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EvoloPy: An Open-source Nature-inspired Optimization Framework in Python

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Abstract: EvoloPy is an open source and cross-platform Python framework that implements a wide range of classical and recent nature-inspired metaheuristic algorithms. The goal of this framework is to facilitate the use of metaheuristic algorithms by non-specialists coming from different domains. With a simple interface and minimal dependencies, it is easier for researchers and practitioners to utilize EvoloPy for optimizing and benchmarking their own defined problems using the most powerful metaheuristic optimizers in the literature. This framework facilitates designing new algorithms or improving, hybridizing and analyzing the current ones. The source code of EvoloPy is publicly available at GitHub (https://github.com/7ossam81/EvoloPy).

1 INTRODUCTION

In general, nature-inspired algorithms are population-based metaheuristics which are inspired by different phenomena in nature. Due to their stochastic and non-deterministic nature, there has been a growing interest in investigating their applications for solving complex problems when the search space is extremely large and when it is impossible to solve them with conventional search methods (Yang, 2013).

In general, nature-inspired algorithms can fall into two main categories: Swarm Intelligence and Evolutionary Algorithms. Swarm intelligence algorithms simulate the natural swarms such as flocks of birds, ant colonies, and schools of fishes. Popular algorithms that fall in this category are Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), and Ant Colony Optimization (ACO) (Korošec and Šilc, 2009). More recent Swarm intelligence algorithms include Cuckoo Search (CS) (Yang and Deb, 2009), Grey Wolf Optimizer (GWO) (Mirjalili et al., 2014), Multi-Verse Optimizer (MVO) (Mirjalili et al., 2016), Moth-flame optimization (MFO) (Mirjalili, 2015), Whale Optimization Algorithm (WOA) (Mirjalili and Lewis, 2016), Bat Algorithm (BAT) (Yang, 2010b), Firefly Algorithm (FFA) (Yang, 2010a), and many others. Most of Swarm intelligence algorithms reach the best solution by exchanging the information between the swarm's individuals.

On the other hand, evolutionary-based algorithms are inspired by some concepts from the Darwinian theory about evolution and natural selection. Such algorithms include Genetic algorithm (GA) (Holland, 1992), Genetic Programming (GP)(Koza, 1992), and Evolution Strategy (ES) (Beyer and Schwefel, 2002). These algorithms maintain different strategies to evolve and find good solutions for difficult problems based on evolutionary operators like mutation, crossover and elitism.

An important twist in the research field was made when the No Free Lunch Theorem (NFL) was released (Wolpert and Macready, 1997; Ho and Pepyne, 2002). NFL states that no algorithm is superior to all other algorithms when considering all optimization problems. This means that if an algorithm A outperforms another algorithm B on some type of optimization problems then algorithm B outperforms A in another types of problems. Since the release of NFL, researchers and practitioners have developed a wide range of metaheuristic algorithms and investigated their applications in different types of challenging optimization problems. In the last decade, most of the researchers implemented and shared their proposed optimizers in Matlab (Yang, 2010a; Yang, 2010b; Mirjalili et al., 2014; Mirjalili, 2015). This is due to its simplicity and ease of use. However, Matlab

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is a commercial and expensive software and portability is a big issue.

In this paper, we introduce EvoloPy which is a framework written in Python that provides well-regarded and recent nature-inspired optimizers. The goal of the framework is to take the advantage of the rapidly growing scientific community of Python and provide a set of robust optimizers as free and open source software. We believe that implementing such algorithms in Python will increase their popularity and portability among researchers. Moreover, the powerful libraries and packages available in Python will make it more feasible to apply metaheuristic algorithms for solving complex problems on a much higher scale.

2 RELATED WORK

Today, many different nature-inspired optimization libraries and frameworks are available. Some of them are developed for special type of nature-inspired optimization like GEATbx (Hartmut Pohlheim, 2006), which is a framework that contains many variants of the Genetic Algorithms, and Genetic Programming. GEATbx is implemented in MATLAB environment and provides many global optimization capabilities. The authors in (Matthew Wall, 1996) developed GAlib library, which contains a set of C++ genetic algorithm tools and operators for different optimization problems. In addtion, GAlib is built on UNIX platforms and is implemented to support distributed/parallel environments.

