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Comprehensive Taxonomies of Nature- and Bio-inspired Optimization: Inspiration Versus Algorithmic Behavior, Critical Analysis Recommendations

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Abstract
In recent algorithmic family simulates different biological processes observed in Nature in order to efficiently address complex optimization problems. In the last years the number of bio-inspired optimization approaches in literature has grown considerably, reaching unprecedented levels that dark the future prospects of this field of research. This paper addresses this problem by proposing two comprehensive, principle-based taxonomies that allow researchers to organize existing and future algorithmic developments into well-defined categories, considering two different criteria: the source of inspiration and the behavior of each algorithm. Using these taxonomies we review more than three hundred publications dealing with nature-inspired and bio-inspired algorithms, and proposals falling within each of these categories are examined, leading to a critical summary of design trends and similarities between them, and the identification of the most similar classical algorithm for each reviewed paper. From our analysis we conclude that a poor relationship is often found between the natural inspiration of an algorithm and its behavior. Furthermore, similarities in terms of behavior between different algorithms are greater than what is claimed in their public disclosure: specifically, we show that more than one-third of the reviewed bio-inspired solvers are versions of classical algorithms. Grounded on the conclusions of our critical analysis, we give several recommendations and points of improvement for better methodological practices in this active and growing research field.

Keywords Nature-inspired algorithms · Bio-inspired optimization · Taxonomy · Classification

Introduction

In years, a great variety of nature- and bio-inspired algorithms has been reported in the literature. This many real-world optimization problems, no exact solver can be applied to solve them at an affordable computational cost or within a reasonable time, due to their complexity or the amount of data to use. In such cases the use of traditional techniques has been widely proven to be unsuccessful, thereby calling for the consideration of alternative optimization approaches.

In this context, complexity is not unusual in Nature: a plethora of complex systems, processes and behaviors have evinced a surprising performance to efficiently address intricate optimization tasks. The most clear example can be found in the different animal species, which have developed over generations very specialized capabilities by virtue of evolutionary mechanisms. Indeed, evolution has allowed animals to adapt to harsh environments, foraging, very difficult tasks of orientation, and to resiliently withstand radical climatic changes, among other threats. Animals, when organized in independent systems, groups or swarms or colonies (systems quite complex in their own) have managed to colonize the Earth completely, and eventually achieve a global equilibrium that has permitted them to endure for thousands of years.

This renowned success of biological organisms has inspired all kinds of solvers for optimization problems, which have been so far referred to as *bio-inspired optimization algorithms*. This family of optimization methods simulate biological processes such as natural evolution, where solutions are represented by individuals that reproduce and mutate to generate new, potentially improved candidate solutions for the problem at hand.

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Similarly, some other bio-inspired algorithms hinge on mimicking a collective behavior springing from the collaboration and interaction between simple agents, giving rise to the concept of Swarm Intelligence [1]. These are inspired by different biological animals: the movement of birds [2], bats [3], small insects such as fireflies [4], grasshoppers [5]; mechanisms to locate food exhibited by colony animals such as ants in Ant Colony Optimization (ACO, [6, 7]), or bees in Artificial Bee Colony algorithms (ABC, [8]); hunting mechanisms used by different animals, from small ones such as dragonflies [9], to wild wolfs [10] or marine animals such as dolphins [9] or whales [11]; or other assorted biological phenomena such as the reproduction of coral reefs [12], the behavior of very small animals such as krill [13] or bacteria [14], to name a few. Inspiration in Nature could also stem from the observation and study of physical processes, without any biological motif. This is the case of rain [15], electromagnetism [16, 17], astronomy concepts like planets [18] or galaxies [19, 20], music [21], gases movement [22], or thermodynamics [23], among others. More recently, algorithms inspired in human activities have also entered the scene, like sports [24, 25], decision-making [26], or political systems [27, 28].

Disregarding their source of inspiration, there is clear evidence of the increasing popularity and notoriety gained by nature- and bio-inspired optimization algorithms in the last two decades. This momentum finds its reason in the capability of these algorithms to learn, adapt and provide good solutions to complex problems that otherwise would have remained unsolved. Many overviews have capitalized on this spectrum of algorithms applied to a wide range of problem casuistry, from combinatorial [29] to large-scale optimization [30], evolutionary data mining [1] and other alike. As a result, almost all business sectors have leveraged this success in recent times.

From a design perspective, nature- and bio-inspired optimization algorithms are usually conceived after observing a natural process or the behavioral patterns of biological organisms, which are then converted into a computational optimization algorithm. New discoveries in Nature and the undoubted increase of worldwide investigation efforts have ignited the interest of the research community in biological processes and their extrapolation to computational problems. As a result, many new bio-inspired meta-heuristics have appeared in the literature, unchaining an outbreak of proposals and applications every year. Nowadays, every natural process can be thought to be adaptable and emulated to produce a new meta-heuristic approach, yet with different capabilities of reaching global optimum solutions to optimization problems.

The above statement is quantitatively supported by Fig. 1, which depicts the increasing number of papers/book chapters published in the last years with *bio-inspired optimization* and *nature-inspired optimization* in their title, abstract and/or keywords. We have considered both *bio-inspired* and *nature-inspired optimization* because sometimes both terms are confused and indistinctly used, although the nature-inspiration includes bio-inspired inspiration and complements it with other sources of inspirations (like physics-based optimization, chemistry-based optimization). A major fraction of the publications comprising this plot proposed new bio-inspired algorithms

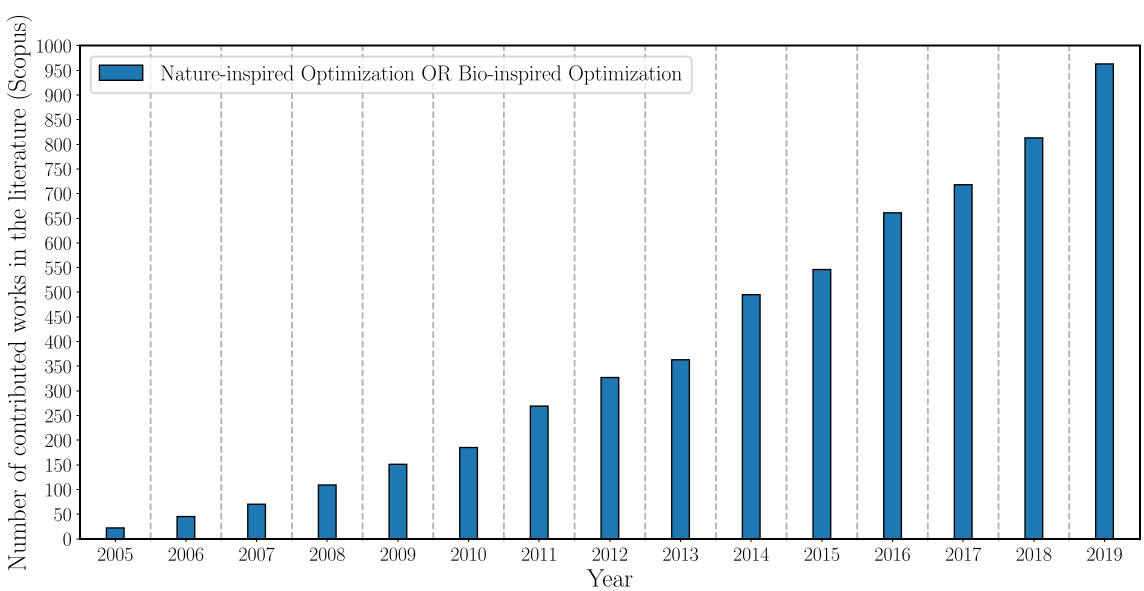


Fig. 1 Number of papers with *bio-inspired optimization* and *nature-inspired optimization* in the title, abstract and/or keywords, over the period 2005–2019 (Scopus database)

at their time. From this rising number of nature- and bio-inspired algorithms one can easily conclude that it would convenient to organize them into a taxonomy with well-defined criteria where to classify both the existing bio-inspired algorithms and new proposals to appear in the future. Unfortunately, the majority of such publications do not include any type of taxonomy, nor do they perform an exhaustive analysis of the similarity of their proposed algorithms with respect to other counterparts. Instead, they only focus on the nature or biological metaphor motivating the design of their meta-heuristic. This metaphor-driven research trend has been already denounced in several contributions [31–33], which have unleashed hot debates around specific meta-heuristic schemes that remain unresolved to date [34, 35]. It is our firm belief that this controversy could be lessened by a comprehensive taxonomy of nature- and bio-inspired optimization algorithms that settled the criteria to justify the novelty and true contributions of current and future advances in the field.

In this paper we have analyzed more than three hundred papers of different types of meta-heuristics and using that knowledge we present two different taxonomies for nature- and bio-inspired optimization algorithms:

- The first taxonomy classifies algorithms based on its natural or biological inspiration, so that given a specific algorithm, we can find its category quickly and without any ambiguity. The goal of this first taxonomy is to allow easily group the upsurge of solvers published in the literature.
- The second taxonomy classifies the reviewed algorithms based exclusively on their behavior, i.e., how they generate new candidate solutions for the function to be optimized. Our aim is to group together algorithms with a similar behavior, without considering its inspirational metaphor.

We believe that this dual criterion can be very useful for researchers. The first one helps classify the different proposals by its origin of inspiration, whereas the second one provides valuable information about their algorithmic similarities and differences. This double classification allows researchers to identify each new proposal in the adequate context. To the best of our knowledge, there has been no previous attempt as ambitious as the one presented in this overview to organize the existing literature on nature- and bio-inspired optimization.

Considering the classifications obtained in our wide study, we have critically examined the reviewed literature classification in the different taxonomies proposed in this work. The goal is to analyze if there is a relationship between the algorithms classified in a same category in one category and the classification on the other taxonomy. Next, similarities detected among algorithms will allow us to discover the most influential meta-heuristics, whose behavior has inspired many other nature- and bio-inspired proposals.

Finally, we do a critical analysis and provide several recommendations towards improving research practices in this field. The growing number of nature-inspired proposals could be seen as a symptom of the active status of this field; however, its sharp evolution suggests that research efforts should be also invested towards new behavioral differences and verifiable performance evidences in practical problems.

The rest of this paper is organized as follows. In the "Related Literature Studies" section, we examine previous surveys, taxonomies and reviews of nature- and bio-inspired algorithms reported so far in the literature. The "Taxonomy by Source of Inspiration" section delves the taxonomy based on the inspiration of the algorithms. In the "Taxonomy by Behavior" section, we present and populate the taxonomy based on the behavior of the algorithm. In the "Taxonomies Analysis: Comparison and More Influential Algorithms" section, we analyzes similarities and differences found between both taxonomies, ultimately identifying the most influential algorithms in our reviewed papers. In the "Lessons Learnt and Critical Analysis: Recommendations on Research Practices" section, some conclusions and suggestions for improvement are given, remarking that the behavior of algorithms is more relevant than their natural inspiration. We thereby encourage researchers to be more focused on applying these algorithms to more problems, and to participate in competitions to assess their good performance. Finally, in the "Conclusions" section, we summarize our main conclusions.

Related Literature Studies

The diversity of bio-inspired algorithms and their flexibility to tackle optimization problems for many research fields have inspired several surveys and overviews to date. Most of them have focused on different types of problems [36, 37], including continuous [38], combinatorial [29], or multi-objective optimization problems [39]. For specific real-world problems, the prolific literature about nature- and bio-inspired algorithms has sparked specific state-of-the-art studies revolving on their application to different fields, such as telecommunications [40], robotics [41], data mining [42], structural engineering [39] or transportation [43]. Even specific real-world problems have been dedicated exclusive overviews due to the vast research reported around the topic, like power systems [44], the design of computer networks [45], automatic clustering [46], face recognition [47], molecular docking [48], or intrusion detection [49], to mention a few.

Seen from the algorithmic perspective, many particular bio-inspired solvers have been modified along the years to yield different versions analyzed in surveys devoted to that type of algorithms, from classical approaches such as PSO [50] and DE [51–53] to more modern ones, e.g., ABC [54, 55], Bacterial Foraging Optimization Algorithm (BFOA, [56]) or the Bat Algorithm [57]. From a more general albeit still algorithmic point of view, [31] explains how the metaphor and the biological idea is used to create a bio-inspired meta-heuristic optimization algorithm. In this study the reader is also provided with some examples and characteristics of this design process. Books like [58] or [59] show many nature-inspired algorithms. However, they are more focused on describing the different algorithms available in the literature than on classifying and analyzing them in depth.

Several comparison studies among bio-inspired algorithms with very different behaviors can be found in the current literature, which mostly aim at deciding which approach to use for solving a problem. In [60], the popular PSO and DE versions are compared. This research line is followed by [61], which compared the performance of different bio-inspired algorithms, again with prescribing which one to use as its primary goal. More recently, [62] examined the features of several recent bio-inspired algorithms, suggesting, on a concluding note, to which type of problem each of the examined algorithms should be applied. More specific is the work in [63], which compares several different algorithms considering its parallel implementation on GPU devices. More recently, the focus has shifted towards comparing *groups* of algorithms instead of making a comparison between individual solvers: this is the case of [64], which compares Swarm Intelligence and Evolutionary Computation methods in order to assess their properties and behavior (e.g., their convergence speed). Once again, the main purpose of this recent literature strand is to compare bio-inspired algorithms, not to classify them nor to find similarities and design patterns among them. In [65], foraging algorithms (such as the aforementioned BFOA) are compared against other evolutionary algorithms. In that paper, algorithms are classified in two large groups: algorithms *with* and *without* cooperation. In [66, 67], PSO was proven to outperform other bio-inspired approaches (namely, DE, GA and ABC) when used for efficiently training and configuring Echo State Networks.

