

# A Computational Comparison of Three Nature-Inspired, Population-Based Metaheuristic Algorithms for Modelling-to-Generate Alternatives

Julian Scott Yeomans, York University, Canada\*

## ABSTRACT

In “real life” decision-making situations, inevitably, there are numerous unmodelled components, not incorporated into the underlying mathematical programming models, that hold substantial influence on the overall acceptability of the solutions calculated. Under such circumstances, it is frequently beneficial to produce a set of dissimilar–yet “good”–alternatives that contribute very different perspectives to the original problems. The approach for creating maximally different solutions is known as modelling-to-generate alternatives (MGA). Recently, a data structure that permits MGA using any population-based solution procedure has been formulated that can efficiently construct sets of maximally different solution alternatives. This new approach permits the production of an overall best solution together with  $n$  locally optimal, maximally different alternatives in a single computational run. The efficacy of this novel computational approach is tested on four benchmark optimization problems.

## KEYWORDS

Bat Algorithm, Cuckoo Algorithm, Firefly Algorithm, Metaheuristic Algorithms, Modelling-to-Generate Alternatives, Population-Based Algorithms

## INTRODUCTION

Multifarious real-world decision-making environments are frequently confounded by ambiguous and incompatible structural specifications that can prove difficult to incorporate into mathematical decision models (Belarbi et al., 2017; Brugnach et al., 2007; Janssen et al., 2010; Matallah et al., 2017; Matthies et al., 2007; Mowrer, 2000; Walker et al., 2003). While “optimal” solutions can normally be calculated for the mathematical formulations, these answers may not produce the best outcomes in the original real system (Acharjya & Anitha, 2017; Brugnach et al., 2007; Fahad et al., 2017; Janssen et al., 2010; Loughlin et al., 2001). To improve decision-making under such circumstances,

DOI: 10.4018/IJORIS.321119

\*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

it is often preferable to create a limited number of dissimilar options that contribute very different perspectives (Matthies et al., 2007; Puri et al., 2020; Yeomans & Gunalay, 2011). Preferably these alternatives should all possess good (i.e. near-optimal) objective measures with respect to their modelled objective(s), but be maximally different from each other in terms of the system structures characterized by their decision variables. Several approaches collectively referred to as modelling-to-generate-alternatives (MGA) have been developed in response to this multi-solution creation requirement (Brill et al., 1982; Loughlin et al., 2001; Yeomans & Gunalay, 2011).

The primary impetus behind modelling-to-generate-alternatives (MGA) is to create a manageably small set of alternatives that are good with respect to all measured objective(s) yet are as fundamentally different as possible from each other within the prescribed decision space. By adopting a maximally different approach, the resultant alternative solution set is likely to provide very different perspectives with respect to any unmodelled issues, while simultaneously providing different choices that all perform somewhat similarly with respect to the modelled objectives (Walker et al., 2003). Decision-makers must conduct subsequent assessments of the alternatives to ascertain which specific option(s) most closely satisfies their underlying circumstances (Arrais-Castro et al., 2015). Consequently, MGA approaches are necessarily classified as decision support processes rather than as the explicit solution determination methods generally assumed for optimization (see Benatia et al., 2016; Sharma & Virmani, 2017; Strand et al., 2017).

The earliest MGA procedures employed a relatively straightforward approach in which each alternative was incrementally formulated by re-running the solution generation algorithm whenever a new option had to be produced (Baugh et al., 1997; Brill et al., 1982; Loughlin et al., 2001; Yeomans & Gunalay, 2011; Zechman & Ranjithan, 2004). These iterative procedures mimicked the seminal Hop-Skip-Jump (HSJ) MGA approach of Brill et al. (1982) in which, once an initial problem formulation has been optimized, all supplementary alternatives are produced one-by-one. Consequently, these iterative procedures all require  $n+1$  runnings of their respective algorithms to optimize the initial problem followed by the creation of  $n$  alternatives (Imanirad & Yeomans, 2013; Imanirad et al., 2012a; Yeomans & Gunalay, 2011). These MGA approaches were subsequently extended to generate sets of maximally different solution alternatives in Yeomans (2018a, 2018b, 2018c), Imanirad and Yeomans (2013), and Imanirad et al. (2012b, 2013a, 2013b, 2013c).

