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Intelligent Search Strategies of Global Optima in Nature Inspired Metaheuristics

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Abstract

Global optimization sets itself the mission of identifying the most interesting solutions in the overall search space. But actually, it is only the best of all discovered candidate solutions in the explored search space, which depends, in turn, on initial positions of searching points. It is practically impossible to cover the entire search space of NP-hard problems, in a reasonable time, whatever the method used, since the size of this space exceed the capabilities of all sophisticated algorithms implemented on any powerful computer even parallel ones. That is what justify the increased interest to nature-inspired metaheuristics, currently, based on a strategy of balance between exploitation and exploration, which make their approaches looking like smart. Exploration guarantees that the used algorithm will reach the widest possible extent of the undiscovered areas, whereas exploitation guarantees that such algorithm will search for the best solutions inside the most promising areas, already discovered. Authors study, in this work, different implementations of exploration and exploitation mechanisms utilized in many well-known nature-inspired metaheuristics applied to both uni-model and multi-model benchmarks. Uni-model benchmarks aim to test exploitation while multi-model benchmarks aim to test exploration. Obtained results show the superiority of TSO metaheuristic to find the adequate balance between exploration and exploitation leading it to discover in all tested cases, at least, one of the global optima or one of the best near global optima.

Keywords: Smart search; Load balancing; Exploitation; Exploration; Relative best solution; Nature inspired metaheuristics

Introduction

Nature-inspired metaheuristics (NIMs) are the results of analyzing and understanding complex behaviors of natural systems, stemming from areas such as biology, chemistry, physics, sociology, psychology, and this to inspire from in order to solve theoretical or real complex optimization problems (Zheng).Exploitation and exploration are fundamental concepts in any NIM and especially when it comes to deal with multi-model optimization problems. The exploitation aims to enhance algorithm convergence and solution quality. In contrast, exploration is used to widen the search space and also avoid premature convergence and entrapment in local optimums during visits to unexplored areas. The primary purpose behind the research work done here is to show at what point an adequate balancing between exploration and exploitation mechanisms can affect the success of NIMs to find a good solution (global in the most favorable case and one of the best local solutions else).

What remains of this article is structured as follow: The second section is about nature inspired metaheuristics. To well understand how they transform natural phenomena into algorithms dedicated to resolve optimization problems, authors summarize, within this section, several known methods, inspired from different natural sources. In section three, they review the effect of exploitation and exploration techniques on the targeted methods (see Table 1) by comparing them between each other via 13 benchmarks. In section four, they analyze and discuss the obtained results. Finally, the authors give a conclusion where they summarize the study thus accomplished and suggest some perspectives for further research.

Nature inspired metaheuristics

Nature inspired metaheuristics are optimization methods mimed from natural phenomena, used to resolve theoretical or real-life hard problems. Those algorithms can be based on biology, physics, chemistry, sociology, and many other fields (Blum, Roli and Sampels). To study this class, authors chose 12 famous and powerful methods from different historical arias and inspiration sources, as presented below:

1. ***Particle Swarm Optimization (PSO) (1980) (bio-inspired)***: This algorithm is inspired by the displacement phenomenon of certain species of animals, like boards flock or fish school, in order to look for optimal food sources. This algorithm is a matter of having a population of solutions evaluated using a multi-objective/single-objective function. Those candidate solutions (particles) have position and velocity and move in the direction of their best performances, in search space, using adequate mathematical equations (Kennedy and Eberhart).
2. ***Differential Evolution (DE) (1990) (bio-inspired)***: DE algorithm uses a set of possible solutions to solve the problem. Simple mathematical formulas combine the positions of existing solutions candidates in the current population to move them around in the space of search towards new positions. If new solution is an improvement, it is accepted and integrated directly into the aforementioned set of solutions, else it is discarded. The procedure is repeated in the hope to find a suitable solution, but this is not guaranteed (Feoktistov).
3. ***Ant Colony Optimization (ACO) (1990) (bio-inspired)***: Between the most renowned algorithms, we found that of the shortest way: Let us consider having two ways, one shorter than the other but both lead to the same food source. When ants leave their nest searching for food, some go through the shorter way, and the others go through the long one. Logically, ants following the shortest way return earlier than the others, guided by the pheromone that they left behind them, so they reinforce the concentration of pheromone along this way. After that, any ant left the nest prefers to follow the shortest way due to its high pheromone concentration. With time, all ants finish by converging to the food source via this shortest way (Dorigo, Birattari and Stutzle).
4. ***Harmony Search (HS) (2001) (music-inspired)***: In art music, the ultimate goal is to seek perfect harmony. So, finding the optimal in a process of optimization is akin to finding harmony in music. Searching in optimization can be compared to the process of improvisation of a jazz musician. On the one hand, the audio aesthetic standard determines the most agreeable harmony. A musician's goal is to create perfect harmony in his/her music. An optimal solution to a problem of optimization, on the other hand, should be the best possible solution to this problem under the given objectives and constraints. Both procedures aim to provide most best result (Yang).
5. ***Artificial Bee Colony (ABC) (2005) (bio-inspired)***: It is an algorithm based on population, inspired by foraging behavior of honey bees. This algorithm starts by sending a given number of bees as scouts, in order to explore the nearby environment and discover the wealthiest flowers field. Those scouts move in random manner from one zone toward another; after that, they come back to the hive. Those who find the source food of a good quality leave behind them their nectar and then go to the floor of dance to perform the waggle-dance, which is an interaction way with other bees. Three elements of information are given by this dance: direction, distance and quality, which help other bees to find their way. After the dance, the dancer bee returns from the hive to the flowers field with the other bees. Note that the swarm of bees, who moves from the hive, always goes toward the flower field with the highest quality, measured by nectar concentration; it represents the best food source (Karaboga).
6. ***Invasive Weed Optimization (IWO) (2006) (bio-inspired)***: Invasive Weed Optimization (IWO) metaheuristic consists on spreading strategy of weeds. According to r/K selection theory, artificial weeds (solutions) utilize r-Selection policy at start of