It has not been until relatively recent times when the community has embraced the need for arranging the myriad of existing bio-inspired algorithms and classifying them under principled, coherent criteria. In 2013, [68] presented a classification of meta-heuristic algorithms as per their biological inspiration that discerned categories with similar approaches in this regard: *Swarm Intelligence*, *Physics and Chemistry Based*, *Bio-inspired algorithms (not SI-based)*, and an *Other algorithms* category. However, the classification given in this paper is not actually hierarchical, so it can not be regarded as a true taxonomy. Another classification was proposed in [69, 70], composed by *Evolution-Based Methods*, *Physics-Based Methods*, *Swarm-Based Methods*, and *Human-Based Methods*. With respect to the preceding classification, a new *Human-Based* category is proposed, which collectively refers to algorithms inspired in the human behavior. The classification criteria underneath these categories is used to build up a catalog of more than 40 algorithmic proposals, obtaining similar groups in size. In this case, there is no *miscellaneous* category as in the previous classification. Similarly to [68], categories are disjoint groups without subcategories.

Recently, [71] offers a review of meta-heuristics from the 1970s until 2015, i.e., from the development of neural networks to novel algorithms like Cuckoo Search. Specifically a broad view of new proposals is given, but without proposing any category. The most recent survey to date is that in [72], in which nature-inspired algorithms are classified not in terms of their source of inspiration, but rather by their behavior. Consequently, algorithms are classified as per three different principles. The first one is *learning behavior*, namely, how solutions are learned from others preceding them. The learning behavior can be individual, local (i.e., only inside a neighborhood), global (between all individuals), and none (no learning). The second principle is *interaction-collective behavior*, denoting whether individuals cooperate or compete between them. The third principle is referred to as *diversification-population control*, by which algorithms are classified based on whether the population has a converging tendency, a diffuse tendency, or no specific tendency. Then, 22 bio-inspired algorithms are classified by each of these principles, and approaches grouped by each principle are experimentally compared.

The prior related work reviewed above indicates that the community widely acknowledges (with more emphasis in recent times) the need for properly organizing the plethora of bio- and nature-inspired algorithms in a coherent taxonomy. However, the majority of them are only focused on the natural inspiration of the algorithms for creating the taxonomy, not giving any attention to their behavior. Only [72] considers this aspect, but does not propose a real taxonomy, but rather different independent design principles. On the contrary, as will be next described, our proposed taxonomies consider (1) the source of inspiration; and (2) the procedure by which new solutions are produced over the search process of every algorithm (*behavior*). Furthermore, we note that efforts invested in this regard to date are not up to the level of ambition and thoroughness pursued in our study. In addition, no study published so far has been specifically devoted to unveiling structural similarities among classical and modern meta-heuristics. There lies the novelty and core contribution of our study, along with the aforementioned novel behavior-based taxonomy.

Taxonomy by Source of Inspiration

In this section, we propose a novel taxonomy based on the inspirational source in which nature- and bio-inspired algorithms are claimed to find their design rationale in the literature. This allows classifying the great amount and variety of contributions reported in related fora.

The proposed taxonomy presented in what follows was developed reviewing more than 300 papers over different years, starting from the most classical proposals in the late 1980s (such as Simulated Annealing [23] or PSO [2]) to more novel techniques appearing in the literature until 2018 [73] and 2019 [74]. Thus, to our knowledge, this exercise can be considered the most exhaustive review in the area to date.

Taking in account all the reviewed papers, we group the proposals therein in a hierarchy of categories. In the hierarchy, not all proposals of a category must fit in one of its subcategories. In our classification, categories laying at the same level are disjoint sets, which involves that each proposed algorithm can be only a member of one of these categories. To this end, for each algorithm we select the category considered to be most suitable considering the nuances of the algorithm that allow us to differentiate it from its remaining counterparts.

Methodologically, a classification of all nature- and bio-inspired algorithms that can be found in the literature can become complicated, considering the different sources of inspiration as biological, physical, human-being, ... In some papers, authors suggest a possible categorization of more well-established groups, but not in all of them. Also, its classification could not be the more appropriate and become eventually obsolete, since the number of proposals—and thereby, the diversity of sources of inspiration motivating them—increases over time. Algorithms within each proposed category were selected by their relative importance in the field, considering the number of citations, the number of algorithmic variants that were inspired by that algorithm, and other similar factors.

When establishing a hierarchical classification, it is important to achieve a good trade-off between information and simplicity by the following criteria:

- When to establish a new division of a category into subcategories: a coarse split criterion for the taxonomy can imply categories of little utility for the subsequent analysis, since in that case, the same category would group very different algorithms. On the other hand, a fine-grained taxonomy can produce very complex hierarchies and, therefore, with little usefulness. For keeping the taxonomy simple yet informative for our analytical purposes, we decided that a category should have at least four algorithms in order to be kept in the taxonomy. Thus, a category is only decomposed in subcategories if each of them has coherence and a minimum representativeness (as per the number of algorithms it contains).
- Which number of subcategories into which to divide a category: the criterion followed in this regard must produce meaningful subcategories. In order to ensure a reduced number of subcategories, we consider that not all algorithms inside one category must be a member of one of its subcategories. In that way, we avoid introducing mess categories that lack cohesion.

Figure 2 depicts the classification we have reached, indicating, for the more than 300 reviewed algorithms, the number and ratio of proposals classified in each category and subcategory. It can be observed that the largest group of all is *Swarm Intelligence* category (near the half of the proposed, 47%), inspired in the Swarm Intelligence concept [58], followed by the *Physics and Chemistry* category, inspired by different physical behaviors or chemical reactions (19% of proposals). Other relevant categories are *Social Human Behavior Algorithms* (12%), inspired by human aspects, and *Breeding-based Evolution* (8%), inspired by the Theory of Evolution over a population of individuals, that includes very renowned algorithms such as Genetic Algorithms. A new category emerges from our study—*Plants Based*—which has not been included in other taxonomies. Nearly 10% of proposals are so different between them that they cannot be grouped in new categories. The percentage of classification of each category is visually displayed in Fig. 3.

For the sake of clarity regarding the classification criteria, in the next subsections we provide a brief description of the different categories in this first taxonomy, including their main characteristics, an example, and a table listing the algorithms belonging to each category.

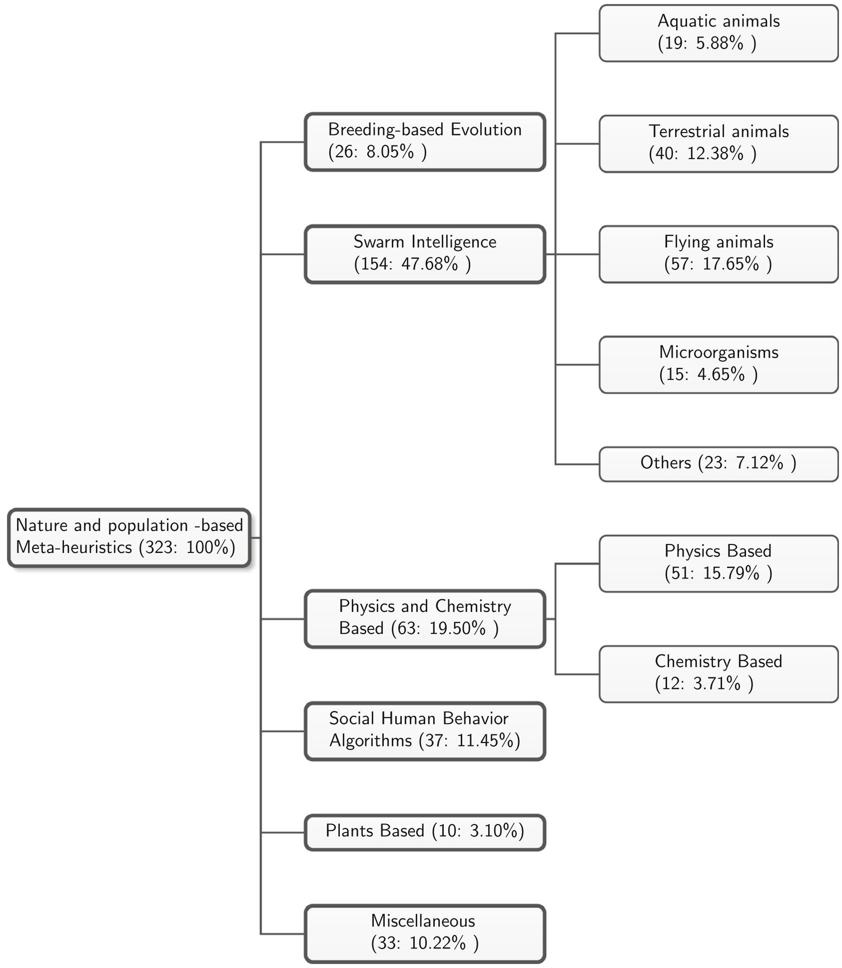


Fig. 2 Classification of the reviewed papers using the *inspiration source* based taxonomy

Breeding-Based Evolutionary Algorithms

This category comprises population-based algorithms inspired in the principles of natural evolution. Each individual in the population represents a solution of the problem, and has an associated fitness value (namely, the value of the problem objective function for that solution). In these algorithms, a process of reproduction (also referred to breeding or crossover) and survival iterated over successive generations makes the population of solutions potentially evolve towards regions of higher optimality (as told by the best solution in the population). Thus, this category is characterized by

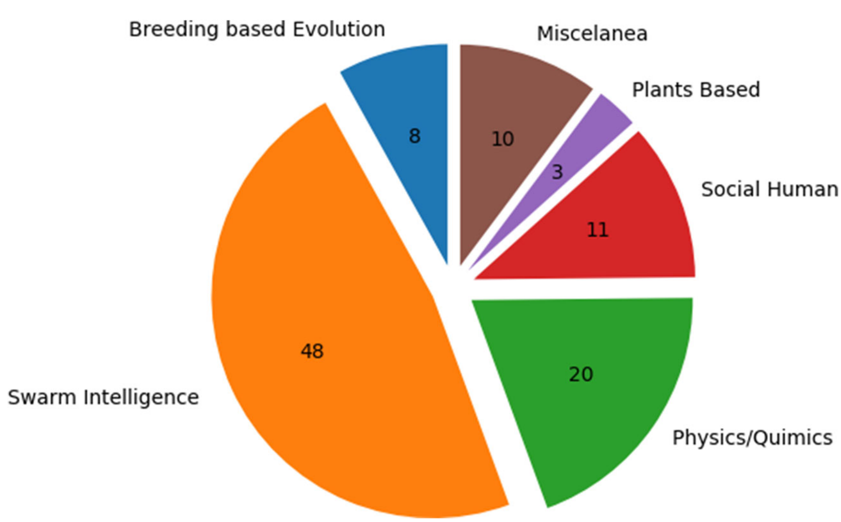


Fig. 3 Ratio of reviewed algorithms by its category (first taxonomy)

the fact of being inspired by the concept of breeding-based evolution, without considering other operators performed on individuals than reproduction (e.g., mutation).

More in detail, in these algorithms we have a population with individuals that have the ability to breed and produce new offspring. Therefore, from the parents we get children, which introduce some variety with respect to their parents. These characteristics allow them to adapt to the environment which, translated to the optimization realm, permits to search more efficiently over the solution space of the problem at hand. By virtue of this mechanism we have a population that evolves through generations and, when combined with a selection (survival) and—possibly—other operators, results are improved. Nevertheless, the breeding characteristic is what makes algorithms within this category unique with respect to those in other categories.

Table 1 compiles all reviewed algorithms that fall within this category. As could have been a priori expected, well-known classical Evolutionary Computation algorithms can be observed in this list, such as Genetic Algorithm (GA), Evolution Strategies (ES) and Differential Evolution (DE). However, other algorithms based in the reproduction of different biological organisms are also notable, such as queen bees and weeds.

Swarm Intelligence-Based Algorithms

Swarm Intelligence (SI) is already a consolidated term in the community, which was first introduced by Gerardo Beni and Jing Wang in 1989 [41]. It can be defined as the collective behavior of decentralized, self-organized systems, in either natural or artificial environments. The expression was proposed in the context of robotic systems, but has generalized over the years to denote the emergence of collective intelligence from a group of simple agents, governed by simple behavioral rules. Thus, bio-inspired

Table 1 Nature- and bio-inspired meta-heuristics within the *Breeding-based Evolution* category.

