

Raymond Chiong (Ed.)

Nature-Inspired Algorithms for Optimisation

Studies in Computational Intelligence, Volume 193

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Nature-Inspired Algorithms for Optimisation



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Foreword

Research on stochastic optimisation methods emerged around half a century ago. One of these methods, evolutionary algorithms (EAs) first came into sight in the 1960s. At that time EAs were merely an academic curiosity without much practical significance. It was not until the 1980s that the research on EAs became less theoretical and more applicable. With the dramatic increase in computational power today, many practical uses of EAs can now be found in various disciplines, including scientific and engineering fields.

EAs, together with other nature-inspired approaches such as artificial neural networks, swarm intelligence, or artificial immune systems, subsequently formed the field of natural computation. While EAs use natural evolution as a paradigm for solving search and optimisation problems, other methods draw on the inspiration from the human brain, collective behaviour of natural systems, biological immune systems, etc. The main motivation behind nature-inspired algorithms is the success of nature in solving its own myriad problems. Indeed, many researchers have found these nature-inspired methods appealing in solving practical problems where a high degree of intricacy is involved and a bagful of constraints need to be dealt with on a regular basis. Numerous algorithms aimed at disentangling such problems have been proposed in the past, and new algorithms are being proposed nowadays.

This book assembles some of the most innovative and intriguing nature-inspired algorithms for solving various optimisation problems. It also presents a range of new studies which are important and timely. All the chapters are written by active researchers in the field of natural computation, and are carefully presented with challenging and rewarding technical content. I am sure the book will serve as a good reference for all researchers and practitioners, who can build on the many ideas introduced here and make more valuable contributions in the future. Enjoy!

November 2008

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Preface

Nature has always been a source of inspiration. In recent years, new concepts, techniques and computational applications stimulated by nature are being continually proposed and exploited to solve a wide range of optimisation problems in diverse fields. Various kinds of nature-inspired algorithms have been designed and applied, and many of them are producing high quality solutions to a variety of real-world optimisation tasks. The success of these algorithms has led to competitive advantages and cost savings not only to the scientific community but also the society at large.

The use of nature-inspired algorithms stands out to be promising due to the fact that many real-world problems have become increasingly complex. The size and complexity of the optimisation problems nowadays require the development of methods and solutions whose efficiency is measured by their ability to find acceptable results within a reasonable amount of time. Despite there is no guarantee of finding the optimal solution, approaches based on the influence of biology and life sciences such as evolutionary algorithms, neural networks, swarm intelligence algorithms, artificial immune systems, and many others have been shown to be highly practical and have provided state-of-the-art solutions to various optimisation problems.

This book provides a central source of reference by collecting and disseminating the progressive body of knowledge on the novel implementations and important studies of nature-inspired algorithms for optimisation purposes. Addressing the various issues of optimisation problems using some new and intriguing intelligent algorithms is the novelty of this edited volume. It comprises 18 chapters, which can be categorised into the following 5 sections:

- Section I Introduction
- Section II Evolutionary Intelligence
- Section III Collective Intelligence
- Section IV Social-Natural Intelligence
- Section V Multi-Objective Optimisation

The first section contains two introductory chapters. In the first chapter, *Weise et al.* explain why optimisation problems are difficult to solve by addressing some of the fundamental issues that are often encountered in optimisation tasks such as premature convergence, ruggedness, causality, deceptiveness, neutrality, epistasis,

robustness, overfitting, oversimplification, multi-objectivity, dynamic fitness, the No Free Lunch Theorem, etc. They also present some possible countermeasures, focusing on the stochastic based nature-inspired solutions, for dealing with these problematic features. This is probably the very first time in the literature that all these features have been discussed within a single document. Their discussion also leads to the conclusion of why so many different types of algorithms are needed.

While parallels can certainly be drawn between these algorithms and various natural processes, the extent of the natural inspiration is not always clear. *Steer et al.* thus attempt to clarify what it means to say an algorithm is nature-inspired and examine the rationale behind the use of nature as a source of inspiration for such algorithm in the second chapter. In addition, they also discuss the features of nature which make it a valuable resource in the design of successful new algorithms. Finally, the history of some well-known algorithms are discussed, with particular focus on the role nature has played in their development.