the algorithm and progressively transits to K-selection policy as the algorithm runs (Mehrabian and Lucas).

7. ***Imperialist Competitive Algorithm (ICA) (2007) (Socially-inspired)***: Imperialism is the act of taking political control, by force, of a country by another country to benefit from its resources. This algorithm focuses on the positive side of imperialism when an imperialist country tries to increase civilization in its colonies. In the initial stages, countries with the best fitness value become imperialists and take control of other countries' colonies. Also, this algorithm concentrates on competition between imperialist countries to get more colonies, in each iteration, based on their power (Atashpaz-Gargari and Lucas).
8. ***Cuckoo search Algorithm (CS) (2009) (bio-inspired)***: The cuckoo is a parasitic bird because of its aggressive reproduction strategy, where it puts its eggs in other birds' nest and take some of their eggs, so the bird owner of the nest does not observe the existence of extra strange eggs. Aggressive act does not stop here; eggs of cuckoo, generally, hatch earlier than the others within the nest. Cuckoo babies, then, start throwing the other eggs from the nest to have more food. If parents that owns the nest discover existence of a strange egg, they will throw it or go to build another nest elsewhere; else, they will treat it like their own eggs. The algorithm deriving from these facts is based on three main laws inspired by cuckoo bird behavior: - each bird of cuckoo lays one egg at a one, to put randomly in any nest; - the nest which gives the best solution goes to the next generation; - finally, if the nest owners discover, basing on some probability, the existence of a strange egg they will throw it or change their nest i.e. the nest in question will be eliminated or replaced with another nest in another position (Yang and Deb).
9. ***Teaching Learning Based Optimization (TLBO) (2010)(Socially-inspired)***: TLBO is a method based on population that progresses to best solution through a set of initial solutions. A population is defined as a class of students. TLBO method is separated into 2 parts: in first one, called Teacher-Phase, a teacher taught class learners. In the second part, called Learner-Phase, students learn from interactions between them (Rao).
10. ***Firefly Algorithm (FA) (2015) (bio-inspired)***: It is an algorithm of swarm optimization based on firefly behavior that goes toward a light source. Fireflies themselves are flushing so that they attract each other; less flushing individual is attracted to more flushing one, which allows to converge toward best solution. This algorithm applies an objective function to individuals, determining the brightness of each firefly. Next, fireflies are ranked in order to find the best. Each firefly, then, moves to the brighter one in its vicinity. This process is repeated a given iteration number; at the end, the algorithm returns results (Fister, Yang and Fister).
11. ***Transient Search Optimization (TSO) (2020) (physical-inspired)***: Overall response of an electrical circuit integrating resistances (R) and capacitors (C) and/or inductors (L) comprises a transient response and a steady state response. Electrical circuits having a single storing component (RL or RC) are known as first order circuits, while circuits containing 2 storage components (RLC) are called second order circuits. Switching these circuits cannot immediately change the situation to the following steady state because capacitor or inductor takes time to charge/discharge until it reaches the steady state value. The TSO algorithm is based on the transient action of switched electrical circuits including components of storage like inductors and capacitors (Qais, Hasanien and Alghuwainem).
12. ***Archimedes optimization algorithm (AOA) (2020) (physical-inspired)***: AOA was inspired by a famous physical rule known as Archimedes' Principle. It mimics the idea that thrust force produced upward on a given object partially or completely immersed in a given fluid is proportionate to displaced fluid weight (Hashim et al.).

Exploitation and exploration mechanisms

Two basic search behaviors commonly used in metaheuristics are exploration and exploitation. Exploration implies searching for a solution in unexplored areas of the possibilities space, and exploitation refers to search near promising areas. Both mechanisms ease control of the search process, allowing to find, by hand or automatically, the adequate equilibrium between exploration and exploitation, increasing the probability of converging towards the global optimum or getting closer to it. Those techniques can be expressed in terms of: individuals, parameters or operations types (see Table 1).

For PSO, exploitation and exploration are expressed via three parameters regrouped in the velocity equation, the inertia coefficient that causes more diversity, c1 and c2 that rise convergence toward personal best and global best respectively (Binkley and Hagiwara).

DE is an example of when exploration and exploitation are expressed via operations. The crossover operation enhances the local search while mutation offers more diversity in the population, which enhances exploration.

