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Editorial

Xin-She Yang

School of Science and Technology,
Middlesex University London,
London NW4 4BT, UK
Email: x.yang@mdx.ac.uk
Email: xy227@cam.ac.uk

Biographical notes: Xin-She Yang is a Reader in modelling and optimisation at the Middlesex University and an elected Bye-Fellow at the Downing College of Cambridge University. He is also an Adjunct Professor at the Reykjavik University, Iceland. He worked at the UK's National Physical Laboratory as a Senior Research Scientist after receiving his DPhil in Applied Mathematics from the University of Oxford. His research interests include applied mathematics, nature-inspired computation, swarm intelligence, modelling and design optimisation. More than ten of his papers are among the highly cited according to the Essential Science Indicators (Web of Science). He is the Chair of the Task Force on Business Intelligence and Knowledge Management of the IEEE Computational Intelligence Society.

1 Introduction

Nature-inspired algorithms (NIAs) have become an effective tool for solving optimisation problems in real-world applications. Their applications have permeated into almost every area of science, engineering and industry (Coello Coello, 2002; Yang et al., 2013). Such NIAs for optimisation are also diverse, ranging from classical evolutionary algorithms to contemporary swarm intelligence (SI)-based metaheuristics (Cui and Gao, 2012; Duan and Luo, 2015; Yang, 2014). The effectiveness of these algorithms has increased their popularity, and certain unresolved issues also lead to some criticism about some of the algorithms. Challenges also bring opportunities for future research. This special issue tries to address some of the issues and also intends to provide some suggestions for future research.

2 Nature-inspired algorithms

NIAs have become promising and effective in solving a wide range of problems in optimisation, data mining, machine learning and image processing. Bio-inspired algorithms for computation can be considered as a subset of NIAs, while bio-inspired computation includes in turn SI as its subset. A majority of NIAs are SI-based, including ant colony optimisation, particle swarm optimisation, cuckoo search, bat algorithm, firefly algorithm, artificial bee colony and many others (Yang, 2014; Gandomi and Yang, 2014). Obviously, the classification can depend on the perspective and angle. For example, the flower pollination algorithm is a bio-inspired algorithm and can also be loosely put into the category of SI (Yang et al., 2014), while eagle strategy with differential evolution cannot fit into SI easily (Yang and Deb, 2012). Whatever the classification may be, there is some sufficiently evidence that such algorithms are effective in solving a diverse range of problems (Fister et al., 2013; Gandomi and Yang, 2014; Yang, 2014; Duan and Luo, 2015). These algorithms, together with other algorithms such artificial immune system, harmony search and gravitational search, have formed the wide research area, called metaheuristic algorithms or simply metaheuristics.

It is no exaggeration to say that nature-inspired metaheuristic computation has been applied to many areas of science and engineering with applications in industry. They can solve complex optimisation problems, multi-objective optimisation problems (Coello Coello et al., 2002), combinatorial optimisation (Ouaarab et al., 2014) and design optimisation in engineering (Yang et al., 2014). In fact, nature-inspired computation has formed an essential part of computational intelligence and machine learning.

3 Popularity and diversity

The success of these algorithms in applications has increased their popularity in recent years, and active research has also led to the significant increase of the number of algorithms in the last few years. It is estimated that about 140 different types of algorithms now exist in the literature, and this number is certainly gradually increasing. Researchers have tried to find inspiration from various sources in nature, such as ants, bees, fish, birds, mammals, plants, physical and chemical systems such as gravity, river systems, waves and pheromone. This leads to a diverse of range of algorithms with different capabilities and different levels of performance.

However, such diversity may also cause confusion and distractions from important research topics. For example, many researchers wonder why such algorithms work and what their mathematical foundations for different search algorithms are. At the moment, it still lacks good theoretical understanding of metaheuristics. In fact, without a good mathematical framework, it is difficult to establish any solid mathematical foundation for analysing such algorithms.

Such lack of theoretical analysis, together with different claims of results, it is understandable that misunderstanding and criticism have arisen in the research community concerning some metaheuristic algorithms.

4 Criticism and misunderstanding

Among the criticism and doubts about metaheuristic algorithms, one main criticism is that the diverse range of algorithms may not increase the understanding of metaheuristic algorithms, and some of the novelties may be questionable. On the one hand, the diversity of various algorithms such as butterflies, cats, dogs, salmon, dolphins and vulture may broaden the horizon of thinking in algorithm developments. On the other hand, it is understandable that some researchers may think this can cause concerns and distractions. Though such concern is reasonable and understandable, it has to allow the freedom of scientific thinking and also to ensure truly new, insightful innovation to appear. This may require the whole research community to carefully look at the developments concerning metaheuristics and bio-inspired computation so as to encourage innovative research that can help to develop effective tools for tackling hard problems in applications.