Breeding-based Evolution			
Algorithm name	Acronym	Year	Reference
Artificial Infections Disease Optimization	AIDO	2016	[75]
Asexual Reproduction Optimization	ARO	2010	[76]
Biogeography Based Optimization	BBO	2008	[77]
Bird Mating Optimization	BMO	2014	[78]
Bean Optimization Algorithm	BOA	2011	[79]
Coral Reefs Optimization	CRO	2014	[12]
Dendritic Cells Algorithm	DCA	2005	[80]
Differential Evolution	DE	1997	[81]
Ecogeography-Based Optimization	EBO	2014	[82]
Eco-Inspired Evolutionary Algorithm	EEA	2011	[83]
Earthworm Optimization Algorithm	EOA	2018	[84]
Evolution Strategies	ES	2002	[85]
Genetic Algorithms	GA	1989	[86]
Gene Expression	GE	2001	[87]
Immune-Inspired Computational Intelligence	ICI	2008	[88]
Improved Genetic Immune Algorithm	IGIA	2017	[89]
Weed Colonization Optimization	IWO	2006	[90]
Marriage In Honey Bees Optimization	MHBO	2001	[91]
Queen-Bee Evolution	QBE	2003	[92]
SuperBug Algorithm	SuA	2012	[93]
Stem Cells Algorithm	SCA	2011	[94]
Sheep Flock Heredity Model	SFHM	2001	[95]
Swine Influenza Models Based Optimization	SIMBO	2013	[96]
Self-Organizing Migrating Algorithm	SOMA	2004	[97]
Variable Mesh Optimization	VMO	2012	[98]
Virulence Optimization Algorithm	VOA	2016	[99]

meta-heuristics based on Swarm Intelligence are those inspired on the collective behavior of animal societies, such as insect colonies or bird flocks, wherein the collective intelligence emerging from the swarm permits to efficiently undertake optimization problems. The seminal bio-inspired algorithm relying on SI concepts was PSO [2], followed shortly thereafter by ACO [6]. These early findings around SI concepts applied to optimization spurred many SI-based algorithms in subsequent years, such as ABC [8] and more recently, Firefly Algorithm (FA, [4]) and Grasshopper Optimization Algorithm (GOA, [5]).

Reviewed algorithms that fall under the Swarm Intelligence umbrella are shown in Tables 2, 3, 4, and 5. This is the most populated category of all our study, characterized

Table 2 Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (I)

Swarm Intelligence (I)					
Algorithm name	Acronym	Subcategory	Type	Year	Reference
Artificial Algae Algorithm	AAA	Micro	Movement	2015	[101]
Artificial Beehive Algorithm	ABA	Flying	Foraging	2009	[102]
Artificial Bee Colony	ABC	Flying	Foraging	2007	[8]
Animal Behavior Hunting	ABH	Other	Foraging	2014	[103]
African Buffalo Optimization	ABO	Terrestrial	Foraging	2016	[104]
Andean Condor Algorithm	ACA	Flying	Foraging	2019	[105]
Ant Colony Optimization	ACO	Terrestrial	Foraging	1996	[6]
Ant Lion Optimizer	ALO	Terrestrial	Foraging	2015	[106]
Artificial Searching Swarm Algorithm	ASSA	Other	Movement	2009	[107]
Artificial Tribe Algorithm	ATA	Other	Movement	2009	[108]
African Wild Dog Algorithm	AWDA	Terrestrial	Foraging	2013	[109]
Bald Eagle Search	BES	Flying	Foraging	2019	[110]
Bees Algorithm	BA	Flying	Foraging	2006	[111]
Bumblebees	BB	Flying	Foraging	2009	[112]
Bison Behavior Algorithm	BBA	Terrestrial	Movement	2019	[113]
Bee Colony-Inspired Algorithm	BCIA	Flying	Foraging	2009	[114]
Bee Colony Optimization	BCO	Flying	Foraging	2005	[115]
Bacterial Colony Optimization	BCO.1	Micro	Foraging	2012	[116]
Bacterial Chemotaxis Optimization	BCO.2	Micro	Foraging	2002	[117]
Biomimicry Of Social Foraging Bacteria for Distributed Optimization	BFOA	Micro	Foraging	2002	[14]
Bacterial Foraging Optimization	BFOA.1	Micro	Foraging	2009	[56]
Bacterial-GA Foraging	BGAF	Micro	Foraging	2007	[118]
BeeHive Algorithm	BHA	Flying	Foraging	2004	[119]
Bees Life Algorithm	BLA	Flying	Foraging	2018	[120]
Bat Intelligence	BI	Flying	Foraging	2012	[121]
Bat Inspired Algorithm	BIA	Flying	Foraging	2010	[3]
Biology Migration Algorithm	BMA	Other	Movement	2019	[122]
Blind, Naked Mole-Rats Algorithm	BNMR	Terrestrial	Foraging	2013	[123]
Butterfly Optimizer	BO	Flying	Movement	2015	[124]
Bee System	BS	Flying	Foraging	1997	[125]
Bee System	BS.1	Flying	Foraging	2002	[126]
Bird Swarm Algorithm	BSA	Flying	Movement	2016	[127]
Bee Swarm Optimization	BSO	Flying	Foraging	2010	[128]
Bioluminiscent Swarm Optimization Algorithm	BSO.1	Flying	Foraging	2011	[129]
Bees Swarm Optimization Algorithm	BSOA	Flying	Foraging	2005	[130]
Binary Whale Optimization Algorithm	BWOA	Aquatic	Foraging	2019	[131]

Table 3 Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (II)

Swarm Intelligence (II)					
Algorithm name	Acronym	Subcategory	Type	Year	Reference
Collective Animal Behavior	CAB	Other	Foraging	2012	[132]
Cheetah Based Algorithm	CBA	Terrestrial	Movement	2018	[133]
Catfish Optimization Algorithm	CAO	Aquatic	Movement	2011	[134]
Cricket Behavior-Based Algorithm	CBBE	Terrestrial	Movement	2016	[135]
Cultural Coyote Optimization Algorithm	CCOA	Terrestrial	Movement	2019	[136]
Chaotic Dragonfly Algorithm	CDA	Flying	Foraging	2018	[137]
Cuttlefish Algorithm	CFA	Aquatic	Movement	2013	[138]
Consultant Guide Search	CGS	Other	Movement	2010	[139]
Cuckoo Optimization Algorithm	COA	Flying	Foraging	2011	[140]
Camel Travelling Behavior	COA.1	Terrestrial	Movement	2016	[141]
Coyote Optimization Algorithm	COA.2	Terrestrial	Movement	2018	[142]
Cuckoo Search	CS	Flying	Foraging	2009	[143]
Crow Search Algorithm	CSA	Flying	Movement	2016	[144]
Cat Swarm Optimization	CSO	Terrestrial	Movement	2006	[145]
Chicken Swarm Optimization	CSO.1	Terrestrial	Movement	2014	[146]
Dragonfly Algorithm	DA	Flying	Foraging	2016	[9]
Dolphin Echolocation	DE.1	Aquatic	Foraging	2013	[147]
Dolphin Partner Optimization	DPO	Aquatic	Movement	2009	[148]
Elephant Herding Optimization	EHO	Terrestrial	Movement	2016	[149]
Eagle Strategy	ES.1	Flying	Foraging	2010	[150]
Elephant Search Algorithm	ESA	Terrestrial	Foraging	2015	[151]
Egyptian Vulture Optimization Algorithm	EV	Flying	Foraging	2013	[152]
Firefly Algorithm	FA	Flying	Foraging	2009	[4]
Flocking Base Algorithms	FBA	Flying	Movement	2006	[153]
Fast Bacterial Swarming Algorithm	FBSA	Micro	Foraging	2008	[154]
Frog Call Inspired Algorithm	FCA	Terrestrial	Movement	2009	[155]
Flock by Leader	FL	Flying	Movement	2012	[156]
Fruit Fly Optimization Algorithm	FOA	Flying	Foraging	2012	[157]
Fish Swarm Algorithm	FSA	Aquatic	Foraging	2011	[158]
Fish School Search	FSS	Aquatic	Foraging	2008	[159]
Group Escape Behavior	GEB	Aquatic	Movement	2011	[160]
Good Lattice Swarm Optimization	GLSO	Other	Movement	2007	[161]
Grasshopper Optimisation Algorithm	GOA	Terrestrial	Foraging	2017	[5]
Glowworm Swarm Optimization	GSO	Micro	Movement	2013	[20]
Group Search Optimizer	GSO.1	Other	Movement	2009	[162]
Goose Team Optimization	GTO	Flying	Movement	2008	[163]
Grey Wolf Optimizer	GWO	Terrestrial	Foraging	2014	[164]

by a first category that relates to the type of animal that have inspired each algorithm: as such, we find (i) *flying animals*, namely, algorithms inspired in the flying movement of birds and flying animals like insects; (ii) *terrestrial animals*, inspired by the foraging and hunter mechanisms of land animals; (iii) *aquatic animals*, whose inspiration emerges from the movement of fish schools or other aquatic animals like dolphins; and (iv) *microorganisms*, inspired by virus, bacteria, algae and others alike.

Inside each subcategory, we have also distinguished whether they are inspired by the foraging action of the inspired living creature—*Foraging-inspired* is in fact another popular term related to this type of inspiration [100]—or, instead, by its movement patterns in general.

Table 4 Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (III)

Swarm Intelligence (III)

Algorithm name	Acronym	Subcategory	Type	Year	Reference
Harry's Hawk Optimization Algorithm	HHO	Flying	Foraging	2019	[74]
Hoopoe Heuristic Optimization	HHO.1	Flying	Foraging	2012	[165]
Hunting Search	HuS	Other	Foraging	2010	[166]
Honeybee Social Foraging	HSF	Flying	Foraging	2007	[167]
Hierarchical Swarm Model	HSM	Other	Movement	2010	[168]
Hypercube Natural Aggregation Algorithm	HYNAA	Other	Movement	2019	[169]
Improved Raven Roosting Algorithm	IRRO	Flying	Movement	2018	[170]
Invasive Tumor Optimization Algorithm	ITGO	Micro	Movement	2015	[171]
Jaguar Algorithm	JA	Terrestrial	Foraging	2015	[172]
Krill Herd	KH	Aquatic	Foraging	2012	[13]
Killer Whale Algorithm	KWA	Aquatic	Foraging	2017	[173]
Lion Algorithm	LA	Terrestrial	Foraging	2012	[174]
Seven-Spot Labybird Optimization	LBO	Flying	Foraging	2013	[175]
Laying Chicken Algorithm	LCA	Terrestrial	Movement	2017	[176]
Lion Optimization Algorithm	LOA	Terrestrial	Foraging	2016	[177]
Locust Swarms Optimization	LSO	Aquatic	Foraging	2009	[178]
Magnetotactic Bacteria Optimization Algorithm	MBO	Micro	Movement	2013	[179]
Monarch Butterfly Optimization	MBO.1	Flying	Movement	2017	[180]
Migrating Birds Optimization	MBO.2	Flying	Movement	2012	[181]
Mouth Breeding Fish Algorithm	MBF	Aquatic	Foraging	2018	[182]
Modified Cuckoo Search	MCS	Flying	Foraging	2009	[183]
Modified Cockroach Swarm Optimization	MCSO	Terrestrial	Foraging	2011	[184]
Moth Flame Optimization Algorithm	MFO	Flying	Movement	2015	[185]
Mosquito Flying Optimization	MFO.1	Flying	Foraging	2016	[186]
Meerkats Inspired Algorithm	MIA	Terrestrial	Movement	2018	[187]
Mox Optimization Algorithm	MOX	Flying	Movement	2011	[188]
Monkey Search	MS	Terrestrial	Foraging	2007	[189]
Natural Aggregation Algorithm	NAA	Other	Movement	2016	[190]
Naked Moled Rat	NMR	Terrestrial	Movement	2019	[191]
Nomadic People Optimizer	NPO	Other	Movement	2019	[192]
OptBees	OB	Flying	Foraging	2012	[193]
Optimal Foraging Algorithm	OFA	Other	Foraging	2017	[194]
Pity Beetle Algorithm	PBA	Terrestrial	Foraging	2018	[195]
Pigeon Inspired Optimization	PIO	Flying	Movement	2014	[196]
Population Migration Algorithm	PMA	Other	Movement	2009	[197]
Prey Predator Algorithm	PPA	Other	Foraging	2015	[198]
Particle Swarm Optimization	PSO	Flying	Movement	1995	[2]
Penguins Search Optimization Algorithm	PSOA	Aquatic	Foraging	2013	[199]
Regular Butterfly Optimization Algorithm	RBOA	Flying	Foraging	2019	[200]

When the behavior of the algorithm is inspired in both the movement and the foraging behavior of the animal, it is cataloged as foraging inside our first taxonomy. We will next examine in depth each of these subcategories.