In ACO, the pheromone trail represents an indirect communication between ants; it leads these social insects to converge via the shortest path toward the food source (optimal solution). With time, the pheromone decreases via the evaporation process to avoid stagnation caused by a high pheromone concentrated on a few paths; this leads to more exploring the space of search (Jabbar).

For harmony search, adjustment of pitch process is alike mutation in DE; it comports 2 parameters: pitch adjustment rate (PAR) and bandwidth (BW). Pitch adjustment process is used to increase diversity. Harmony memory (HM) guarantees that good harmonies are considered while creating new solution. This memory is represented via a parameter named HS memory-accepting rate (HMCR), which is ranged between 0 and 1 (Ingram and Zhang).

ABC is an example of when exploration and exploitation are represented in terms of individual type. ABC has three individuals: employed bees, onlooker bees and scout bees. Employed bees represent sources of food or optimal solutions, while onlooker bees represent individuals that converge to optimal solutions. If any of the optimal solutions remains unchanged after a given number of iterations (trail limit), food source is abandoned, and scout bee operator is activated by generating a new one randomly, which enhances diversity (Singh and Deep).

In IWO, local and global searches are not explicitly clarified. The algorithm is based on reproducing new solutions surrounding existing ones based on the fitness value, where the best individuals generate more seeds representing the exploitation phase. Furthermore, the same operation contributes to exploration by producing seeds surrounding the worst individuals, enhancing diversity. The second step is to spread the reproduced seeds in space of search (spectral spread) based on variance (standard deviation). As well, the standard deviation is one of the foremost parameters to evaluate exploration and exploitation, its value decreased progressively with time intending to search around best solutions which increase exploitation, but it seems to cause luck of exploration with time (Misaghi and Yaghoobi; Zheng et al.; Karimkashi and Kishk).

For ICA, the local search is achieved by updating the colonies of an empire based on the imperialism principle; while the global search is assured with the revolution process by replacing some colonies in an empire with some randomly generated countries (Abdollahi, Isazadeh and Abdollahi).

For CS, levy flight is used for both search behaviors; it is a kind of random displacement used by many species and insects when searching for a food source. The process starts by generating a new solution using levy flight and comparing them to the old one; if the new one is better, this implies that the cuckoo egg was not discovered, and the solution is kept. Otherwise, the new solution is rejected (the egg is discovered and thrown from the nest).

TLBO algorithm do not need specific parameters; it is divided into 2 phases: teacher phase allowing learners to update according to teachers, considering that teachers represent the best individuals in the population. This phase represents exploitation. The second is phase of learner; it simulates the process of learning via interactions of students. The fact that this phase is based on selecting two random individuals adds more randomization, which allows exploring more of the search space (Mittal et al.).

FA bases its exploitation process on the attractive behavior of fireflies, where less bright fireflies move toward brighter ones, considering that the brighter fireflies represent the best solutions. In the case where no fireflies bright more than a given one, this last move randomly to assure exploration (Yang and Slowik).

TSO exploring behavior is influenced by oscillations of second order RLC circuits near zero. On the other hand, TSO exploitation is motivated by exponential decay of the first order discharge [13].

For AOA, a collision between objects occurs to assure exploration by updating acceleration based on random material; for exploitation, no collision between objects occurs; in this case, acceleration is updated based on the best material. The authors used a switch operation (transfer operator) to transform between exploration and exploitation. Generally, exploration is realized by adding some randomization, while exploitation is achieved by updating individuals depending on the best solutions in the population.

Method	Exploration	Exploitation	How those techniques are expressed?
PSO	The inertia coefficient '*w*'	The acceleration constants *c*1 and *c*2.	In term of parameters
DE	Mutation	Crossover	In term of Operations
ACO	Evaporation process	Pheromone trail	In terms of Operations
HS	pitch adjustment	HS memory-accepting rate (HMCR)	In term of parameters
ABC	Scout bees	Employed bees and onlooker bees	Individuals type
IWO	Reproduction and Spectral Spread		In term of Operations
ICA	Revolution	Assimilation and imperialistic Competition	In term of Operations
CS	Levy flight		In term of Operations
TLBO	Learner phase	Teacher phase	In term of Operations
FA	Random walk	Attractiveness	In term of Operations
TSO	Oscillations of the second-order RLC circuits around the zero.	Exponential decaying of the first order discharge.	In terms of Operations
AOA	Collision between objects occurs	No collision between objects occurs	In term of Operations

Table 1: Exploration and exploitation in targeted methods.

Experimental Results

Used benchmarks

To compare targeted methods in terms of exploitation and exploration techniques, authors used 4 uni-model and 9 multi-model benchmarks. Uni-model benchmarks are used for local search (exploitation) capabilities of a given algorithm, while multi-model benchmarks are used for global search (exploration) because of the existence of many local optima, which allows testing the ability of the algorithm to escape being trapped into local optima [13]; chosen benchmarks are presented in table 2.