In addition, there is also some misunderstanding about metaheuristic algorithms, partly due to the lack of theoretical analysis. People may not understand the sophisticated theory about beauty or love, but this does not prevent people appreciating beauty and love in practice. This seemingly laughable metaphor is true for metaheuristics. Researchers may struggle to understand why metaheuristic algorithms work, but this does not mean that these algorithms will not work in practice. In fact, there are thousands of research papers each year published in scientific journals demonstrated at different levels and with various details that these algorithms can work well if implemented properly and used appropriately. Even the well-known evolutionary strategy and genetic algorithms had a hard time to convince the research community at the early stage of their developments. Another good example is the artificial neural networks (ANN) that have now become a powerful tool for many applications such as machine learning; however, it took almost half a century from the basic concepts to the wide acceptance of this powerful technique.

Sometimes, it is unfortunate that some researchers do not provide enough details in their papers, and some papers can even have conflicting results about metaheuristics. It is even more unfortunate that a small number of researchers misunderstand certain concepts while writing their own papers, and thus can cause frustration and concerns in readers. However, researchers should not treat it as a reason to object metaheuristics. Rather, researchers should be more careful when reading such papers and investigate the ideas more carefully, and try to remedy the situation in a scientific way.

5 Challenges and opportunities

Put the criticism and misunderstanding aside, there are indeed some important challenges concerning metaheuristics and such challenges also provide opportunities for researchers (Cui and Gao, 2012; Duan and Luo, 2015; Yang, 2014). As there are so many challenging issues concerning metaheuristics, we will not intend to list even a good fraction of them. Instead, we highlight the following areas to encourage further research:

a *Theoretical analysis*: It is highly needed to establish a rigorous mathematical framework to analyse metaheuristic algorithms theoretically. It can be expected that such frameworks can be a combination of various techniques such as dynamic systems (Clerc and Kennedy, 2002) and Markov chain Monte Carlo (Ghate and Smith, 2008; Yang, 2014) as well as Bayesian inferencing. The framework should be used to analyse the convergence, stability and robustness of NIAs.

b *Benchmarking*: There are so many different algorithms, it is not clear what methods are the most effective to benchmark algorithms. Though there are some test functions such as the IEEE Congress on Evolutionary Computation (CEC) test set in 2005 and more than 150 test functions in the literature to validate new algorithms, these functions are not real-world problems and they may have substantial drawbacks.

c *Performance comparison*: The diversity of metaheuristic algorithms necessitates a fair comparison in terms of some performance measures. It is not quite clear what performance measures are appropriate to ensure the fairness. As performance results will largely depend on the measure used, measures should be defined properly, ideally based on some solid mathematical foundations. In addition, even with a proper performance measure, is it fair to compare a well-tuned algorithm with one that is not well tuned? Is it fair to compare two algorithms on a selected subset of problems? How many test problems is sufficient to draw a sensible conclusion. These questions still remain unresolved.

d *Parameter tuning and control*: It is well-known that an algorithm's performance may depend on its algorithm-dependent parameter setting and the type of the problem to be solved. How to tune these parameters so as to achieve optimal performance for the algorithm under consideration is another unresolved problem. The tuning of parameters and the subsequent control of their variations can be considered as a higher level optimisation problem, which can be even more challenging to solve.

e *Landscape knowledge*: One of the reasons that some classical algorithms such as hill-climbing are efficient is that they use some information about the objective landscape to guide the search process. How to incorporate problem-specific knowledge before the search and during the search to speed up the search process can be very tricky, and the knowledge obtained for one type of problem may not be transferable or beneficial to solve another type of problem. There may be a trade-off between the generality of a tool and its effectiveness, though many relevant issues are not well understood yet.

In addition to the above challenging issues, there are other issues such as scalability, robustness and algorithm complexity. For example, it is not yet clear if an algorithm that has been tested to solve small-scale or moderate-scale problems well can be used to solve large-scale problems of the same type equally well. Why the low computational complexity of metaheuristics can cope with problems of high complexity?

6 Summary of this special issue

The above challenges and opportunities are the main motivation for editing this special issue with the primary aim to focus on the theoretical analysis and benchmarking of NIAs. Though the responses were overwhelming and all manuscripts had gone through the peer-review process, many high-quality papers had to be rejected due to the limitation of space in this special issue.

Though the main theme is theoretical analysis and benchmarking, it is really difficult to achieve such an ambitious objective in a short time and this is indeed one of the long-term aims for metaheuristic community. Therefore, for this special issue, we can only focus on a small step forward in this direction. Among the accepted papers in this special, the topics and coverage can still be wide, representing a timely snapshot of the current developments. First, Chu et al. discussed a study of orthogonal design hybrid particle swarm optimiser, followed by a hybrid algorithm based on krill herd and cuckoo search by Wang et al. Then, Gálvez and Iglesias presents a new memetic approach of self-adaptive firefly algorithm, and Marichelvam and Geetha study the flow shop scheduling problem by a discrete firefly algorithm hybrid. Furthermore, the optimisation in dynamic and uncertain environment has been investigated by Nasiri and Meybodi using history-driven firefly algorithm. Finally, the convergence analysis of bee colony optimisation was carried out by Krüger et al.

Obviously, it is hoped that this special issue can inspire further research in this active area of research, focusing on the important topics such as theoretical analysis, benchmarking, performance measure and comparison, parameter tuning and control, and knowledge incorporation as outlined in Section 4. These topics are far more important than developing new algorithms. The research community should encourage the development of truly innovative, insightful and effective tools for solving highly complex problems of both theoretical and practical importance.

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