The second section of this book deals with evolutionary intelligence. It contains six chapters, presenting several novel algorithms based on simulated learning and evolution – a process of adaptation that occurs in nature. The first chapter in this section by *Salomon and Arnold* describes a hybrid evolutionary algorithm, called the Evolutionary-Gradient-Search (EGS) procedure. This procedure initially uses random variations to estimate the gradient direction, and then deterministically searches along that direction in order to advance to the optimum. The idea behind it is to utilise all individuals in the search space to gain as much information as possible, rather than selecting only the best offspring. Through both theoretical analysis and empirical studies, the authors show that the EGS procedure works well on most optimisation problems where evolution strategies also work well, in particular those with unimodal functions. Besides that, this chapter also discusses the EGS procedure's behaviour in the presence of noise. Due to some performance degradations, the authors introduce the concept of inverse mutation, a new idea that proves very useful in the presence of noise, which is omnipresent in almost any real-world application.

In an attempt to address some limitations of the standard genetic algorithm, *Le-naerts et al.* in the second chapter of this section present an algorithm that mimics evolutionary transitions from biology called the Evolutionary Transition Algorithm (ETA). They use the Binary Constraint Satisfaction Problem (BINCSP) as an illustration to show how ETA is able to evolve increasingly complex solutions from the interactions of simpler evolving solutions. Their experimental results on BINCSP confirm that the ETA is a promising approach that requires more extensive investigation from both theoretical and practical optimisation perspectives.

Following which, *Tenne* proposes a new model-assisted Memetic Algorithm for expensive optimisation problems. The proposed algorithm uses a radial basis function neural network as a global model and performs a global search on this model. It then uses a local search with a trust-region framework to converge to a true optimum. The local search uses Kriging models and adapts them during the search to improve convergence. The author benchmarks the proposed algorithm

against four model-assisted evolutionary algorithms using eight well-known mathematical test functions, and shows that this new model-assisted Memetic Algorithm is able to outperform the four reference algorithms. Finally, the proposed algorithm is applied to a real-world application of airfoil shape optimisation, where better performance than the four reference algorithms is also obtained.

In the next chapter, *Wang and Li* propose a new self-adaptive estimation of distribution algorithm (EDA) for large scale global optimisation (LSGO) called the Mixed model Uni-variate EDA (MUEDA). They begin with an analysis on the behaviour and performances of uni-variate EDAs with different kernel probability densities via fitness landscape analysis. Based on the analysis, the self-adaptive MUEDA is devised. To assess the effectiveness and efficiency of MUEDA, the authors test it on typical function optimisation tasks with dimensionality scaling from 30 to 1500. Compared to other recently published LSGO algorithms, the MUEDA shows excellent convergence speed, final solution quality and dimensional scalability.

Subsequently, *Tirronen and Neri* propose a Differential Evolution (DE) with integrated fitness diversity self-adaptation. In their algorithm, the authors introduce a modified probabilistic criterion which is based on a novel measurement of the fitness diversity. In addition, the algorithm contains an adaptive population size which is determined by variations in the fitness diversity. Extensive experimental studies have been carried out, where the proposed DE is being compared to a standard DE and four modern DE based algorithms. Numerical results show that the proposed DE is able to produce promising solutions and is competitive with the modern DEs. Its convergence speed is also comparable to those state-of-the-art DE based algorithms.

In the final chapter of this section, *Patel* uses genetic algorithms to optimise a class of biological neural networks, called Central Pattern Generators (CPGs), with a view to providing autonomous, reactive and self-modulatory control for practical engineering solutions. This work is precursory to producing controllers for marine energy devices with similar locomotive properties. Neural circuits are evolved using evolutionary techniques. The lamprey CPG, responsible for swimming movements, forms the basis of evolution, and is optimised to operate with a wider range of frequencies and speeds. The author demonstrates via experimental results that simpler versions of the CPG network can be generated, whilst outperforming the swimming capabilities of the original CPG network.