Function	***No.***	***Modality***	***Function***	***No.***	***Modality***	***Function***	***No.***	***Modality***
Ackley	*F*01	Multimodal	Penalty #2	*F*06	Multimodal	Schwefel 2.22	*F*10	Unimodal
Dixon & Price	*F*02	Multimodal	Perm	*F*07	Multimodal	Schwefe l2.21	*F*11	Unimodal
Griewank	*F*03	Multimodal	Schwefel 2.26	*F*08	Multimodal	Step	*F*12	Unimodal
Pathological function	*F*04	Multimodal	Schwefel 1.2	*F*09	Unimodal	Zakharov	*F*13	Multimodal
Penalty #1	*F*05	Multimodal						

Table 2: Benchmark functions.

Setting parameters

Algorithm	Parameters
ABC	Number of Onlooker Bees=Colony Size(Population Size)= 50. Trial Limit=round(0.6*Number of Decision Variables*Population Size). Acceleration Coefficient Upper Bound =1.
ACO	Sample Size= 40. Intensification Factor (Selection Pressure)= 0.5. Deviation-Distance Ratio= 1.
AOA	*C*1 = 2. *C*2 = 6. Volume=rand Density= rand
CS	Discovery rate of alien eggs/solutions=0.25. Beta=3/2.
DE	Crossover Probability=0.2;
FA	Light Absorption Coefficient=1. Attraction Coefficient Base Value0=2. Mutation Coefficient=0.2. Mutation Coefficient Damping Ratio=0.98. Uniform Mutation Range=0.05*(VarMax-VarMin)
HSA	Number of New Harmonies=20. Harmony Memory Consideration Rate=0.9. Pitch Adjustment Rate=0.1. Bandwidth=0.02*(VarMax-VarMin). Fret Width Damp Ratio=0.995.
ICA	Number of Empires/Imperialists=10. Selection Pressure=1. Assimilation Coefficient=1.5. Revolution Probability=0.05. Revolution Rate=0.1. Colonies Mean Cost Coefficient=0.2.
IWO	Minimum Number of Seeds= 0. Maximum Number of Seeds= 5. Variance Reduction Exponent= 2. Initial Value of Standard Deviation= 0.5. Final Value of Standard Deviation= 0.001.
PSO	Inertia Weight *W*=1. Inertia Weight Damping Ratio=0.99. Personal Learning Coefficient *C*1=1.5. Global Learning Coefficient *C*2=2.0.
TLBO	TLBO does not have any particular parameters.
TSO	TSO does not have any particular parameters.

Table 3: Specific parameters of targeted methods.

For being located on the same referential, all algorithms have same population size (50), same number of iterations (500), same benchmarks dimension (30) and same number of independent runs (20). However, each method has its specific parameters (see Table 3).

Results

Results, after comparison, are presented in this section (see Table 4), including best, mean, worst and STD results. TSO algorithm is ranked first in quality of best, mean, STD and worst values. TSO succeeds, also, in discovering the fittest solutions over 9/13 benchmarks. In more detail, it is ranked best over 4/4 uni-model and 5/9 multi-model benchmarks and has good results for most of the rest benchmarks. For mean and worst results, TSO succeeds in finding the best solutions over 7/13 benchmarks. For STD results, TSO finds the best standard deviation over 6/13 benchmarks, proving its suitability. Based on those results, TSO shows its capabilities of balancing between exploration and exploitation processes.

AOA is ranked second; it can be noticed that AOA succeeds in finding the fittest solutions over 3/13 benchmarks for best, mean, STD, and worst results, while most of them concern multi-model benchmarks.

TLBO, PSO, and FA are ranked third with 2/13 benchmarks for best results. PSO ranked results are both in multi-model functions, which means that its capability of exploration is better than its capability of exploitation. TLBO and FA ranked best results in one multi-model and one uni-modal benchmark, but since TLBO shows better results in quality of mean, worst and STD, this shows that TLBO is a few more suitable than FA. Regardless, TLBO and FA show good results in most benchmarks, which signifies that they have a good equilibrium over exploration and exploitation. ABC, ACO, CS, DE, and ICA rank fourth with 1/13 benchmarks which is F12 except for CS (F7); this reveals the weakness of those algorithms in quality of exploration and exploitation compared to the other aforementioned algorithms. IWO and HSA show the worse performance compared to other algorithms. Figure 1 represents convergence rate of compared methods. As clearly observed, TSO has the fastest convergence speed for most benchmarks because of its ability to equilibrate over exploration and exploitation. At the same time, IWO is trapped easily in local optima, as its curves become steady in the early stages. ACO shows slow convergence, but it continues to converge, so it is unclear whether the algorithm is trapped into a local optimum. The remaining of methods have close convergence speeds to each other.