Subcategories of SI-Based Algorithms by the Environment

As mentioned previously, the global set of Swarm Intelligence algorithms can be divided as a function of the

Table 5 Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (IV)

Swarm Intelligence (IV)

Algorithm name	Acronym	Subcategory	Type	Year	Reference
Red Deer Algorithm	RDA	Terrestrial	Movement	2016	[201]
Rhino Herd Behavior	RHB	Terrestrial	Movement	2018	[202]
Roach Infestation Problem	RIO	Terrestrial	Foraging	2008	[203]
Reincarnation Concept Optimization Algorithm	ROA	Other	Movement	2010	[204]
Shark Search Algorithm	SA	Aquatic	Foraging	1998	[205]
Simulated Bee Colony	SBC	Flying	Foraging	2009	[206]
Satin Bowerbird Optimizer	SBO	Flying	Movement	2017	[207]
Sine Cosine Algorithm	SCA.2	Other	Movement	2016	[208]
Snap-Drift Cuckoo Search	SDCS	Flying	Foraging	2016	[209]
Shuffled Frog-Leaping Algorithm	SFLA	Terrestrial	Movement	2006	[210]
Spotted Hyena Optimizer	SHO	Terrestrial	Foraging	2017	[211]
Swarm Inspired Projection Algorithm	SIP	Flying	Foraging	2009	[212]
Slime Mould Algorithm	SMA	Micro	Foraging	2008	[213]
Spider Monkey Optimization	SMO	Terrestrial	Foraging	2014	[214]
Seeker Optimization Algorithm	SOA	Other	Movement	2007	[215]
Symbiosis Organisms Search	SOS	Other	Movement	2014	[216]
Social Spider Algorithm	SSA	Terrestrial	Foraging	2015	[217]
Squirrel Search Algorithm	SSA.1	Flying	Movement	2019	[218]
Salp Swarm Algorithm	SSA.2	Aquatic	Foraging	2017	[219]
Shark Smell Optimization	SSO	Aquatic	Foraging	2016	[220]
Swallow Swarm Optimization	SSO.1	Flying	Foraging	2013	[221]
Social Spider Optimization	SSO.2	Terrestrial	Foraging	2013	[222]
See-See Partidge Chicks Optimization	SSPCO	Flying	Movement	2015	[223]
Surface-Simplex Swarm Evolution Algorithm	SSSE	Other	Movement	2017	[224]
Sperm Whale Algorithm	SWA	Aquatic	Movement	2016	[225]
Termite Hill Algorithm	TA	Terrestrial	Foraging	2012	[226]
Termite Colony Optimization	TCO	Terrestrial	Foraging	2010	[227]
The Great Salmon Run Algorithm	TGSR	Aquatic	Movement	2013	[228]
Virtual Ants Algorithm	VAA	Flying	Foraging	2006	[229]
Virtual Bees Algorithm	VBA	Flying	Foraging	2005	[230]
Virus Colony Search	VCS	Micro	Movement	2016	[231]
Virus Optimization Algorithm	VOA .1	Micro	Movement	2009	[232]
Viral Systems Optimization	VSO	Micro	Movement	2008	[233]
Wasp Colonies Algorithm	WCA	Flying	Foraging	1991	[10]
Wolf Colony Algorithm	WCA.1	Terrestrial	Foraging	2011	[234]
Worm Optimization	WO	Micro	Foraging	2014	[235]
Whale Optimization Algorithm	WOA	Aquatic	Foraging	2016	[11]
Wolf Pack Search	WPS	Terrestrial	Foraging	2007	[236]
Weightless Swarm Algorithm	WSA	Other	Movement	2012	[237]
Wolf Search Algorithm	WSA.1	Terrestrial	Foraging	2012	[238]
Wasp Swarm Optimization	WSO	Flying	Foraging	2005	[239]
Zombie Survival Optimization	ZSO	Other	Foraging	2012	[240]

type of animals. Between the possible categories stemming from this criteria, we have grouped them according to the environmental medium inhibited by the inspiring animal (aquatic, terrestrial or aerial). This criterion not only is very intuitive, since it inherits a criterion already applied in animal taxonomies, but also relies on the fact that these environments condition the movement and hunting mode of the different species. As such, the following subcategories have been established:

- *Flying animals:* This category comprises meta-heuristics based on the concept of Swarm Intelligence in which the trajectory of agents is inspired by flying movements, as those observed in birds, bats, or other

Table 6 Nature- and bio-inspired meta-heuristics within the *Physics based* category (I)

Physics based (I)			
Algorithm Name	Acronym	Year	Reference
Artificial Electric Field Algorithm	AEFA	2019	[242]
Artificial Physics Optimization	APO	2009	[243]
Big Bang Big Crunch	BBBC	2006	[244]
Black Hole Optimization	BH	2013	[241]
Colliding Bodies Optimization	CBO	2014	[245]
Crystal Energy Optimization Algorithm	CEO	2016	[246]
Central Force Optimization	CFO	2008	[247]
Charged Systems Search	CSS	2010	[248]
Electromagnetic Field Optimization	EFO	2016	[16]
Electromagnetism Mechanism Optimization	EMO	2003	[17]
Galaxy Based Search Algorithm	GBSA	2011	[19]
Gravitational Clustering Algorithm	GCA	1999	[249]
Gravitational Emulation Local Search	GELS	2009	[250]
Gravitational Field Algorithm	GFA	2010	[251]
Gravitational Interactions Algorithm	GIO	2011	[252]
General Relativity Search Algorithm	GRSA	2015	[253]
Gravitational Search Algorithm	GSA	2009	[18]
Galactic Swarm Optimization	GSO.2	2016	[254]
Harmony Elements Algorithm	HEA	2009	[255]
Hysteresis for Optimization	HO	2002	[256]
Hurricane Based Optimization Algorithm	HO.2	2014	[257]
Harmony Search	HS	2005	[21]
Intelligence Water Drops Algorithm	IWD	2009	[258]
Light Ray Optimization	LRO	2010	[259]
Lightning Search Algorithm	LSA	2015	[260]
Magnetic Optimization Algorithm	MFO.2	2008	[261]
Method of Musical Composition	MMC	2014	[262]
Melody Search	MS.1	2011	[263]
Multi-Verse Optimizer	MVO	2016	[264]
Optics Inspired Optimization	OIO	2015	[265]
Particle Collision Algorithm	PCA	2007	[266]
PopMusic Algorithm	PopMusic	2002	[267]
Quantum Superposition Algorithm	QSA	2015	[268]
Rain-Fall Optimization Algorithm	RFOA	2017	[269]
River Formation Dynamics	RFD	2007	[270]
Radial Movement Optimization	RMO	2014	[271]
Ray Optimization	RO	2012	[272]
Space Gravitational Algorithm	SGA	2005	[273]

flying insects. The most well-known algorithms in this subcategory are PSO [2] and ABC [8].

- *Terrestrial animals:* Meta-heuristics in this category are inspired by foraging or movements in terrestrial animals. The most renowned approach within this category is the classical ACO meta-heuristic [6], which replicates the stigmergic mechanism used by ants to locate food sources and inform of their existence to their counterparts in the colony. This category also includes other popular algorithms like Grey Wolf Optimization (GWO, [164]), inspired in the wild wolf hunting strategy; Lion Optimization Algorithm (LOA, [177]), which imitates hunting methods used by these animals; or the more recent Grasshopper Optimization Algorithm (GOA, [5]), which finds its motivation in the jumping motion of grasshoppers.

Table 7 Nature- and bio-inspired meta-heuristics within the *Physics based* category (II)

Physics based (II)			
Algorithm name	Acronym	Year	Reference
Sonar Inspired Optimization	SIO	2017	[274]
States Matter Optimization Algorithm	SMS	2014	[275]
Spiral Dynamics Optimization	SO	2011	[276]
Spiral Optimization Algorithm	SPOA	2010	[277]
Self-Driven Particles	SPP	1995	[278]
Vibrating Particle Systems Algorithm	VPO	2017	[279]
Vortex Search Algorithm	VS	2015	[280]
Water Cycle Algorithm	WCA.2	2012	[281]
Water Evaporation Optimization	WEO	2016	[282]
Water Flow-Like Algorithms	WFA	2007	[283]
Water-Flow Algorithm	WFA.1	2007	[284]
Water Flow Algorithm Optimization	WFO	2011	[285]
Water Wave Optimization Algorithm	WWA	2015	[286]

- *Aquatic animals:* This type of meta-heuristic algorithms focuses on aquatic animals. The aquatic ecosystem in which they live have inspired different exploration mechanisms. It contains popular algorithms as Krill Herd (KH, [13]), Whale Optimization Algorithm (WOA, [11]), and algorithms based on the echolocation used by dolphins to detect fish like Dolphin Partner Optimization (DPO, [148]) and Dolphin Echolocation [147].
- *Microorganisms:* Meta-heuristics based on microorganisms are related with the food search performed by bacteria. A bacteria colony performs a movement to search for food. Once they have found and taken it, they split to search again in the environment. Other types of meta-heuristics that can be part of this category are the ones related with virus, which usually replicate the infection process of the cell by virus. The most known algorithm of this category is Bacterial Foraging Optimization Algorithm (BFOA, [14]).

Subcategories of SI-Based Algorithms by the Inspirational Behavior

Another criterion to group SI-based algorithms is the specific behavior of the animal that captured the attention of researchers and inspired the algorithm. This second criterion is also reflected in Tables 2, 3, 4, and 5, classifying each algorithm as belonging to one of the following behavioral patterns:

- *Movement:* We have considered that an algorithm belongs to the *movement inspiration* subcategory if the biological inspiration resides mainly in the way the animal inspiring the algorithm regularly moves around its environment. As such, the differential aspect of the movement could hinge on the dynamics of the movement itself (e.g. the flying movement of birds in PSO [2], jumping actions as in Shuffled Frog-Leaping Algorithm, SFLA [210], or by aquatic movements as in DPO [148]), or by the movement of the population (correspondingly, swarming movements as in Bird Swarm Algorithm, BSA [127], the migration of populations like Population Migration Algorithm, PMA [197], or the migration of particular animals like salmon [228], among others).
- *Foraging:* Rather than the movement strategy, in some other algorithmic variants it is the mechanism used to obtain their food what drives the behavior of the animal and, ultimately, the design of the meta-heuristic algorithm. This foraging behavior can in turn be observed in many flavors, from the tactics used by the animal at hand to surround its food source (as in the aforementioned GWO [164] and LA [174]), inspired in breeding nutrition (as Cuckoo Search [143]), inspired in hunting techniques observed in grey wolves and lions, respectively), particular mechanisms to locate food sources and communicate its existence to the rest of the swarm (as in ACO [6]), or other exploration strategies such as the echolocation in dolphins [147], or the flashing attraction between partners observed in fireflies [4]. Sometimes, the movement of the animal also obeys to food search and retrieval. In this case, we consider that the algorithm belongs to the *foraging* inspiration type, rather than to the movement

type. Nowadays, inspiration by foraging mechanisms is becoming more and more consolidated in the research community, appearing explicitly in the name of several bio-inspired algorithms.

Physics/Chemistry-Based Algorithms

Algorithms under this category are characterized by the fact that they imitate the behavior of physical or chemical phenomena, such as gravitational forces, electromagnetism, electric charges and water movement (in relation with physics-based approaches), and chemical reactions and gases particles movement as for chemistry-based optimization algorithms.

The complete list of reviewed algorithms in this category is provided in Tables 6 and 7 (physics-based algorithms) and Table 8 (chemistry-based methods). In this category we can find some well-known algorithms reported in the last century such as Simulated Annealing [23], or one of the most important algorithms in physics-based meta-heuristic optimization, Gravitational Search Algorithm (GSA, [18]). Interestingly, a variety of space-based algorithms are rooted on GSA, such as Black Hole optimization (BH, [241]) or Galaxy Based Search Algorithm (GBSA, [19]). Other algorithms such as Harmony Search (HS, [21]) relate to the music composition process, a human invention that has more in common with other physical algorithms in what refers to the usage of sound waves than with Social Human Behavior-based algorithms, the category discussed in what follows.

Social Human Behavior-Based Algorithms

Algorithms falling in this category are inspired by human social concepts, such as decision-making and ideas related to the expansion/competition of ideologies inside the society as ideology (Ideology Algorithm (IA), [297]), or political concepts such as the Imperialist Colony Algorithm (ICA, [28]). This category also includes algorithms that emulate sport competitions such as the Soccer League Competition Algorithm (SLC, [24]). Brainstorming processes have also laid the inspirational foundations of several algorithms such as Brain Storm Optimization algorithm (BSO.2, [26]) and Global-Best Brain Storm Optimization algorithm (GBSO, [298]). The complete list of algorithms in this category is given in Table 9.

Plants-Based Algorithms

This category essentially gathers all optimization algorithms whose search process is inspired by plants. In this case, as opposed to other methods within the Swarm Intelligence category, there is no communication between agents. One of the most well-known is Forest Optimization Algorithms (FOA.1, [329]), inspired by the process of plant reproduction. Table 10 details the specific algorithms classified in this category.

