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Experimental Study of Swarm Migration Algorithms on Stochastic and Global Optimisation Problem

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ABSTRACT

Complex computational problems are occurrences in our daily lives that need to be analyzed effectively and efficiently in order to make an informed decision. This paper undertakes an experimental study into the performances of six optimization algorithms, based on swarm intelligence on nine well-known stochastic and global optimization problems to identify an algorithm that returns an optimum output on selected problems under study. Extensive experiments show that Multi-Swarm and Pigeon-inspired optimization algorithms outperform Particle Swarm, Firefly, and Evolutionary optimizations in both convergence speed and global solution. The algorithms adopted in this paper give an indication of which algorithmic solution presents optimal results for a particular problem with regards to the quality of performance, precision, and efficiency.

KEYWORDS

Combinatorial Optimization, Evolutionary Algorithm, Meta-Heuristic, Stochastic Optimisation, Swarm Intelligence

INTRODUCTION

According to Pham & Karaboga (2000), solutions to most optimization problems cannot be obtained by traditional mathematical programming approaches. They opined that present heuristic algorithms have been created for solving combinatorial and numeric optimization problems to obtain universal optimum solutions. Optimization problems are pervasive in our daily lives and usually take different forms. Generally speaking, optimization problems can be found in broad applications such as finance and logistics, manufacturing, and engineering. For example, logistic regression classification prepares classifiers in a unique situation as it tries to discover a set of values for the weights related to the input

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variables so that for a set of training data, the calculated output values directly match the identified output variable values. Over the past decade, there has been tremendous development in countless optimization algorithms in varied communities that cross intersect various fields that include artificial intelligence, computational intelligence, and soft computing (Gholizadeh & Barati, 2012).

Inspired by nature, several successful algorithms are suggested and categorized into diverse groups depending on the measure being considered, thus, stochastic, iterative based, population-based or deterministic, with examples as, Artificial Fish Swarm Algorithm (Li, 2002; Tan & Zhu, 2010), Flower Pollination Algorithm (Yang, 2012), Differential Evolution (Das & Suganthan, 2011), Firefly Algorithm (Yang, 2009), imperialist competitive algorithm (Atashpaz-Gargari & Lucas, 2007), brainstorm optimization (Shi, 2011) among others. Among the listed criteria, a population-based algorithm works with a set of solutions with a specific aim of trying to improve upon them, whereas an iterative algorithm uses multiple iterations to search after a solution. On the other hand, when an algorithm makes use of a probabilistic rule for recovering a solution then it is said to be stochastic.

These nature-inspired algorithms with their simple structure, fewer adjustment to their parameters, and their ability to obtain optimum results, have over the years drawn the attention of most researchers to apply them to diverse fields of research including mechanic control, machine engineering, software checking, traditional combinatorial problems, and cluster investigations. Some practical applications of these nature-inspired algorithms include intrusion detection (Srivastava et al., 2021), the medical field (Gadekallu et al., 2020), machine learning, and deep learning (Abidi et al., 2021), IoT networks (Alazab et al., 2021) among others. Different proposals of nature-inspired algorithms for different purposes have created great confusion as to which method fits what situation, and it is strongly required to understand what the common characteristics are of these algorithms and what the differences are. To study and compare the characteristics of these algorithms can provide not only a broader perspective to the improvement of the current nature-inspired algorithms but also a solid and feasible cornerstone for building up the new problem-oriented nature-inspired algorithms (Wang et al., 2021).

Nature-inspired algorithms can be classified as those based on biology and those inspired by natural phenomena. The algorithms based on biology can be further divided into those based on evolution and those based on swarm behavior. The evolutionary algorithms include genetic algorithms, differential evolution, cultural evolution, evolutionary strategies, and genetic programming. The swarm category includes particle swarm optimization, ant colony optimization, artificial bees, termites, bats, birds, cats, bacterial foraging, cuckoo search, and firefly algorithm (Valdez et al., 2021). Bio-inspired algorithms form a majority of all nature-inspired algorithms. From the set theory point of view, the swarm intelligence-based algorithms are a subset of bio-inspired algorithms, while the bio-inspired algorithms are a subset of nature-inspired algorithms.

The focus of this paper is to illustrate the capabilities of six bio-inspired based algorithms for solving constrained and unconstrained optimization problems to find the algorithm that returns the global best. The algorithm efficiency is verified by performing a meta-heuristic search on nine complex stochastic and global benchmark problems. The obtained optimization results of the algorithms are compared and discussed. In general, an optimization algorithm is evaluated regarding three major aspects (Maringer, 2006; Meirelles & Brentan, 2020): ease of implementation due to the number of parameters to be adjusted (sometimes costly fine-tuned), computational complexity, which reflects in the convergence speed and reliability of the results, with consistent optimal values obtained through a series of tests.

The rest of this paper is arranged as follows. Section 2 details brief .discussion of the bio-inspired algorithms chosen for this study; section 3 in brief examines the random objective functions for experimentation. The simulation experiments of the proposed algorithms are presented in Section 4 and compared. Finally, remarks and conclusions are provided in Section 5.

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