		ABC	ACO	AOA	CS	DE	FA	HSA	ICA	IWO	PSO	TLBO	TSO
F1	Best	2,75E+00	7,90E+00	**8,88E-16**	4,61E+00	4,90E-03	5,57E-05	5,27E+00	4,87E-04	1,84E+01	4,33E-12	4,44E-15	**8,88E-16**
	Mean	3,79E+00	9,98E+00	2,66E-15	5,69E+00	6,79E-03	7,01E-05	6,24E+00	1,17E-01	1,92E+01	7,82E-01	6,04E-15	**8,88E-16**
	STD	5,24E-01	9,90E-01	1,82E-15	6,58E-01	1,12E-03	5,13E-06	5,21E-01	3,24E-01	2,46E-01	7,79E-01	1,81E-15	**0,00E+00**
	Worst	4,85E+00	1,12E+01	4,44E-15	7,69E+00	1,01E-02	7,63E-05	7,64E+00	1,16E+00	1,95E+01	2,22E+00	7,99E-15	**8,88E-16**
F2	Best	3,82E+02	7,40E+03	6,70E-01	6,46E+00	7,44E-01	6,67E-01	1,17E+02	2,89E-01	6,68E-01	6,67E-01	6,67E-01	**1,65E-01**
	Mean	1,80E+03	2,06E+04	7,95E-01	9,55E+00	1,26E+00	6,67E-01	4,54E+02	2,79E+00	8,28E-01	6,67E-01	6,67E-01	**2,42E-01**
	STD	8,27E+02	7,34E+03	9,36E-02	1,63E+00	3,32E-01	3,02E-09	1,68E+02	1,66E+00	2,40E-01	2,07E-05	**8,83E-15**	2,58E-02
	Worst	3,66E+03	3,49E+04	9,93E-01	1,26E+01	1,94E+00	6,67E-01	7,97E+02	5,78E+00	1,54E+00	6,67E-01	6,67E-01	**2,53E-01**
F3	Best	1,03E+00	8,03E+00	**0,00E+00**	1,07E+00	9,74E-04	1,02E-07	3,66E+00	7,83E-08	4,14E+02	3,33E-16	**0,00E+00**	**0,00E+00**
	Mean	1,08E+00	1,47E+01	**0,00E+00**	1,15E+00	5,20E-03	9,86E-04	5,51E+00	3,96E-02	5,90E+02	1,80E-02	**0,00E+00**	**0,00E+00**
	STD	2,57E-02	3,44E+00	**0,00E+00**	4,57E-02	7,70E-03	3,04E-03	1,20E+00	4,04E-02	8,64E+01	2,69E-02	**0,00E+00**	**0,00E+00**
	Worst	1,12E+00	1,98E+01	**0,00E+00**	1,23E+00	3,67E-02	9,86E-03	7,83E+00	1,44E-01	7,09E+02	8,08E-02	**0,00E+00**	**0,00E+00**
F4	Best	1,23E+01	6,90E+00	2,79E+00	1,99E+00	2,48E+00	2,78E+00	5,24E+00	5,71E+00	1,18E+01	7,06E+00	4,74E+00	**0,00E+00**
	Mean	1,27E+01	7,73E+00	2,87E+00	3,57E+00	3,11E+00	4,07E+00	6,23E+00	7,02E+00	1,24E+01	9,18E+00	5,58E+00	**2,61E-04**
	STD	2,20E-01	5,13E-01	4,69E-02	7,48E-01	3,01E-01	7,13E-01	5,39E-01	7,90E-01	3,56E-01	9,46E-01	5,54E-01	**8,09E-04**
	Worst	1,31E+01	8,89E+00	2,91E+00	4,54E+00	3,61E+00	5,51E+00	7,39E+00	8,51E+00	1,30E+01	1,11E+01	6,50E+00	**2,95E-03**
F5	Best	5,31E+03	1,65E+06	3,69E-01	2,26E+00	2,19E-05	1,94E-10	1,16E+01	2,34E-08	2,08E+01	**1,35E-26**	1,87E-13	1,78E-08
	Mean	4,54E+05	8,71E+06	7,39E-01	3,47E+00	6,07E-05	2,43E-10	2,17E+01	1,56E-05	3,56E+01	5,70E-02	**2,96E-11**	2,29E-05
	STD	4,97E+05	4,93E+06	1,64E-01	7,32E-01	3,74E-05	**2,58E-11**	6,20E+00	2,70E-05	9,57E+00	7,87E-02	4,83E-11	3,21E-05
	Worst	1,84E+06	2,03E+07	1,07E+00	5,02E+00	1,64E-04	2,93E-10	3,92E+01	9,91E-05	5,56E+01	2,07E-01	**1,66E-10**	1,32E-04
F6	Best	1,77E+03	1,06E+06	2,82E+00	1,46E+01	4,38E-04	2,62E-09	6,81E+01	1,51E-07	2,03E+02	**6,84E-21**	8,82E-11	4,26E-06
	Mean	5,29E+05	1,08E+07	2,91E+00	2,53E+01	8,70E-04	**3,49E-09**	1,07E+02	6,18E-03	2,56E+02	1,82E-01	6,66E-02	1,16E-04
	STD	7,56E+05	6,76E+06	6,36E-02	5,30E+00	2,72E-04	**5,33E-10**	2,60E+01	1,62E-02	4,34E+01	2,81E-01	8,23E-02	1,50E-04
	Worst	2,58E+06	3,07E+07	3,11E+00	3,45E+01	1,52E-03	**4,45E-09**	1,70E+02	6,94E-02	3,68E+02	1,22E+00	2,22E-01	5,69E-04
F7	Best	4,41E+82	6,62E+82	2,03E+83	**1,00E+10**	8,54E+78	8,82E+73	1,01E+80	7,56E+78	2,60E+76	7,74E+79	9,18E+80	1,87E+81
	Mean	8,81E+84	4,04E+85	8,60E+85	**1,00E+10**	4,02E+81	1,52E+77	2,64E+82	8,97E+81	1,05E+82	6,09E+81	3,93E+82	1,01E+83
	STD	1,21E+85	5,21E+85	1,05E+86	**0,00E+00**	6,48E+81	6,05E+77	3,75E+82	1,36E+82	1,56E+82	4,76E+81	6,01E+82	1,58E+83
	Worst	4,46E+85	1,99E+86	4,29E+86	**1,00E+10**	2,90E+82	2,72E+78	1,59E+83	6,21E+82	5,36E+82	1,59E+82	2,72E+83	5,03E+83
F8	Best	3,22E+01	1,72E+01	4,22E+01	9,11E-01	2,93E-01	**9,51E-03**	9,13E+00	3,53E-01	3,09E+03	4,08E+03	3,75E+00	6,38E-02
	Mean	2,86E+02	4,43E+02	4,35E+03	6,97E+02	7,79E+00	**7,22E-01**	1,41E+02	1,14E+03	4,55E+03	5,70E+03	1,10E+02	3,61E+00
	STD	2,15E+02	3,51E+02	3,15E+03	5,41E+02	7,91E+00	**8,49E-01**	1,08E+02	9,15E+02	8,59E+02	9,03E+02	1,79E+02	5,97E+00
	Worst	9,03E+02	1,29E+03	8,82E+03	2,03E+03	2,66E+01	**2,95E+00**	3,82E+02	2,83E+03	6,22E+03	7,47E+03	5,71E+02	2,24E+01
F9	Best	4,68E+04	5,34E+04	7,80E-99	1,80E+03	1,68E+04	6,95E-07	1,29E+04	1,17E+03	1,63E+04	2,32E+00	3,67E-19	**1,41E-127**
	Mean	6,08E+04	6,28E+04	**1,56E-77**	2,83E+03	3,00E+04	1,11E-06	2,62E+04	2,18E+03	3,72E+04	1,44E+01	3,47E-16	6,19E-48
	STD	8,51E+03	5,22E+03	**5,43E-77**	5,27E+02	4,50E+03	3,96E-07	5,80E+03	9,11E+02	1,95E+04	1,67E+01	8,11E-16	2,61E-47
	Worst	8,01E+04	7,11E+04	**2,34E-76**	3,96E+03	3,59E+04	2,44E-06	3,38E+04	5,02E+03	8,80E+04	6,13E+01	3,45E-15	1,17E-46