Algorithms with Miscellaneous Sources of Inspiration

In this category there are include the algorithms that do not fit in any of the previous categories, i.e., we can find algorithms of diverse characteristics such as the Ying-Yang Pair Optimization (YYOP, [338]). Although this defined category is heterogeneous and does not exhibit any uniformity among the algorithms it represents, its inclusion in the taxonomy serves as an exemplifying fact of the very different sources of inspiration existing in the literature. The

Table 8 Nature- and bio-inspired meta-heuristics within the *Chemistry based* category

Chemistry based			
Algorithm name	Acronym	Year	Reference
Artificial Chemical Process	ACP	2005	[287]
Artificial Chemical Reaction Optimization Algorithm	ACROA	2011	[288]
Artificial Reaction Algorithm	ARA	2013	[289]
Chemical Reaction Optimization Algorithm	CRO.1	2010	[290]
Gases Brownian Motion Optimization	GBMO	2013	[22]
Ions Motion Optimization Algoirthm	IMO	2015	[291]
Integrated Radiation Optimization	IRO	2007	[292]
Kinetic Gas Molecules Optimization	KGMO	2014	[293]
Photosynthetic Algorithm	PA	1999	[294]
Simulated Annealing	SA.1	1989	[23]
Synergistic Fibroblast Optimization	SFO	2017	[295]
Thermal Exchange Optimization	TEO	2017	[296]

Table 9 Nature- and bio-inspired meta-heuristics within the *Social Human Behavior* based category

Social Human Behavior			
Algorithm name	Acronym	Year	Reference
Anarchic Society Optimization	ASO	2012	[27]
Brain Storm Optimization Algorithm	BSO.2	2011	[26]
Bus Transportation Behavior	BTA	2019	[299]
Collective Decision Optimization Algorithm	CDOA	2017	[300]
Cognitive Behavior Optimization Algorithm	COA.3	2016	[301]
Competitive Optimization Algorithm	COOA	2016	[302]
Cultural Algorithms	CA	1999	[303]
Duelist Optimization Algorithm	DOA	2016	[304]
Football Game Inspired Algorithms	FCA.1	2009	[305]
FIFA World Cup Competitions	FIFAAO	2016	[306]
Golden Ball Algorithm	GBA	2014	[307]
Global-Best Brain Storm Optimization Algorithm	GBSO	2017	[298]
Group Counseling Optimization	GCO	2010	[308]
Group Leaders Optimization Algorithm	GLOA	2011	[309]
Greedy Politics Optimization Algorithm	GPO	2014	[310]
Human Evolutionary Model	HEM	2007	[311]
Human Group Formation	HGF	2010	[312]
Human-Inspired Algorithms	HIA	2009	[313]
Ideology Algorithm	IA	2016	[297]
Imperialist Competitive Algorithm	ICA	2007	[28]
League Championship Algorithm	LCA .1	2014	[25]
Leaders and Followers Algorithm	LFA	2015	[314]
Old Bachelor Acceptance	OBA	1995	[315]
Oriented Search Algorithm	OSA	2008	[316]
Parliamentary Optimization Algorithm	POA	2008	[317]
Queuing Search Algorithm	QSA.1	2018	[318]
Social Behavior Optimization Algorithm	SBO.1	2003	[319]
Social Cognitive Optimization Algorithm	SCOA	2010	[320]
Social Emotional Optimization Algorithm	SEA	2010	[321]
Stochastic Focusing Search	SFS	2008	[322]
Soccer Game Optimization	SGO	2012	[323]
Soccer League Competition	SLC	2014	[24]
Teaching-Learning Based Optimization Algorithm	TLBO	2011	[324]
Tug Of War Optimization	TWO	2016	[325]
Unconscious Search	US	2012	[326]
Volleyball Premier League Algorithm	VPL	2017	[327]
Wisdom of Artificial Crowds	WAC	2011	[328]

ultimate goal to reflect this miscellaneous set of algorithms is to spawn new categories once more algorithms are created by recreating similar inspirational concepts that the assorted ones already present in this category.

The complete list of algorithms in this category is in Table 11. In this regard, we stress on this pressing need for grouping assorted algorithms in years to come so as to give rise to new categories. Otherwise, if we just stockpile new algorithms without a clear correspondence to the aforementioned categories in this miscellaneous group, the overall taxonomy will not evolve and will eventually lack its main purpose: to systematically sort and ease the analysis of future advances and achievements in the field.

Taxonomy by Behavior

We now proceed with our second proposed taxonomy. In this case we sort the different algorithmic proposals reported by the community by its behavior, without any regards

Table 10 Nature- and bio-inspired meta-heuristics within the *Plants based* category.

Plants based			
Algorithm name	Acronym	Year	Reference
Artificial Plants Optimization Algorithm	APO.1	2013	[330]
Forest Optimization Algorithm	FOA.1	2014	[329]
Flower Pollination Algorithm	FPA	2012	[331]
Natural Forest Regeneration Algorithm	NFR	2016	[332]
Plant Propagation Algorithm	PPA.1	2009	[333]
Paddy Field Algorithm	PFA	2009	[334]
Runner Root Algorithm	RRA	2015	[335]
Saplings Growing Up Algorithm	SGA.1	2007	[336]
Self-Defense Mechanism Of The Plants Algorithm	SDMA	2018	[73]
Tree Growth Algorithm	TGA	2019	[337]

to their source of inspiration. To this end, a clear sorting criterion is needed that, while keeping itself agnostic with respect to its inspiration, could summarize as much as possible the different behavioral procedures characterizing the algorithms under review. The criterion adopted for this purpose is the mechanisms used for creating new solutions, or for changing existing solutions to the optimization problem. These are the main features that define the search process of each algorithm.

First, we have divided the reviewed optimization algorithms in two categories:

- *Differential Vector Movement*, in which new solutions are produced by a shift or a mutation performed onto a previous solution. The newly generated solution could compete against previous ones, or against other solutions in the population to achieve a space and remain therein in subsequent search iterations. This solution generation scheme implies selecting a solution as the reference, which is changed to explore the space of variables and, effectively, produce the search for the solution to the problem at hand. The most representative method of this category is arguably PSO [2], in which each solution evolves with a velocity vector to explore the search domain. Another popular algorithm with differential movement at its core is DE [53], in which new solutions are produced by adding differential vectors to existing solutions in the population. Once a solution is selected as the reference one, it is perturbed by adding the difference between other solutions. The decision as to which solutions from the population are influential in the movement is a decision that has an enormous influence on the behavior of the overall search. Consequently, we further divide this category by that decision. The movement—thus, the search—can be guided by (i) all the population (Fig. 4a); (ii) only the significant/relevant solutions, e.g., the best and/or the worst candidates in the population (Fig. 4b); or (iii) a small group, which could stand for the neighborhood around each solution or, in algorithms with subpopulations, only the subpopulation to which each solution belongs (Fig. 4c).
- *Solution creation*, in which new solutions are not generated by mutation/movement of a single reference solution, but instead by combining several solutions (so there is not only a single parent solution), or other similar mechanism. Two approaches can be utilized for creating new solutions. The first one is by combination, or crossover of several solutions (Fig. 4d). The classical GA [86] is the most straightforward example of this type. Another approach is by stigmergy (Fig. 4e), in which there is an indirect coordination between the different solutions or agents, usually using an intermediate structure, to generate better ones. A classical example of stigmergy for creating solutions is ACO [7], in which new solutions are generated by the trace of pheromones left by different agents on a graph representing the solution space of the problem under analysis.

Bearing the above criteria in mind, Fig. 5 shows the classification reached after our literature analysis. The plot indicates, for the 323 reviewed algorithms, the number and ratio of proposals classified in each category and subcategory. It can be observed that in most nature- and bio-inspired algorithms, new solutions are generated by differential vector movement over existing ones (64% vs 36%). Among them, the search process is mainly guided by representative solutions (near 52% in global, almost 82 % from this category), mainly the so-called current best solution (in a very similar fashion to the naive version of the PSO solver). Thus, the creation of new solutions by

Table 11 Nature- and bio-inspired meta-heuristics within the *Miscellaneous* category

Miscellaneous			
Algorithm name	Acronym	Year	Reference
Atmosphere Clouds Model	ACM	2013	[339]
Artificial Cooperative Search	ACS	2012	[340]
Across Neighborhood Search	ANS	2016	[341]
Bar Systems	BS.2	2008	[342]
Backtracking Search Optimization	BSO.3	2012	[343]
Cloud Model-Based Algorithm	CMBDE	2012	[344]
Chaos Optimization Algorithm	COA .4	1998	[345]
Clonal Selection Algorithm	CSA .1	2000	[346]
Differential Search Algorithm	DSA	2012	[347]
Exchange Market Algorithm	EMA	2014	[348]
Extremal Optimization	EO	2000	[349]
Fireworks Algorithm Optimization	FAO	2010	[350]
Grenade Explosion Method	GEM	2010	[351]
Golden Sine Algorithm	GSA.1	2017	[352]
Heart Optimization	HO.1	2014	[353]
Interior Search Algorithm	ISA	2014	[354]
Keshtel Algorithm	KA	2014	[355]
Kaizen Programming	KP	2014	[356]
Membrane Algorithms	MA	2005	[357]
Mine Blast Algorithm	MBA	2013	[358]
Neuronal Communication Algorithm	NCA	2017	[359]
Pearl Hunting Algorithm	PHA	2012	[360]
Passing Vehicle Search	PVS	2016	[361]
Artificial Raindrop Algorithm	RDA .1	2014	[15]
Scientifics Algoritmhs	SA.2	2014	[362]
Social Engineering Optimization	SEO	2017	[363]
Stochastic Fractal Search	SFS.1	2015	[364]
Search Group Algorithm	SGA.2	2015	[365]
Simple Optimization	SOPT	2012	[366]
Small World Optimization	SWO	2006	[367]
The Great Deluge Algorithm	TGD	1993	[368]
Wind Driven Optimization	WDO	2010	[369]
Ying-Yang Pair Optimization	YYOP	2016	[338]

movement vectors oriented towards the best solution is the search mechanism found in more than half (52%) of all the 323 reviewed proposals.

The following subsections provide a brief global view of the different categories introduced above. For each category we describe its main characteristics, an example, and a table with the algorithms belonging to that category.

Differential Vector Movement

This category of our behavior-based taxonomy amounts up to 64% of the analyzed algorithms. In all of them, new solutions are obtained by a movement departing from existing solutions. By using a solution as the reference, a differential vector is used to *move* from the reference towards a new candidate, that could replace the previous one or instead compete to be included into the population.

The crucial decision in differential vector movement is how the differential vector (namely, the intensity and direction of the movement) is calculated. This differential vector could be calculated so as to move the reference solution to another solution (usually a better one), or as a lineal combination of other different solutions, allowing the combination of attraction vectors (towards best solutions)

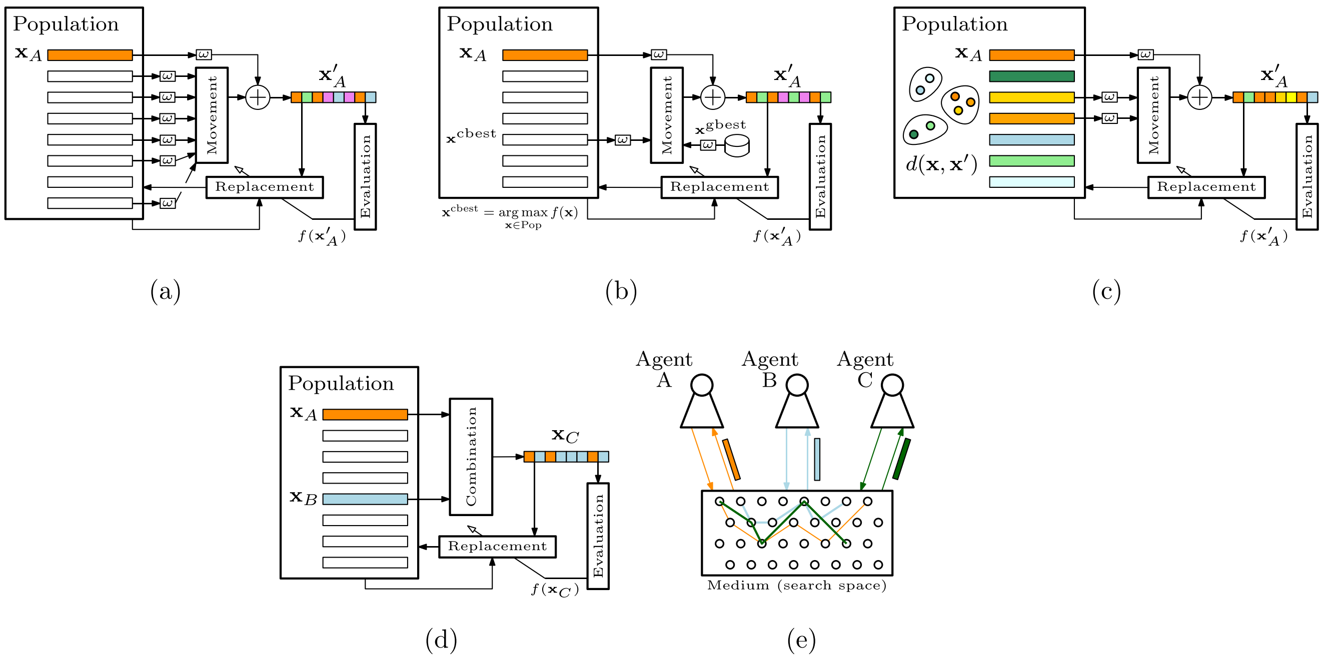
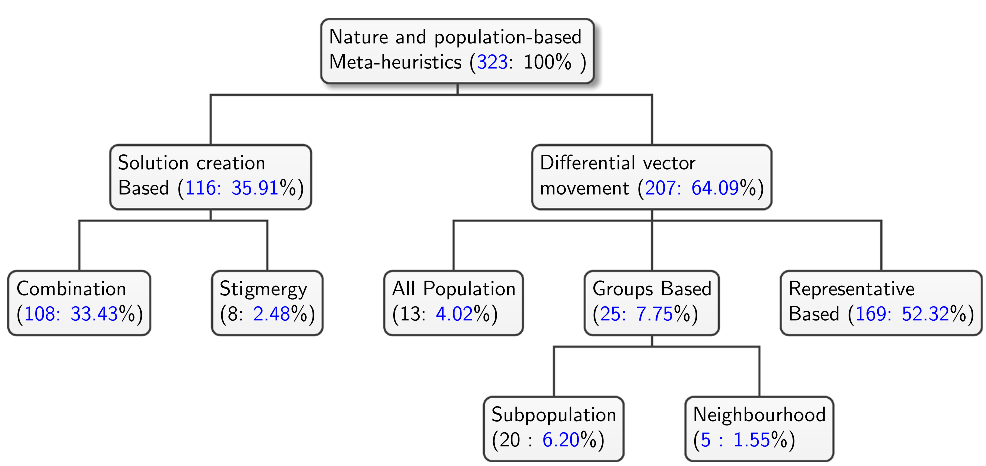


Fig. 4 Schematic diagrams of the different algorithmic behaviors on which our second taxonomy relies. The upper plots illustrate the process of generating new solutions by *Differential Vector Movement* from a given solution $\mathbf{x}_A$, using **a** the entire population; **b** relevant individuals (in the example, the movement results from a weighted combination—ω—of the current best solution in the population and the best solution found so far by the algorithm); and **c** neighboring solutions in the population to the reference individual. The lower plots show the same process using *solution creation* by **d** combination; and **e** stigmergy

with repulsion vectors (away from worse ones, or from other solutions, to enforce diversity). The mathematical nature of this operation usually restricts the domain of the representation to a numerical, usually real-valued representation.