In (Fortin et al., 2012), the authors developed a novel evolutionary computation Python framework called DEAP to simplify the execution of many optimization ideas with parallelization features. The DEAP Framework includes many nature-inspired algorithms with different variations such as: GA, GP, ES, PSO, Differential Evolution (DE), and multi-objective optimization. In addition, DEAP includes Benchmarks modules containing many test functions for evaluations. In (Wagner and Affenzeller, 2004), the authors present a generic optimization environment named HeuristicLab, which is implemented using C# language. HeuristicLab is a framework for heuristic, evolutionary algorithms, and machine learning. HeuristicLab includes many algorithms such as: Genetic Programming, Age-layered Population, Structure (ALPS), Evolution Strategy, Genetic Algorithm, Island Genetic Algorithm, Particle Swarm Optimization, Relevant Alleles Preserving GA, and many others.

In (Durillo and Nebro, 2011), jMetal is developed, which is a framework that contains many metaheuristic algorithms implemented in Java language. The authors employ the object-oriented architecture to develop the framework. jMetal includes many features such as: multi-objective algorithms, parallel algorithms, constrained problems, and different representations of the problem variables. In (Cahon et al., 2004; Humeau et al., 2013), the authors present a white-box object-oriented framework called ParadisEO. ParadisEO is developed by integrating Evolving Objects (EO) - which is an C++ evolutionary computation framework - and many distributed metaheuristics including local searches (LS), and hybridization mechanisms.

Most of the existing optimization and metaheuristic based frameworks include classical evolutionary and nature-inspired algorithms such as: GA, GP, PSO and ES. However few of them implement recent metaheuristic algorithms. In contrast to previous frameworks, we propose our framework as an initiative to keep an implementation of the recent nature-inspired metaheuristics as well as the classical and well regarded ones in a single open source framework. To the best of our knowledge, EvoloPy framework is the first tool that implements most of these algorithms in Python language. EvoloPy is designed in an efficient way to solve computationally expensive optimization functions with very high dimensions.

Our own research group has been involved on the development of many metaheuristic libraries, from EO (Merelo-Guervós et al., 2000) to, lately, Algorithm::Evolutionary (Merelo-Guervs et al., 2010) and NodEO (Merelo Guervós, 2014). These libraries have been mainly focused on evolutionary algorithms. The library we present in this paper has a wider breadth and, besides explores the possibilities of a new language, Python. We will explain this election next.

3 WHY PYTHON?

Python is a general purpose scripting language which has a clear and simple syntax. With the rapid development of mature, advanced and open source scientific computing libraries and packages, Python became as one of the most popular and powerful languages for scientific computing. Moreover, Python has cross-platform runability, which works with different operating systems, and has ability to access libraries written in different programming languages and computing environments. Python also can support small-form devices, embedded systems, and microcontrollers. In addition, Python needs very minimal setup procedure to start with. Python uses modu-

lar and object based programming, which is a popular methodology to organize classes, functions, and procedures into hierarchical namespaces. All these reasons have turned Python to be a popular language in a huge community of scientists.

4 FRAMEWORK OVERVIEW

EvoloPy provides a set of classical and recent nature-inspired metaheuristic optimizers with an easy-to-use interface. The framework incorporates four main components which are described as follows:

- The Optimizer: this is the main interface of the framework in which the users can select a list of optimizers to run in their experiment. Using this interface, the user can configure common parameters for the algorithms like the maximum number of iterations for each run, the size of the population and the number of runs. In addition, a list of benchmark problems can be selected.
- The metaheuristic algorithms: simply this part includes the list of implemented optimizers in the framework. At the time of writing this paper, the following eight algorithms have been implemented:
  - Particle Swarm Optimization (PSO)
  - Firefly Algorithm (FFA) (Yang, 2010a)
  - Gray Wolf Optimizer (GWO)(Mirjalili et al., 2014)
  - Whale Optimization Algorithm (WOA) (Mirjalili and Lewis, 2016)
  - Multi-Verse Optimizer (MVO) (Mirjalili et al., 2016)
  - Moth Flame Optimizer (MFO) (Mirjalili, 2015)
  - Bat Algorithm (BAT) (Yang, 2010b)
  - Cuckoo Search Algorithm (CS) (Yang and Deb, 2009)
- Benchmark functions and problem definitions: This part includes a set of benchmark problems commonly used in the literature for the purpose of comparing different metaheuristic algorithms. Any new user-defined cost function could be added to this list.
- Results management: this component is responsible for exporting the results and storing them in one common CSV file.

5 DESIGN ISSUES

Most of nature-inspired metaheuristics are population-based algorithms. These algorithms start by randomly initializing a set of individuals each of which represents a candidate solution. Conventionally, in most of state-of-art evolutionary algorithms frameworks, populations are implemented as 2-dimensional arrays while individuals are implemented as 1-dimensional arrays. For example an individual I and a population P can be represented as given in equations 1 and 2.

$$I_i = \begin{bmatrix} x_i^1 & x_i^2 & \dots & x_i^d \end{bmatrix} \tag{1}$$

$$P = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^d \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \dots & x_n^d \end{bmatrix} \tag{2}$$

In EvoloPy, `Numpy` is chosen to define and represent the populations and individuals in the optimizers. `Numpy` is an open-source extension to Python that provides common scientific computing and mathematical routines as pre-compiled and fast functions. `NumPy` also supports large multidimensional arrays and matrices and it offers a varied range of functions to handle and perform common operations on these arrays. `Numpy` has many things in common with Matlab. This makes it easier for researchers who are familiar with Matlab to use EvoloPy.

The core data structure `ndarray` (abbreviation for N-dimensional array) in `Numpy` is used to define 1-dimensional and 2-dimensional arrays that represent individuals and populations, respectively. For example, to define a randomly generated initial population with 50 individuals and 100 dimensions the following python line of code can be used

```
initialPop = np.random.rand(50,100)
```

Moreover, with `Numpy` it is possible to perform vector operations in simple and compact syntax. For example, one of the common operations used in many metaheuristic algorithms is to check the boundaries of the elements of the individuals after updating them. This can be performed all at once with `Numpy` as follows:

```
newPop=numpy.clip(oldPop, lb, ub)
```

Where `lb` and `ub` are the upper and lower bounds respectively.

To demonstrate the main components of EvoloPy framework we use the UML representation. A class diagram illustrating the EvoloPy components and their relationships is presented in Figure 1. The EvoloPy framework consists of eleven classes, three