F10	Best	2,53E+00	1,73E+01	7,56E-62	1,15E+01	1,76E-03	1,13E-04	2,74E+00	4,24E-06	3,65E-02	5,26E-06	3,60E-44	**1,81E-72**
	Mean	2,64E+01	4,06E+01	4,91E-47	1,94E+01	2,53E-03	1,28E-04	4,33E+00	3,46E-05	5,32E-02	1,23E-02	9,92E-44	**6,72E-52**
	STD	1,67E+01	1,32E+01	2,18E-46	6,19E+00	4,99E-04	8,27E-06	6,84E-01	3,48E-05	1,01E-02	3,66E-02	4,85E-44	**2,76E-51**
	Worst	6,76E+01	6,04E+01	9,74E-46	3,35E+01	3,57E-03	1,42E-04	5,55E+00	1,42E-04	7,14E-02	1,60E-01	2,36E-43	**1,24E-50**
F11	Best	4,51E+01	7,66E+01	4,05E-55	9,47E+00	9,42E+00	1,01E-04	1,97E+01	7,05E+00	4,46E+01	3,25E-01	8,94E-36	**3,14E-77**
	Mean	5,46E+01	8,39E+01	1,51E-43	1,12E+01	1,27E+01	1,42E-04	2,65E+01	1,36E+01	5,58E+01	7,68E-01	2,97E-35	**1,29E-57**
	STD	5,96E+00	3,94E+00	3,07E-43	1,33E+00	1,50E+00	1,20E-05	2,34E+00	5,41E+00	5,65E+00	3,36E-01	1,89E-35	**5,06E-57**
	Worst	6,36E+01	8,94E+01	1,13E-42	1,51E+01	1,56E+01	1,54E-04	2,96E+01	2,60E+01	6,40E+01	1,72E+00	8,88E-35	**2,26E-56**
F12	Best	**0**	**0**	**0**	4	**0**	**0**	6	**0**	2	7	**0**	**0**
	Mean	2,70E+00	**0**	3,40E+01	1,17E+01	**0**	5,00E-02	9,60E+00	7,50E-01	4,60E+00	2,07E+01	1,00E-01	**0**
	STD	3,73E+00	**0**	3,24E+01	3,45E+00	**0**	2,24E-01	2,66E+00	8,51E-01	1,90E+00	8,28E+00	3,08E-01	**0**
	Worst	14	**0**	100	18	**0**	1	16	3	8	40	1	**0**
F13	Best	6,12E+02	2,84E+02	1,85E-63	9,01E+01	2,01E+02	1,20E-09	1,41E+02	3,61E+01	3,41E-02	3,35E-02	3,89E-10	**1,09E-116**
	Mean	1,35E+03	3,69E+02	**3,02E-42**	1,47E+02	2,58E+02	2,14E-09	2,44E+02	6,77E+01	1,86E-01	4,00E-01	4,52E-09	2,86E-37
	STD	4,73E+02	4,59E+01	**1,29E-41**	2,77E+01	3,24E+01	4,43E-10	3,93E+01	2,27E+01	2,03E-01	1,03E+00	3,79E-09	1,28E-36
	Worst	2,41E+03	4,34E+02	**5,78E-41**	1,93E+02	3,09E+02	3,27E-09	3,07E+02	1,18E+02	9,15E-01	4,73E+00	1,26E-08	5,71E-36
Total	Best	1/13	1/13	3/13	1/13	1/13	2/13	0/13	1/13	0/13	2/13	2/13	**9/13**
	Mean	0/13	1/13	3/13	1/13	1/13	2/13	0/13	0/13	0/13	0/13	2/13	**7/13**
	STD	0/13	1/13	3/13	1/13	1/13	3/13	0/13	0/13	0/13	0/13	2/13	**6/13**
	Worst	0/13	1/13	3/13	1/13	1/13	2/13	0/13	0/13	0/13	0/13	2/13	**7/13**