Recently, Gunalay & Yeomans (2019) and Yeomans (2018d, 2019a, 2019b) introduced a data structure that permits both optimization and MGA using any population-based solution procedure. Specifically, this new data-structure-based approach to MGA enables the simultaneous generation of the overall best solution together with an additional set of  $m-1$  locally optimal, maximally different alternatives in a single computational run. Namely, to generate the additional  $m-1$  maximally different solution alternatives, the MGA algorithm would need to run exactly the same number of times that an optimization procedure would need to be run for function optimization purposes alone (i.e. once) irrespective of the value of  $m$  (Yeomans 2017a, 2017b). Consequently, this simultaneous procedure could be considered extremely computationally efficient for MGA purposes.

Numerous metaheuristic approaches have been developed for use in a variety of decision-making environments (for some recent examples, see: Gergin et al. 2019; Jain & Yada 2021; Murali et al. 2022; Vasant et al. 2020). For calculation and optimization purposes, Yang (2009, 2010) created three population-based metaheuristics: the Firefly Algorithm (FA), the Bat Algorithm (BA), and the Cuckoo Algorithm (CA). These three nature-inspired procedures have been shown to be more computationally efficient than the more commonly-used enhanced particle swarm, genetic algorithm, and simulated annealing metaheuristic procedures (Cagnina et al., 2008; Gandomi et al., 2011; Yang & Yeomans 2014) and have been applied to an extremely diverse spectrum of problem settings (Acharjee & Chaudhuri 2022; Aggrawal & Anuja 2022; Bangyal et al. 2021; Bharathi 2022; Chandrasekaran & Simon 2014; Garg & Kumar 2021; Gopu & Venkataraman 2021; Pandey & Bannerjee 2021; Rahman et al. 2019; Rautry et al. 2019; Wang & Ji 2021).

In this paper, for the first time, the efficacy of employing the novel population-based MGA data structure approach in conjunction with the FA, BA, and CA is computationally examined using

18 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: [www.igi-global.com/article/a-computational-comparison-of-three-nature-inspired-population-based-metaheuristic-algorithms-for-modelling-to-generate-alternatives/321119](http://www.igi-global.com/article/a-computational-comparison-of-three-nature-inspired-population-based-metaheuristic-algorithms-for-modelling-to-generate-alternatives/321119)

## Related Content

---

### Applied Sequence Clustering Techniques for Process Mining

Diogo R. Ferreira (2009). *Handbook of Research on Business Process Modeling* (pp. 481-502).

[www.irma-international.org/chapter/applied-sequence-clustering-techniques-process/19706](http://www.irma-international.org/chapter/applied-sequence-clustering-techniques-process/19706)

### Everyone's Watching: The Remarkably Public Reorganization of the Nevada Department of Motor Vehicles

W. L. Kuechler (2006). *Cases on Information Technology and Business Process Reengineering* (pp. 173-191).

[www.irma-international.org/chapter/everyone-watching-remarkably-public-reorganization/6287](http://www.irma-international.org/chapter/everyone-watching-remarkably-public-reorganization/6287)

### To Be on the Edge of Chaos with Organizational Intelligence and Health

efika ule Erçetin, Nihan Potas, Nuray Kisaand Suay Nilhan Açikalin (2013). *Chaos and Complexity Theory for Management: Nonlinear Dynamics* (pp. 182-201).

[www.irma-international.org/chapter/edge-chaos-organizational-intelligence-health/70889](http://www.irma-international.org/chapter/edge-chaos-organizational-intelligence-health/70889)

### Robust Optimization Model for Runway Configurations Management

Rui Zhangand Rex Kincaid (2014). *International Journal of Operations Research and Information Systems* (pp. 1-26).

[www.irma-international.org/article/robust-optimization-model-for-runway-configurations-management/117777](http://www.irma-international.org/article/robust-optimization-model-for-runway-configurations-management/117777)

### Designing E-Learning Environments in Higher Education to Match Technological Trends

Chad Manian (2020). *Trends and Issues in International Planning for Businesses* (pp. 152-166).

[www.irma-international.org/chapter/designing-e-learning-environments-in-higher-education-to-match-technological-trends/257175](http://www.irma-international.org/chapter/designing-e-learning-environments-in-higher-education-to-match-technological-trends/257175)