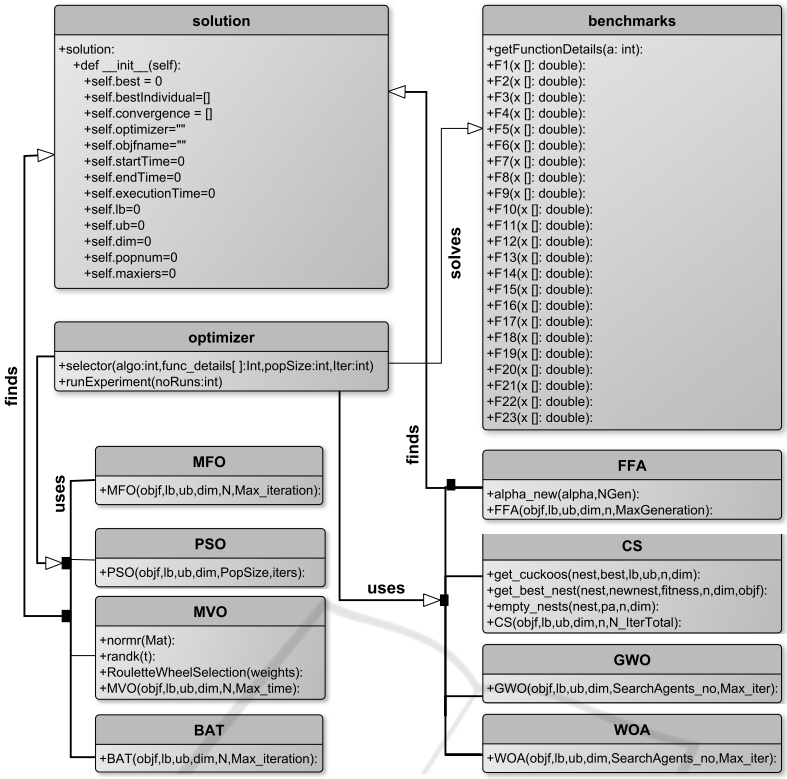


Figure 1: Class diagram of the EvoloPy framework.

of them for coordinating and simplifying the optimization process, namely; optimizer, benchmarks, and solution. On the other hand, the other eight classes represent the actual nature-inspired optimizers. The core flow of EvoloPy relies in that an optimizer solves a benchmark using one or more optimizers to find global solutions. We have used generic classes names in the framework in order to make it very easy to flow and general enough to be modified and usable.