Table 4: comparison results.

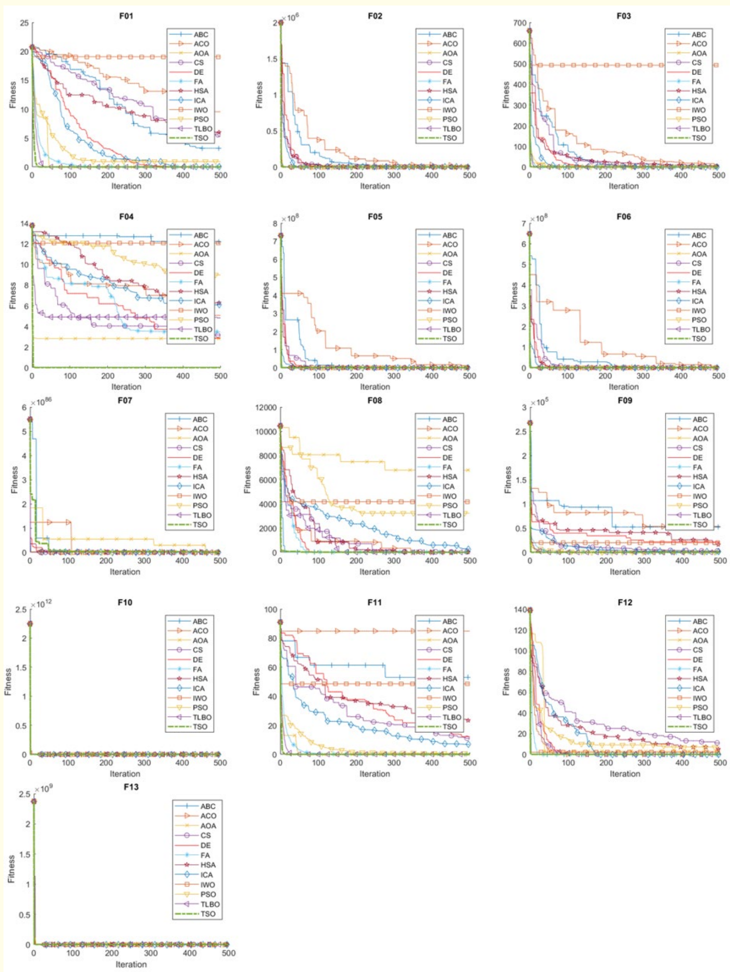

Figure 1: Convergence curves of targeted methods.

Conclusion

In this work, authors studied the two principal search behaviors in nature inspired metaheuristics that influence directly the search process while giving to it this intelligent aspect. The first one, called exploration, alludes to exploring the space of search to add more diversity to the population. Generally, it is achieved by using randomization. The second one, called exploitation, refers to search surrounding the best solutions to assure convergence; it is achieved by updating individuals based on best solutions in the population. The adequate equilibrium between those two techniques offers the best performance, in terms of quality, because exploitation help to enhance the convergence toward best solutions while exploration help to avoid trapping into local optima. Authors start their investigation by taking some renowned methods from different sources of inspiration and different historical areas.