This category is further divided into subcategories as a function of the above decision, i.e., which solutions are considered to create the movement vector. It should be noted that some algorithms can be classified into more than one subcategory. For instance, a particle's update in the PSO solver is affected by the global best particle behavior and certain local best particle(s) behavior. The local best behavior can be either dependent on the particle's previous behavior or the behavior of some particles in its neighborhood. This makes PSO a possible member of two of the subcategories, namely, *Differential Vector as a Function of Representative Solutions* and *Differential Vector as a Function of a Group of Solutions*. Nevertheless, we have considered the classical PSO as a member of *Representative Solutions* because the influence of the best algorithm is stronger than the influence of the neighborhood. In any case, following the above rationale other PSO variants could fall within any other subcategory. We now describe each of such subcategories.

Fig. 5 Classification of the reviewed papers using the *behavior* taxonomy



Differential Vector as a Function of the Entire Population

One possible criterion is used all the individuals in the population to generate the movement of each solution. In these algorithms, all individuals have a degree of influence on the movement of the other solutions. Such a degree is usually weighted according to the fitness difference and/or distance between solutions. A significant example is FA [4], in which a solution suffers a moving force towards better solutions as a function of their distance. Consequently, solutions closer to the reference solution will have a stronger influence than more distant counterparts. As shown in Table 12, algorithms in this subcategory belong to different categories in the previous *inspiration source* based taxonomy.

Differential Vector as a Function of Representative Solutions

In this group (the most populated in this second taxonomy), the different movement of each solution is only influenced by a small group of representative solutions. It is often the case that these representative solutions are selected to be best solutions found by the algorithm (as per the objective of the problem at hand), being able to be guided only by, e.g., the current best individual of the population.

Tables 13, 14, 15, 16, and 17 show the different algorithms in this subcategory. An exemplary algorithm of this category that has been a major meta-heuristic solver in the history of the field is PSO [2]. In this solver, each solution or particle is guided by the global current best solution and the best solution obtained by that particle during the search. Another classical algorithm in this category is the majority of the family of DE approaches [53]. In most of the variants of this evolutionary algorithm, the influence of the best solution(s) is hybridized with a differential vector that perturbs the new solution towards random individuals for the sake of an increased diversity along the search. However, this subcategory also includes many other algorithms with differences as considering nearly better solutions (as in the Bat Inspired Algorithm [3] or the Brain Storm Optimization Algorithm [26]) or the worse solutions (to avoid less promising regions), as in the Grasshopper Optimization Algorithm (GOA, [5]). More than half of all algorithmic proposals dwell into this subcategory, with a prominence of Swarm Intelligence solvers due to their behavioral inspiration in PSO and DE. We will revolve on these identified similarities in the "Taxonomies Analysis: Comparison and More Influential Algorithms" section.

Differential Vector as a Function of a Group of Solutions

Algorithms within this category do not resort to representative solutions of the entire population (such as the current best), but they only consider solutions of a subset or group of the solutions in the population. When the differential movement considers both a group and a representative of all the population, the algorithm under analysis is considered to belong to the previous subcategory, because the representative has usually the strongest influence over the search. Two different subcategories hold when a group of solutions is used for computing the differential movement vector:

Table 12 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by the entire population

Influenced by the entire population			
Algorithm Name	Acronym	Year	Reference
Artificial Electric Field Algorithm	AEFA	2019	[242]
Artificial Plants Optimization Algorithm	APO.1	2013	[330]
Chaotic Dragonfly Algorithm	CDA	2018	[137]
Central Force Optimization	CFO	2008	[247]
Charged Systems Search	CSS	2010	[248]
Electromagnetism Mechanism Optimization	EMO	2003	[17]
Firefly Algorithm	FA	2009	[4]
Gravitational Clustering Algorithm	GCA	1999	[249]
Group Counseling Optimization	GCO	2010	[308]
Gravitational Search Algorithm	GSA	2009	[18]
Human Group Formation	HGF	2010	[312]
Hoopoe Heuristic Optimization	HHO.1	2012	[165]
Integrated Radiation Optimization	IRO	2007	[292]

Table 13 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (I)

Influenced by representative solutions (I)

Algorithm name	Acronym	Year	Reference
Artificial Algae Algorithm	AAA	2015	[101]
Artificial Bee Colony	ABC	2007	[8]
Animal Behavior Hunting	ABH	2014	[103]
African Buffalo Optimization	ABO	2016	[104]
Atmosphere Clouds Model	ACM	2013	[339]
Ant Lion Optimizer	ALO	2015	[106]
Across Neighborhood Search	ANS	2016	[341]
Anarchic Society Optimization	ASO	2012	[27]
Artificial Searching Swarm Algorithm	ASSA	2009	[107]
Artificial Tribe Algorithm	ATA	2009	[108]
African Wild Dog Algorithm	AWDA	2013	[109]
Bison Behavior Algorithm	BBA	2019	[113]
Big Bang Big Crunch	BBBC	2006	[244]
Bacterial Chemotaxis Optimization	BCO.2	2002	[117]
Bacterial Colony Optimization	BCO.1	2012	[116]
Bald Eagle Search Optimization	BES	2019	[110]
Black Hole Optimization	BH	2013	[241]
Bat Intelligence	BI	2012	[121]
Bat Inspired Algorithm	BIA	2010	[3]
Biology Migration Algorithm	BMA	2019	[122]
Blind, Naked Mole-Rats Algorithm	BNMR	2013	[123]
Butterfly Optimizer	BO	2015	[124]
Bird Swarm Algorithm	BSA	2016	[127]
Bee Swarm Optimization	BSO	2010	[128]
Bioluminiscent Swarm Optimization Algorithm	BSO.1	2011	[129]
Brain Storm Optimization Algorithm	BSO.2	2011	[26]
Binary Whale Optimization Algorithm	BWOA	2019	[131]
Collective Animal Behavior	CAB	2012	[132]
Catfish Optimization Algorithm	CAO	2011	[134]
Cheetah Based Algorithm	CBA	2018	[133]
Cricket Behavior-Based Algorithm	CBBE	2016	[135]
Collective Decision Optimization Algorithm	CDOA	2017	[300]
Cloud Model-Based Algorithm	CMBDE	2012	[344]
Camel Traveling Behavior	COA.1	2016	[141]
Coyote Optimization Algorithm	COA.2	2018	[142]
Cognitive Behavior Optimization Algorithm	COA.3	2016	[301]
Chaos Optimization Algorithm	COA.4	1998	[345]
Competitive Optimization Algorithm	COOA	2016	[302]
Crow Search Algorithm	CSA	2016	[144]
Cat Swarm Optimization	CSO	2006	[145]

- *Subpopulation-based differential vector*: In algorithms belonging to this subcategory (listed in Table 18) the population is divided in several subpopulations, such that the movement of each solution is only affected by the other solutions in the same subpopulation. Examples of algorithms in this subcategory are LA [174] or the Monarch Butterfly Optimization algorithm (MBO, [180]).
- *Neighborhood-based differential vector*: In this subcategory, each solution is affected only by solutions

Table 14 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (II)

Influenced by representative solutions (II)			
Algorithm name	Acronym	Year	Reference
Dragonfly Algorithm	DA	2016	[9]
Differential Evolution	DE	1997	[81]
Dolphin Partner Optimization	DPO	2009	[148]
Differential Search Algorithm	DSA	2012	[347]
Elephant Herding Optimization	EHO	2016	[149]
Elephant Search Algorithm	ESA	2015	[151]
Eagle Strategy	ES.1	2010	[150]
Fireworks Algorithm Optimization	FAO	2010	[350]
Flocking Base Algorithms	FBA	2006	[153]
Fast Bacterial Swarming Algorithm	FBSA	2008	[154]
Football Game Inspired Algorithms	FCA.1	2009	[305]
FIFA World Cup Competitions	FIFAAO	2016	[306]
Flock by Leader	FL	2012	[156]
Fruit Fly Optimization Algorithm	FOA	2012	[157]
Flower Pollination Algorithm	FPA	2012	[331]
Fish Swarm Algorithm	FSA	2011	[158]
Fish School Search	FSS	2008	[159]
Gases Brownian Motion Optimization	GBMO	2013	[22]
Global-Best Brain Storm Optimization Algorithm	GBSO	2017	[298]
Group Escape Behavior	GEB	2011	[160]
Grenade Explosion Method	GEM	2010	[351]
Gravitational Field Algorithm	GFA	2010	[251]
Gravitational Interactions Algorithm	GIO	2011	[252]
Good Lattice Swarm Optimization	GLSO	2007	[161]
Grasshopper Optimisation Algorithm	GOA	2017	[5]
General Relativity Search Algorithm	GRSA	2015	[253]
Golden Sine Algorithm	GSA.1	2017	[352]
Glowworm Swarm Optimization	GSO	2013	[20]
Galactic Swarm Optimization	GSO.2	2016	[254]
Goose Team Optimization	GTO	2008	[163]
Grey Wolf Optimizer	GWO	2014	[164]
Harry's Hawk Optimization Algorithm	HHO	2019	[74]
Heart Optimization	HO.1	2014	[353]
Hurricane Based Optimization Algorithm	HO.2	2014	[257]
Hunting Search	HuS	2010	[166]

in its local neighborhood. Table 19 compiles all algorithms that are classified in this subcategory. A notable example in this list is BFOA [14], in which all solutions in the neighborhood impact on the computation of the movement vector, either by attracting the solution (if the neighboring solution has better fitness than the reference solution) or in a repulsive way (when the neighboring solution is worse than the one to be moved).

Solution Creation

This category is composed of algorithms that explore the domain search by generating new solutions, not by moving existing ones. This group is a significant ratio (36%) of all proposals, and includes many classical algorithms like GA [86]. A very widely exploited advantage of these methods is the possibility to adapt the generation method to the particular problem, hence allowing for different possible

Table 15 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (III)

Influenced by representative solutions (III)			
Algorithm name	Acronym	Year	Reference
Honeybee Social Foraging	HSF	2007	[167]
Ideology Algorithm	IA	2016	[297]
Imperialist Competitive Algorithm	ICA	2007	[28]
Interior Search Algorithm	ISA	2014	[354]
Jaguar Algorithm	JA	2015	[172]
Kinetic Gas Molecules Optimization	KGMO	2014	[293]
Krill Herd	KH	2012	[13]
Killer Whale Algorithm	KWA	2017	[173]
Seven-Spot Ladybird Optimization	LBO	2013	[175]
League Championship Algorithm	LCA .1	2014	[25]
Leaders and Followers Algorithm	LFA	2015	[314]
Lightning Search Algorithm	LSA	2015	[260]
Locust Swarms Optimization	LSO	2009	[178]
Membrane Algorithms	MA	2005	[357]
Mine Blast Algorithm	MBA	2013	[358]
Magnetotactic Bacteria Optimization Algorithm	MBO	2013	[179]
Mouth Breeding Fish Algorithm	MBF	2018	[182]
Modified Cuckoo Search	MCS	2009	[183]
Modified Cockroach Swarm Optimization	MCSO	2011	[184]
Moth Flame Optimization Algorithm	MFO	2015	[185]
Magnetic Optimization Algorithm	MFO.2	2008	[261]
Meerkats Inspired Algorithm	MIA	2018	[187]
Monkey Search	MS	2007	[189]
Multi-Verse Optimizer	MVO	2016	[264]
Naked Moled Rat	NMR	2019	[191]
Nomadic People Optimizer	NPO	2019	[192]
OptBees	OB	2012	[193]
Optimal Foraging Algorithm	OFA	2017	[194]
Optics Inspired Optimization	OIO	2015	[265]
Oriented Search Algorithm	OSA	2008	[316]
Paddy Field Algorithm	PFA	2009	[334]
Pigeon Inspired Optimization	PIO	2014	[196]
Population Migration Algorithm	PMA	2009	[197]
Parliamentary Optimization Algorithm	POA	2008	[317]
Prey Predator Algorithm	PPA	2015	[198]
Plant Propagation Algorithm	PPA.1	2009	[333]
Particle Swarm Optimization	PSO	1995	[2]
Penguins Search Optimization Algorithm	PSOA	2013	[199]

representations and, therefore, easing its application to a wider range of problems. In the following, we describe the different subcategories that result from the diverse mechanisms by which solutions can be created.