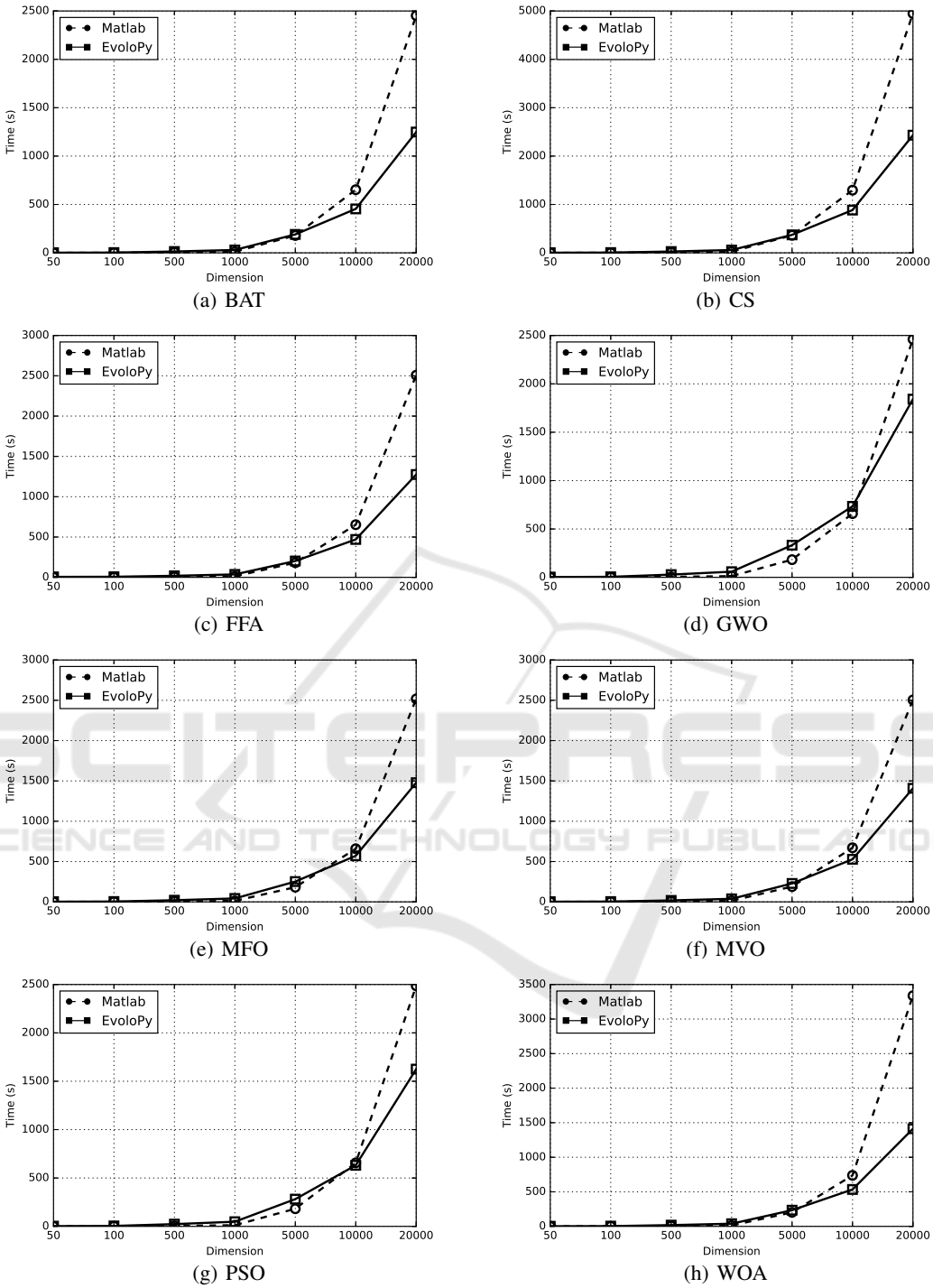
6 COMPARISON WITH MATLAB

In this section we compare the metaheuristic algorithms implemented so far in EvoloPy with their peers in Matlab based on their running time. The idea here is to measure the running time of the main loop of each algorithm in EvoloPy and Matlab with an equal number of function evaluations. The experiments were performed on a personal machine with an Intel(R) Core(TM) i5-2400 CPU at 3.10Ghz and a memory of 4 GB running Windows 7 professional 32bit operating system. In all experiments, the population size and the number of iterations were set to 50, and 100, respectively for all algorithms. In order to study the effect of the size of the problem on the running time of the algorithms, all optimizer were executed using different dimension lengths ranging from a small number of 50 elements reaching up to 20,000 in both implementations, Matlab and EvoloPy. Note that the dimension length here indicates the number of elements in a single individual or in another words, the number of variables in the objective function. All optimizers were applied to minimize the unimodal function given in Equation 3.

$$f(x) = \sum_{i=0}^{n-1} (\sum_{j=0}^{i-1} x_j)^2 \quad (3)$$

The results of EvoloPy and Matlab implementations are shown in Figure 2. It can be noticed that with small dimension sizes there is no significant difference in the running time between the two implementations. In most of the optimizers and up to a dimension size of 500 the running time was less than 250 second. However, for higher sizes, the difference in the running time remarkably increases. On a dimension length of 20,000 the ratio is around 1:2 for most of the optimizers.

The efficient running time of EvoloPy compared to Matlab implementation when applied for solving problems with large number of variables can be ex-



(a) BAT (b) CS

(c) FFA (d) GWO

(e) MFO (f) MVO

(g) PSO (h) WOA

Figure 2: Comparison of running time between the metaheuristic optimizers in EvoloPy and Matlab based on the running time of the main iteration.

plained due to the use of the powerful N-dimensional array object `NumPY` to represent individuals and populations.

7 CONCLUSIONS AND FUTURE WORK

EvoloPy is a framework written in Python that provides and maintains classical and recent nature-

inspired metaheuristic algorithms. Being coded in Python with its NumPy extension, the implemented algorithms are boosted by the powerful and efficient multi-dimensional objects. In comparison with Matlab, EvoloPy shows more efficiency in terms of running time for problems with high dimension and large number of variables. This proves that the open source tool Python should be considered over and preferably other proprietary tools for carrying out experiments in metaheuristics, and, for that matter, scientific computing in general, because besides being free and gratis, it offers better efficiency and, inherently to its open source nature, reproducibility.

The first steps after this paper will be to carry out a profiling of the tool to identify inefficiencies and make it run faster. After that, more recent and robust metaheuristic algorithms are planned to be added to the framework. It is also interesting to expand the experiments presented in this paper to include a comparison with Matlab or other implementations based on more challenging and sophisticated optimization functions rather than simple ones.

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REFERENCES

Beyer, H.-G. and Schwefel, H.-P. (2002). Evolution strategies – a comprehensive introduction. *Natural Computing*, 1(1):3–52.

Cahon, S., Melab, N., and Talbi, E.-G. (2004). Paradiseo: A framework for the reusable design of parallel and distributed metaheuristics. *Journal of Heuristics*, 10(3):357–380.