Then, they study their exploration and exploitation mechanisms. To compare different techniques, some uni-model and multi-model benchmarks are used, since uni-model benchmarks aim to test exploitation (local search) while multi-model benchmarks aim to test exploration (global search) because of the existence of many local optima. Experimental results show that TSO provides the most performing equilibrium between exploration and exploitation; this is based on its excellent results on both types of problems. Also, AOA shows good equilibrium between exploration and exploitation. Knowing that the two methods (TSO & AOA) are considered relatively recent, showing how nature-inspired metaheuristic algorithms become more powerful with time and how new methods can easily compete with famous methods like PSO algorithm. TLBO, PSO, and FA are seen as promising approaches because they provide a good balance between the two search mechanisms mentioned above. ABC, ACO, CS, DE, and ICA show medium solution quality and convergence speed. HSA and IWO have the worst performance, which shows that they are not strong enough in both or one of these two search mechanisms, or they do not have a good balance between them. In the near future, authors plan to propose an original bio-socially-inspired metaheuristic equipped with a service allowing to equilibrate between exploration and exploitation, by tuning some given parameters, automatically or by hand, which will enable to converge easily, at least, towards one of the global solutions or one of the best near global solutions, according to each treated benchmark.

References

1. Abdollahi Mahdi, Ayaz Isazadeh and Davoud Abdollahi. “Imperialist Competitive Algorithm for Solving Systems of Nonlinear Equations”. Computers & Mathematics with Applications 65.12 (2013): 1894-908.
2. Imperialist Competitive Algorithm: An Algorithm for Optimization Inspired by Imperialistic Competition. 2007 IEEE congress on evolutionary computation (2007).
3. Binkley Kevin J and Masafumi Hagiwara. “Balancing Exploitation and Exploration in Particle Swarm Optimization: Velocity-Based Reinitialization”. Information and Media Technologies 3.1 (2008): 103-11.
4. Blum Christian, Andrea Roli and Michael Sampels. “Hybrid Metaheuristics: An Emerging Approach to Optimization”. Springer 114 (2008).
5. Dorigo Marco, Mauro Birattari and Thomas Stutzle. “Ant Colony Optimization”. IEEE computational intelligence magazine 1.4 (2006): 28-39.
6. Feoktistov Vitaliy. Differential Evolution. Springer (2006).
7. Fister Iztok, Xin-She Yang, and Dušan Fister. “Firefly Algorithm: A Brief Review of the Expanding Literature”. Cuckoo search and firefly algorithm (2014): 347-60.
8. Hashim Fatma A., et al. “Archimedes Optimization Algorithm: A New Metaheuristic Algorithm for Solving Optimization Problems”. Applied Intelligence 51.3 (2021): 1531-51.
9. Ingram Gordon and Tonghua Zhang. “Overview of Applications and Developments in the Harmony Search Algorithm”. Music-inspired harmony search algorithm (2009): 15-37.
10. Jabbar Ayad Mohammed. “Controlling the Balance of Exploration and Exploitation in Aco Algorithm”. J. Univ. Babylon 26.4 (2018): 10-17.
11. Karaboga Dervis. An Idea Based on Honey Bee Swarm for Numerical Optimization: Technical report-tr06, Erciyes university, engineering faculty, computer … (2005).

12. Karimkashi Shaya and Ahmed A Kishk. “Invasive Weed Optimization and Its Features in Electromagnetics”. IEEE transactions on antennas and propagation 58.4 (2010): 1269-78.
13. Particle Swarm Optimization. Proceedings of ICNN’95-international conference on neural networks. IEEE (1995).
14. Mehrabian Ali Reza and Caro Lucas. “A Novel Numerical Optimization Algorithm Inspired from Weed Colonization”. Ecological informatics 1.4 (2006): 355-66.
15. Misaghi Mojgan and Mahdi Yaghoobi. “Improved Invasive Weed Optimization Algorithm (Iwo) Based on Chaos Theory for Optimal Design of Pid Controller”. Journal of Computational Design and Engineering 6.3 (2019): 284-95.
16. Mittal Nitin., et al. “Improvement in Learning Enthusiasm-Based Tlbo Algorithm with Enhanced Exploration and Exploitation Properties”. Natural Computing 20.3 (2021): 577-609.
17. Qais Mohammed H, Hany M Hasanien and Saad Alghuwainem. “Transient Search Optimization: A New Meta-Heuristic Optimization Algorithm”. Applied Intelligence 50.11 (2020): 3926-41.
18. Rao R Venkata. “Teaching-Learning-Based Optimization Algorithm”. Teaching Learning Based Optimization Algorithm. Springer (2016): 9-39.
19. Singh Amreek and Kusum Deep. “Exploration–Exploitation Balance in Artificial Bee Colony Algorithm: A Critical Analysis”. Soft Computing 23.19 (2019): 9525-36.
20. Yang Xin-She. “Harmony Search as a Metaheuristic Algorithm”. Music-Inspired Harmony Search Algorithm. Springer (2009): 1-14.
21. Cuckoo Search Via Lévy Flights. 2009 World congress on nature & biologically inspired computing (NaBIC). Ieee (2009).
22. Yang Xin-She and Adam Slowik. “Firefly Algorithm”. Swarm Intelligence Algorithms. CRC Press (2020): 163-74.
23. Zheng Tingting., et al. “Iwormlf: Improved Invasive Weed Optimization with Random Mutation and Lévy Flight for Beam Pattern Optimizations of Linear and Circular Antenna Arrays”. IEEE Access 8 (2020): 19460-78.
24. Zheng Yu-Jun. “Water Wave Optimization: A New Nature-Inspired Metaheuristic”. Computers & Operations Research 55 (2015): 1-11.

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