The third section deals with collective intelligence, a term applied to any situation in which indirect influences cause the emergence of collaborative effort. Four chapters are presented, each addressing one novel algorithm. The first chapter of the section by *Bastos Filho et al.* gives an overview of a new algorithm for searching in high-dimensional spaces, called the Fish School Search (FSS). Based on the behaviours of fish schools, the FSS works through three main operators: feeding, swimming and breeding. Via empirical studies, the authors demonstrate that the FSS is quite promising for dealing with high-dimensional problems with multimodal functions. In particular, it has shown great capability in finding balance between

exploration and exploitation, self-adapting swiftly out of local minima, and self-regulating the search granularity.

The next chapter by *Tan and Zhang* presents another new swarm intelligence algorithm called the Magnifier Particle Swarm Optimisation (MPSO). Based on the idea of magnification transformation, the MPSO enlarges the range around each generation's best individual, while the velocity of particles remains unchanged. This enables a much faster convergence speed and better optimisation solving capability. The authors compare the performance of MPSO to the Standard Particle Swarm Optimisation (SPSO) using the thirteen benchmark test functions from CEC 2005. The experimental results show that the proposed MPSO is indeed able to tremendously speed up the convergence and maintain high accuracy in searching for the global optimum. Finally, the authors also apply the MPSO to spam detection, and demonstrate that the proposed MPSO achieves promising results in spam email classification.

Mezura-Montes and Flores-Mendoza then present a study about the behaviour of Particle Swarm Optimisation (PSO) in constrained search spaces. Four well-known PSO variants are used to solve a set of test problems for comparison purposes. Based on the comparative study, the authors identify the most competitive PSO variant and improve it with two simple modifications related to the dynamic control of some parameters and a variation in the constraint-handling technique, resulting in a new Improved PSO (IPSO). Extensive experimental results show that the IPSO is able to improve the results obtained by the original PSO variants significantly. The convergence behaviour of the IPSO suggests that it has better exploration capability for avoiding local optima in most of the test problems. Finally, the authors compare the IPSO to four state-of-the-art PSO-based approaches, and confirm that it can achieve competitive or even better results than these approaches, with a moderate computational cost.

The last chapter of this section by *Rabanal et al.* describes an intriguing algorithm called the River Formation Dynamics (RFD). This algorithm is inspired by how water forms rivers by eroding the ground and depositing sediments. After drops transform the landscape by increasing or decreasing the altitude of different areas, solutions are given in the form of paths of decreasing altitudes. Decreasing gradients are constructed, and these gradients are followed by subsequent drops to compose new gradients and reinforce the best ones. The authors apply the RFD to solve three NP-complete problems, and compare its performance to Ant Colony Optimisation (ACO). While the RFD normally takes longer than ACO to find good solutions, it is usually able to outperform ACO in terms of solution quality after some additional time passes.

The fourth section contains two survey chapters. The first survey chapter by *Neme and Hernández* discusses optimisation algorithms inspired by social phenomena in human societies. This study is highly important as majority of the natural algorithms in the optimisation domain are inspired by either biological phenomena or social behaviours of mainly animals and insects. As social phenomena often arise as a result of interaction among individuals, the main idea behind

algorithms inspired by social phenomena is that the computational power of the inspired algorithms is correlated to the richness and complexity of the corresponding social behaviour. Apart from presenting social phenomena that have motivated several optimisation algorithms, the authors also refer to some social processes whose metaphor may lead to new algorithms. Their hypothesis is that some of these phenomena - the ones with high complexity, have more computational power than other, less complex phenomena.

The second survey chapter by *Bernardino and Barbosa* focuses on the applications of Artificial Immune Systems (AISs) in solving optimisation problems. AISs are computational methods inspired by the natural immune system. The main types of optimisation problems that have been considered include the unconstrained optimisation problems, the constrained optimisation problems, the multimodal optimisation problems, as well as the multi-objective optimisation problems. While several immune mechanisms are discussed, the authors have paid special attention to two of the most popular immune methodologies: clonal selection and immune networks. They remark that even though AISs are good for solving various optimisation problems, useful features from other techniques are often combined with a “pure” AIS in order to generate hybridised AIS methods with improved performance.