Durillo, J. J. and Nebro, A. J. (2011). jmetal: A java framework for multi-objective optimization. *Advances in Engineering Software*, 42:760–771.

Fortin, F.-A., De Rainville, F.-M., Gardner, M.-A., Parizeau, M., and Gagné, C. (2012). DEAP: Evolutionary algorithms made easy. *Journal of Machine Learning Research*, 13:2171–2175.

Hartmut Pohlheim (2006). Geatbx - the genetic and evolutionary algorithm toolbox for matlab.

Ho, Y.-C. and Pepyne, D. L. (2002). Simple explanation of the no-free-lunch theorem and its implications. *Journal of optimization theory and applications*, 115(3):549–570.

Holland, J. (1992). Genetic algorithms. *Scientific American*, pages 66–72.

Humeau, J., Liefooghe, A., Talbi, E.-G., and Verel, S. (2013). ParadisEO-MO: From Fitness Landscape Analysis to Efficient Local Search Algorithms. Research Report RR-7871, INRIA.

Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In *Neural Networks, 1995. Proceedings., IEEE International Conference on*, volume 4, pages 1942–1948 vol.4.

Korošec, P. and Šilc, J. (2009). A distributed ant-based algorithm for numerical optimization. In *Proceedings of the 2009 workshop on Bio-inspired algorithms for distributed systems - BADS 09*. Association for Computing Machinery (ACM).

Koza, J. R. (1992). *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. MIT Press, Cambridge, MA, USA.

Matthew Wall (1996). Galib: A c++ library of genetic algorithm components.

Merelo Guervós, J. J. (2014). NodEO, a evolutionary algorithm library in Node. Technical report, GeNeura group. Available at http://figshare.com/articles/nodeo/972892.

Merelo-Guervós, J.-J., Arenas, M. G., Carpio, J., Castillo, P., Rivas, V. M., Romero, G., and Schoenauer, M. (2000). Evolving objects. In Wang, P. P., editor, *Proc. JCIS 2000 (Joint Conference on Information Sciences)*, volume I, pages 1083–1086. ISBN: 0-9643456-9-2.

Merelo-Guervs, J.-J., Castillo, P.-A., and Alba, E. (2010). `Algorithm::Evolutionary`, a flexible Perl module for evolutionary computation. *Soft Computing*, 14(10):1091–1109. Accesible at http://sl.ugr.es/000K.

Mirjalili, S. (2015). Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowledge-Based Systems*, 89:228 – 249.

Mirjalili, S. and Lewis, A. (2016). The whale optimization algorithm. *Advances in Engineering Software*, 95:51 – 67.

Mirjalili, S., Mirjalili, S. M., and Hatamlou, A. (2016). Multi-verse optimizer: a nature-inspired algorithm for global optimization. *Neural Computing and Applications*, 27(2):495–513.

Mirjalili, S., Mirjalili, S. M., and Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software*, 69:46 – 61.

Wagner, S. and Affenzeller, M. (2004). The heuristiclab optimization environment. Technical report, University of Applied Sciences Upper Austria.

Wolpert, D. H. and Macready, W. G. (1997). No free lunch theorems for optimization. *Evolutionary Computation, IEEE Transactions on*, 1(1):67–82.

Yang, X.-S. (2010a). Firefly algorithm, stochastic test functions and design optimisation. *Int. J. Bio-Inspired Comput.*, 2(2):78–84.

Yang, X.-S. (2010b). A new metaheuristic bat-inspired algorithm. In González, J. R., Pelta, D. A., Cruz, C., Terrazas, G., and Krasnogor, N., editors, *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*, pages 65–74, Berlin, Heidelberg. Springer Berlin Heidelberg.

Yang, X.-S. (2013). Metaheuristic optimization: Nature-inspired algorithms and applications. In *Studies in*

Computational Intelligence, pages 405–420. Springer Science Business Media.

Yang, X. S. and Deb, S. (2009). Cuckoo search via levy flights. In *Nature Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on*, pages 210–214.