benchmark' problems, such as the travelling salesman problem.

Chapter 2 presents a more detailed study of GAs. In particular, four different variations of GAs are discussed and analysed. A hybrid genetic algorithm (HGA), which addresses the deficiencies caused by the roulette wheel selection method, is presented. Key to the problem of roulette wheel selection is its desire to introduce sufficient randomness into the selection process. HGAs try to keep the stochastic nature of the selection process while balancing the propagation of fit individuals and exploring new territories in the search space. Another GA variation is presented that addresses the problem of premature convergence to non-optimal points, despite the inclusion of probabilistic methodologies in the selection and mating processes. Using cross-breading among sub-population chromosomes, which matured to some degree prior to this step, limits premature convergence without adding to much computational cost to the algorithm. One of the many advantages GAs offer are a feasible solution set, rather one solution. A common solution set of a GA contains solutions closely clustered together, most of them around the best performing chromosome. The book presents an alternative GA that employs deflation and sharing mechanisms such that the dimensions of the solution space within the feasible region is enhanced. A very interesting discussion about variable mutation rate is presented in Chapter 2. It is well known that this process step within the GA plays an important role for the convergence rate and success of finding the global optimum point. Three heuristic approaches for implementing a variable mutation rate are addressed and presented.

Chapter 2 concludes with a set of engineering applications of GAs. In particular, the design of fuzzy logic controllers, the training of recurrent NNs, the design of an adaptive fuzzy logic controller, the design of a gearbox, and the optimization of a workspace layout are demonstrated.

The following chapters contain case studies of the respective algorithms and the analysis of their performance in obtaining an optimal solution. Chapter 3 looks at TS as a means for optimum problems in microstrip antenna, the training of recurrent NN for system identification, the design of FIR filters, and the tuning of PID controllers. Chapter 4 contains application of SA for solving the optimal problem of aligning lasers, optimizing manufacturing processes, and optimizing the lot-size in multi-stage production inventory systems. Chapter 5 presents two applications, one addressing the mapping and hierarchical self-organizing NN for VLSI circuit placement, the second looks at Hopfield NNs for optimizing the schedule of a satellite broadcasting.

The appendix of the book turns out to be very useful for the intended audience, containing a brief discussion on classical optimization algorithms, fuzzy logic controllers, and implementation of GA, SA, TS, and NN into C-code. The code provided is for a generic implementation and easily modifiable for different problem settings. The references are conveniently provided at the end of each chapter and are detailed and sufficient enough to allow for interested readers to conduct further studies in the subjects discussed in the book.

In summary, the book is primarily focusing on GAs, reflecting the contribution history of the authors in this field. The discussion of SA, TS, and NN is very useful for the intended audience, but lacks a more rigor discussion—as compared to the GA section—to balance the depth and substance given in the sections describing GAs. The book is very readable and highly recommended for engineers interested in applying intelligent systems to solve complex optimization problems.

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