The fifth section deals with multi-objective optimisation. There are four chapters in this section. It starts with a chapter by *Jaimes et al.* who present a comparative study of different ranking methods on many-objective problems. The authors consider an optimisation problem to be a many-objective optimisation problem (instead of multi-objective) when it has more than 4 objectives. Their aim is to investigate the effectiveness of different approaches in order to find out the advantages and disadvantages of each of the ranking methods studied and, in general, their performance. The results presented can be an important guide for selecting a suitable ranking method for a particular problem at hand, developing new ranking schemes or extending the Pareto optimality relation.

Next, *Nebro and Durillo* present an interesting chapter that studies the effect of applying a steady-state selection scheme to Non-dominated Sorting Genetic Algorithm II (NSGA-II), a fast and elitist Multi-Objective Evolutionary Algorithm (MOEA). This work is definitely a timely and important one, since not many non-generational MOEAs exist. The authors use a benchmark composed of 21 bi-objective problems for comparing the performance of both the original and the steady-state versions of NSGA-II in terms of the quality of the obtained solutions and their convergence speed towards the optimal Pareto front. Comparative studies between the two versions as well as four state-of-the-art multi-objective optimisers not only demonstrate the significant improvement obtained by the steady-state scheme over the generational one in most of the problems, but also its competitiveness with the state-of-the-art algorithms regarding the quality of the obtained approximation sets and the convergence speed.

The following chapter by *Tan and Teo* proposes two new co-evolutionary algorithms for multi-objective optimisation based on the Strength Pareto Evolutionary Algorithm 2 (SPEA2), another state-of-the-art MOEA. The two new algorithms

introduce the concept of competitive co-evolution and cooperative co-evolution respectively to SPEA2. The authors are able to exhibit, through experimental studies, the superiority of these augmented algorithms over the original one in terms of the non-dominated solutions to the true Pareto front, the diversity of the obtained solutions as well as the coverage level. Moreover, the authors observe an increased performance improvement over the original SPEA2 with an increase in the number of dimensions to be optimised. Overall, this chapter shows that the introduction of co-evolution, especially cooperative co-evolution, is able to furnish significant enhancements to the solution of multi-objective optimisation problems.

The final chapter by *Duran et al.* focuses on portfolio optimisation using multi-objective optimisation techniques. Based on the Venezuelan market mutual funds from year 1994 to 2002, the authors conduct a comparative study of three different evolutionary multi-objective approaches – NSGA-II, SPEA2, and Indicator-Based Evolutionary Algorithm (IBEA) – as well as the optimisation portfolios generated by these approaches. Using Sharpe's index as a measure of risk premium for the final solution selection, the authors observe that NSGA-II is able to provide results similar to SPEA2 for mixed and fixed mutual funds, and superior solutions than SPEA2 for variable funds. This observation, the authors argue, is indication that NSGA-II provides better coverage of the regions containing interesting solutions for Sharpe's index. The experimental results presented also demonstrate that IBEA is superior to both NSGA-II and SPEA2 regarding the index value attained, and the portfolios IBEA generates are more profitable than those indexed by the Caracas Stock Exchange.

In closing, I would like to thank all the authors for their excellent contributions to this book. I also wish to acknowledge the help of the editorial advisory board and all reviewers involved in the review process, without whose support this book project could not have been satisfactorily completed. Special thanks go to all those who provided constructive and comprehensive review comments, as well as those who willingly helped in last-minute urgent reviews. A further special note of thanks goes to Dr Thomas Ditzinger (Engineering Senior Editor, Springer-Verlag) and Ms Heather King (Engineering Editorial, Springer-Verlag) for their editorial assistance and professional support. Finally, I hope that readers would enjoy reading this book as much as I have enjoyed putting it together.

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