Creation by Combination

The most common option to generate new solution is to combine existing ones. In these algorithms, different

Table 16 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (IV)

Influenced by representative solutions (IV)			
Algorithm name	Acronym	Year	Reference
Passing Vehicle Search	PVS	2016	[361]
Queuing Search Algorithm	QSA.1	2018	[318]
Regular Butterfly Optimization Algorithm	RBOA	2019	[200]
Artificial Raindrop Algorithm	RDA .1	2014	[15]
Roach Infestation Problem	RIO	2008	[203]
Radial Movement Optimization	RMO	2014	[271]
Ray Optimization	RO	2012	[272]
Runner Root Algorithm	RRA	2015	[335]
Satin Bowerbird Optimizer	SBO	2017	[207]
Stem Cells Algorithm	SCA	2011	[94]
Sine Cosine Algorithm	SCA.2	2016	[208]
Social Cognitive Optimization Algorithm	SCOA	2010	[320]
Social Emotional Optimization Algorithm	SEA	2010	[321]
Synergistic Fibroblast Optimization	SFO	2017	[295]
Stochastic Focusing Search	SFS	2008	[322]
Stochastic Fractal Search	SFS.1	2015	[364]
Space Gravitational Algorithm	SGA	2005	[273]
Soccer Game Optimization	SGO	2012	[323]
Spotted Hyena Optimizer	SHO	2017	[211]
Swarm Inspired Projection Algorithm	SIP	2009	[212]
Soccer League Competition	SLC	2014	[24]
Slime Mould Algorithm	SMA	2008	[213]
Spider Monkey Optimization	SMO	2014	[214]
States Matter Optimization Algorithm	SMS	2014	[275]
Spiral Dynamics Optimization	SO	2011	[276]
Spiral Optimization Algorithm	SPOA	2010	[277]
Self-Driven Particles	SPP	1995	[278]
Seeker Optimization Algorithm	SOA	2007	[215]
Symbiosis Organisms Search	SOS	2014	[216]
Social Spider Algorithm	SSA	2015	[217]
Squirrel Search Algorithm	SSA.1	2019	[218]
Shark Smell Optimization	SSO	2016	[220]
Swallow Swarm Optimization	SSO.1	2013	[221]
Social Spider Optimization	SSO.2	2013	[222]
See-See Partridge Chicks Optimization	SSPCO	2015	[223]
Surface-Simplex Swarm Evolution Algorithm	SSSE	2017	[224]

solutions are selected and combined using a crossover operator or combining method to give rise to new solutions. The underlying idea is that by combining good solutions, even better solutions can be eventually generated.

The combining method can be specific for the problem to be solved or instead, be conceived for a more general family of problems. In fact, combining methods are usually devised to be adaptable to many different solution representations. As mentioned before, the most popular algorithm in this category is GA [86]. However, many other bio-inspired algorithms exhibit a similar behavior when creating solutions, yet they are inspired by other phenomena, such as Cultural Optimization (CA, [303]) (in the Social Human Behavior category), LA [177] (in the Swarm Intelligence

Table 17 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (V)

Influenced by representative solutions (V)			
Algorithm name	Acronym	Year	Reference
Termite Colony Optimization	TCO	2010	[227]
The Great Salmon Run Algorithm	TGSR	2013	[228]
Teaching-Leaning Based Optimization Algorithm	TLBO	2011	[324]
Tug Of War Optimization	TWO	2016	[325]
Unconscious Search	US	2012	[326]
Virus Colony Search	VCS	2016	[231]
Variable Mesh Optimization	VMO	2012	[98]
Volleyball Premier League Algorithm	VPL	2017	[327]
Vibrating Particle Systems Algorithm	VPO	2017	[279]
Vortex Search Algorithm	VS	2015	[280]
Wolf Colony Algorithm	WCA.1	2011	[234]
Water Cycle Algorithm	WCA.2	2012	[281]
Wind Driven Optimization	WDO	2010	[369]
Water Evaporation Optimization	WEO	2016	[282]
Whale Optimization Algorithm	WOA	2016	[11]
Wolf Pack Search	WPS	2007	[236]
Weightless Swarm Algorithm	WSA	2012	[237]
Wolf Search Algorithm	WSA.1	2012	[238]
Water Wave Optimization Algorithm	WWA	2015	[286]
Zombie Survival Optimization	ZSO	2012	[240]

category), Particle Collision Algorithm (PCA, [266], in the chemistry-based category) or Light Ray Optimization (LRO, [259], in the physics-based category). Tables 20, 21, and 22 show the algorithms that rely on combination when creating new solutions along their search.

Creation by Stigmergy

Another popular option of creating new solutions relies on stigmergy, namely, an indirect communication and coordination between the different solutions or agents used to create new solutions. This communication is usually done using an intermediate structure, with information obtained from the different solutions, used to generate new solutions oriented towards more promising areas of the search space. This is indeed the search mechanism used in the most representative algorithm of this category, ACO [7], which is inspired by the foraging mechanism of ant colonies. Each ant of the colony describes a trajectory over a graph representation of the search space of the problem at hand, and leaves a trace of pheromone along its way whose intensity depends, in part, on the fitness value corresponding to the solution encoded by the trajectory of the ant. In subsequent iterations, new solutions are generated, dimension by dimension, considering the pheromones trail left by preceding ants, enforcing the search around most promising values for each dimension.

Table 23 lists the reviewed algorithms that employ stigmergy when creating new solutions. This is a reduced list when comparing with preceding categories, with the majority of the algorithms relying on Swarm Intelligence among insects (similarly to ACO). However, other algorithms inspired in physics have also a stigmertic behavior when producing new solutions, such as methods inspired by water flow dynamics [285] and the natural formation of rivers [270].

Taxonomies Analysis: Comparison and More Influential Algorithms

We now proceed by critically examining the reviewed literature as per the different taxonomies proposed in this overview. First, we are going to study the similarities between the results of the classifications following each taxonomy. Later, we identify the most influential algorithms over the rest, based on the behavior of the algorithms.

Comparing the different taxonomies with each other and the algorithms falling in each of their categories, it can be observed that there is not a strong relationship between

Table 18 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by subpopulations

Influenced by subpopulations			
Algorithm name	Acronym	Year	Reference
Artificial Chemical Process	ACP	2005	[287]
Artificial Cooperative Search	ACS	2012	[340]
Artificial Physics Optimization	APO	2009	[243]
Bee Colony-Inspired Algorithm	BCIA	2009	[114]
Colliding Bodies Optimization	CBO	2014	[245]
Cuttlefish Algorithm	CFA	2013	[138]
Cuckoo Optimization Algorithm	COA	2011	[140]
Chicken Swarm Optimization	CSO.1	2014	[146]
Exchange Market Algorithm	EMA	2014	[348]
Greedy Politics Optimization Algorithm	GPO	2014	[310]
Group Search Optimizer	GSO.1	2009	[162]
Hierarchical Swarm Model	HSM	2010	[168]
Ions Motion Optimization Algorithm	IMO	2015	[291]
Lion Optimization Algorithm	LOA	2016	[177]
Monarch Butterfly Optimization	MBO.1	2017	[180]
Social Behavior Optimization Algorithm	SBO.1	2003	[319]
Sperm Whale Algorithm	SWA	2016	[225]
Thermal Exchange Optimization	TEO	2017	[296]
Wisdom of Artificial Crowds	WAC	2011	[328]
Worm Optimization	WO	2014	[235]

them. Interestingly, this unveils that features characterizing one algorithm are loosely associated with its inspirational model. For instance, algorithms inspired by very different concepts such as the gravitational forces (GFA, [251]) or animal evolution (ABO, [104]) exhibit a significant similarity with PSO [2]. This statement is supported by the fact that, in the second taxonomy, each category is composed by algorithms that, as per the first taxonomy, are inspired by diverse phenomena. The contrary also holds in general: proposals with very similar natural inspiration fall in the same category of the first taxonomy (as expected), but their search procedures differ significantly from each other, thereby being classified in different categories of the second taxonomy. An illustrative example is the Delphi Echolocation algorithm (DE, [147]) and the Dolphin Partner Optimization [148]. Both are inspired in the same animal (dolphin) and its mechanism to detect fishes (echolocation), but they are very different algorithms: the former creates new solutions by combination, whereas the latter resembles closely the movement performed in the PSO solver, mainly guided by the best solution.

In this same line of reasoning, the largest subcategory of the second taxonomy (Differential Vector Movements guided by representative solutions) not only contains more

Table 19 Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by neighborhoods

Influenced by neighborhoods			
Algorithm Name	Acronym	Year	Reference
Bees Algorithm	BA	2006	[111]
Biomimicry Of Social Foraging Bacteria for Distributed Optimization	BFOA	2002	[14]
Bacterial Foraging Optimization	BFOA.1	2009	[56]
Gravitational Emulation Local Search	GELS	2009	[250]
Neuronal Communication Algorithm	NCA	2017	[359]

Table 20 Nature- and bio-inspired meta-heuristics within the *Solution Creation-Combination* category (I)

Creation-Combination category (I)			
Algorithm name	Acronym	Year	Reference
Artificial Beehive Algorithm	ABA	2009	[102]
Andean Condor Algorithm	ACA	2019	[105]
Artificial Chemical Reaction Optimization Algorithm	ACROA	2011	[288]
Artificial Infections Disease Optimization	AIDO	2016	[75]
Artificial Reaction Algorithm	ARA	2013	[289]
Asexual Reproduction Optimization	ARO	2010	[76]
Bacterial-GA Foraging	BGAF	2007	[118]
Bumblebees	BB	2009	[112]
Biogeography Based Optimization	BBO	2008	[77]
Bee Colony Optimization	BCO	2005	[115]
BeeHive Algorithm	BHA	2004	[119]
Bees Life Algorithm	BLA	2018	[120]
Bird Mating Optimization	BMO	2014	[78]
Bean Optimization Algorithm	BOA	2011	[79]
Bee System	BS	1997	[125]
Bar Systems	BS.2	2008	[342]
Backtracking Search Optimization	BSO.3	2012	[343]
Bees Swarm Optimization Algorithm	BSOA	2005	[130]
Bus Transportation Behavior	BTA	2019	[299]
Cultural Algorithms	CA	1999	[303]
Cultural Coyote Optimization Algorithm	CCOA	2019	[136]
Crystal Energy Optimization Algorithm	CEO	2016	[246]
Consultant Guide Search	CGS	2010	[139]
Coral Reefs Optimization	CRO	2014	[12]
Chemical Reaction Optimization Algorithm	CRO.1	2010	[290]
Cuckoo Search	CS	2009	[143]
Clonal Selection Algorithm	CSA .1	2000	[346]
Dendritic Cells Algorithm	DCA	2005	[80]
Dolphin Echolocation	DE.1	2013	[147]
Duelist Optimization Algorithm	DOA	2016	[304]
Ecogeography-Based Optimization	EBO	2014	[82]
Eco-Inspired Evolutionary Algorithm	EEA	2011	[83]
Electromagnetic Field Optimization	EFO	2016	[16]
Extremal Optimization	EO	2000	[349]
Earthworm Optimization Algorithm	EOA	2018	[84]
Evolution Strategies	ES	2002	[85]
Egyptian Vulture Optimization Algorithm	EV	2013	[152]
Frog Call Inspired Algorithm	FCA	2009	[155]
Forest Optimization Algorithm	FOA.1	2014	[329]

than half of the reviewed algorithms (52%), but it also comprises algorithms from all the different categories in the first taxonomy: Social Human Behavior (as Anarchic Society Optimization (ASO), [27]), microorganisms (Bacterial Colony Optimization, [116]), Physics/Chemistry category (correspondingly, Fireworks Algorithm Optimization (FAO), [350]), Breeding-based Evolution (as Variable Mesh Optimization (VMO), [98]), or even Plants-Based (such as Flower Pollination Algorithm (FPA), [331]). This inspirational diversity is not exclusive of this subcategory. Others, such as Solution Creation, also include algorithms relying on an heterogeneity of natural concepts.

Table 21 Nature- and bio-inspired meta-heuristics within the *Solution Creation-Combination* category (II)

Creation-Combination category (II)			
Algorithm name	Acronym	Year	Reference
Genetic Algorithms	GA	1989	[86]
Golden Ball Algorithm	GBA	2014	[307]
Galaxy Based Search Algorithm	GBSA	2011	[19]
Gene Expression	GE	2001	[87]
Group Leaders Optimization Algorithm	GLOA	2011	[309]
Harmony Search	HS	2005	[21]
Harmony Elements Algorithm	HEA	2009	[255]
Human Evolutionary Model	HEM	2007	[311]
Human-Inspired Algorithms	HIA	2009	[313]
Hysteresis for Optimization	HO	2002	[256]
Hypercube Natural Aggregation Algorithm	HYNAA	2019	[169]
Immune-Inspired Computational Intelligence	ICI	2008	[88]
Improved Genetic Immune Algorithm	IGIA	2017	[89]
Improved Raven Roosting Algorithm	IRRO	2018	[170]
Invasive Tumor Optimization Algorithm	ITGO	2015	[171]
Weed Colonization Optimization	IWO	2006	[90]
Keshtel Algorithm	KA	2014	[355]
Kaizen Programming	KP	2014	[356]
Lion Algorithm	LA	2012	[174]
Laying Chicken Algorithm	LCA	2017	[176]
Light Ray Optimization	LRO	2010	[259]
Migrating Birds Optimization	MBO.2	2012	[181]
Mosquito Flying Optimization	MFO.1	2016	[186]
Marriage In Honey Bees Optimization	MHBO	2001	[91]
Method of Musical Composition	MMC	2014	[262]
Mox Optimization Algorithm	MOX	2011	[188]
Melody Search	MS.1	2011	[263]
Natural Aggregation Algorithm	NAA	2016	[190]
Natural Forest Regeneration Algorithm	NFR	2016	[332]
Old Bachelor Acceptance	OBA	1995	[315]
Photosynthetic Algorithm	PA	1999	[294]
Pity Beetle Algorithm	PBA	2018	[195]
Particle Collision Algorithm	PCA	2007	[266]
Pearl Hunting Algorithm	PHA	2012	[360]
PopMusic Algorithm	PopMusic	2002	[267]
Queen-Bee Evolution	QBE	2003	[92]
Quantum Superposition Algorithm	QSA	2015	[268]
Red Deer Algorithm	RDA	2016	[201]
Rain-Fall Optimization Algorithm	RFOA	2017	[269]
Rhino Herd Behavior	RHB	2018	[202]
Reincarnation Concept Optimization Algorithm	ROA	2010	[204]

Considering the previous examples, it is clear that the real behavior of the algorithm is much more informative than its natural or biological inspiration. Even more, we have observed that in our first proposed taxonomy, built upon the review of more than three hundred proposals, the huge diversity of inspirational sources does not correspond with the lower number of algorithmic behaviors on which our second taxonomy is based. This observation is in

Table 22 Nature- and bio-inspired meta-heuristics within the *Solution Creation-Combination* category (III)

Creation-Combination category (III)			
Algorithm name	Acronym	Year	Reference
Shark Search Algorithm	SA	1998	[205]
Simulated Annealing	SA.1	1989	[23]
Scientifics Algorithms	SA.2	2014	[362]
SuperBug Algorithm	SuA	2012	[93]
Simulated Bee Colony	SBC	2009	[206]
Snap-Drift Cuckoo Search	SDCS	2016	[209]
Self-Defense Mechanism Of The Plants Algorithm	SDMA	2018	[73]
Social Engineering Optimization	SEO	2017	[363]
Sheep Flock Heredity Model	SFHM	2001	[95]
Shuffled Frog-Leaping Algorithm	SFLA	2006	[210]
Saplings Growing Up Algorithm	SGA.1	2007	[336]
Search Group Algorithm	SGA.2	2015	[365]
Swine Influenza Models Based Optimization	SIMBO	2013	[96]
Sonar Inspired Optimization	SIO	2017	[274]
Self-Organizing Migrating Algorithm	SOMA	2004	[97]
Simple Optimization	SOPT	2012	[366]
Salp Swarm Algorithm	SSA.2	2017	[219]
Tree Growth Algorithm	TGA	2019	[337]
The Great Deluge Algorithm	TGD	1993	[368]
Small World Optimization	SWO	2006	[367]
Virulence Optimization Algorithm	VOA	2016	[99]
Virus Optimization Algorithm	VOA .1	2009	[232]
Viral Systems Optimization	VSO	2008	[233]
Wasp Colonies Algorithm	WCA	1991	[10]
Water Flow-Like Algorithms	WFA	2007	[283]
Water Flow Algorithm	WFA.1	2007	[284]
Wasp Swarm Optimization	WSO	2005	[239]
Ying-Yang Pair Optimization	YYOP	2016	[338]

accordance with previous works in the literature, which have put to question whether the novelty in the natural inspiration of the algorithm actually yields different algorithms that could produce competitive results [370, 371].

We further elaborate on the above statement: our literature analysis revealed that the majority of proposals (more than a half, 52%) generates new solutions based on differential vector forces over existing ones, as in the classical PSO or DE. A complementary analysis can be done by departing from this observation towards discriminating which of the classical algorithms (PSO, DE, GA, ACO, ABC or SA) can be declared to be most similar to modern approaches. The results of this analysis are conclusive: 37% of all reviewed algorithms (122 out of 323) were found to be so influenced by classical algorithms that, without their biological inspiration, they could be regarded as incremental variants. The other 201 solvers (about 62%) have enough differences to be considered a new proposal by themselves, instead of another version of an existing algorithm.

Identification of the Most Influential Algorithms

In order to know of which are the most influential reference algorithms used to design other bio-inspired algorithms, we have grouped together reviewed proposals that could be considered to be versions of the same classical algorithm. Figure 6 shows the classification of each algorithm based on its behavior, and the number of proposals in each classification are summarized in Table 24.

Very insightful conclusions can be drawn from this grouping. To begin with, in Table 24 the most influential algorithm was identified to be PSO, appearing in 17% of the reviewed literature (which corresponds to 46% of the proposals that were clearly based on a previous algorithm).

Table 23 Nature- and bio-inspired meta-heuristics within the *Solution Creation-Stigmergy* category

Solution Creation-Stigmergy			
Algorithm name	Acronym	Year	Reference
Ant Colony Optimization	ACO	1996	[6]
Bee System	BS.1	2002	[126]
Intelligence Water Drops Algorithm	IWD	2009	[258]
River Formation Dynamics	RFD	2007	[270]
Termite Hill Algorithm	TA	2012	[226]
Virtual Ants Algorithm	VAA	2006	[229]
Virtual Bees Algorithm	VBA	2005	[230]
Water-Flow Algorithm Optimization	WFO	2011	[285]

This bio-inspired solver is one of the most prominent and historically acknowledged algorithms in the Swarm Intelligence category, and is the reference of many bio-inspired algorithms contributed since its inception. The simplicity of this algorithm and its ability to reach an optimum quickly—as has been comparatively assessed in many application scenarios (see, e.g., [66, 67])—have inspired many authors to create new meta-heuristics characterized by similar solution movement dynamics to those defined by PSO. Thus, many algorithms whose authors claim to simulate the behavior of a biological system eventually perform their search process through movements strongly influenced by PSO (in some cases, without any significant difference).

The second, and third most influential algorithms are GA, a very classic algorithm, and DE, a well-known algorithm whose natural inspiration resides only on to the evolution of a population. Both have been used by around 7% of all reviewed nature-inspired algorithms, and they are the most representative approach in the *Evolutionary Algorithms* category. The search mechanism of GA is solution creation by combination, and the search mechanism of DE is to create new solutions with a lineal combination of existing ones in the population, which is used by 7% of all reviewed proposals, maybe by its superior performance reported for many optimization problems [38].

When inspecting the influential approaches from a higher perspective, two are the categories whose algorithms have

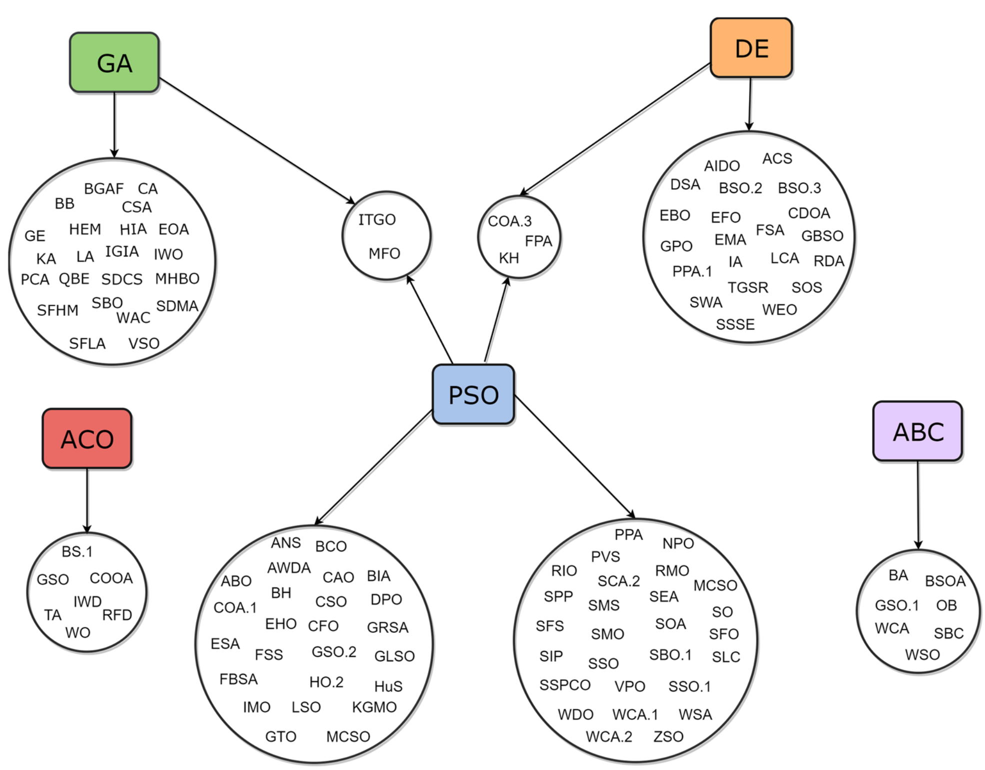


Fig. 6 Classification of proposals by its original algorithm

Table 24 Percentages of similar algorithms in the reviewed literature

Classical algorithm	Number of papers with similar algorithms	Percentage over the total
PSO	57	17.65%
DE	24	7.43%
GA	24	7.43%
ACO	7	2.17%
ABC	7	2.17%
SA	3	0.93%
Total	122	37.77%

been more frequently used to create new nature-based algorithms. The first one is *Swarm Intelligence*: about 20% of all studied nature-inspired algorithms are variations of SI algorithms (PSO, ACO, and ABC). The second one is shared between *Evolutionary Algorithms* and GA, whose represented algorithms are both used in 7% of the reviewed cases. It is noteworthy to highlight that it appears that the influence of more classic algorithms like GA and SA is declining when compared with other algorithms, such as DE and PSO.

In summary, although in the last years many nature-inspired algorithms have been proposed by the community and their number grows steadily every year, more than half of the proposals reviewed in our work are incremental, minor versions of only three very classical algorithms (PSO, DE, and GA). We therefore conclude that a huge number of natural and biological sources of inspiration used so far to justify the design of new optimization solvers have not led to significantly disruptive algorithmic behaviors. This closing note will be at the heart of our critical analysis exposed in the next section.

Lessons Learnt and Critical Analysis: Recommendations on Research Practices

After reviewing the proposals, we have extracted several issues that we consider to be challenges and recommendations that the community working on nature- and bio-inspired optimization should deal with in forthcoming years. We next outline them in no particular order:

- *The behavior is more relevant than the natural inspiration:* As was exposed in the "Taxonomies Analysis: Comparison and More Influential Algorithms" section, the current literature is flooded with a huge number of nature- and bio-inspired algorithms. However, as has been spotted by our proposed taxonomies, several algorithms belonging to categories with different sources of inspiration result to be very similar in terms of behavior. This disparity is a controversial topic in recent years [32, 370]. Therefore, we call for more research efforts around the design of optimization algorithms that focus on their behavior and properties (e.g., good performance, simplicity, ability to run it in parallel or their suitability to a specific type of problems) rather than on new inspiration sources.
- *Nature-based terminology can make it more difficult to understand the proposal:* A great deal of papers presenting new bio-inspired solvers are difficult to understand and replicate due to the extended usage of vocabulary related to the natural source of inspiration. It is logical to use the semantic of the biological or natural domain, but to an extent. It would be desirable that the description of the algorithm could be defined in an inspiration-agnostic fashion, resorting to mathematical terms to describe each component, agent and/or phase of the optimization process (e.g., optimum/a, individuals or solutions). An excessive usage of the domain terminology (without explicitly indicating the correspondences) could make it difficult to follow the details of the algorithm for researchers not acquainted with such a terminology. To overcome this issue, the correspondence between the domain terminology and the optimization terminology should be explicitly indicated.
- *Good comparisons are crucial for new proposals:* The lack of fair comparisons is another important drawback of many proposals published to date. When new algorithms are proposed, unfortunately many of them are only compared with very basic and classical algorithms (such as GA or PSO). These algorithms have been widely surpassed by more advanced versions over the years which, so obtaining better performance than naive version of classical algorithms is relatively easy to achieve, and it does not imply a competitive performance [371]. In some cases, the proposed algorithm is compared with similar algorithms but not with competitive algorithms outside that semantic niche [371, 372]. This methodological practice must be

regarded as a very serious barrier for their application to real-world problems. We encourage researchers to increase the algorithms used in their experimental section, including more competitive or state-of-the-art algorithms: until they are prove to be competitive respect to the state of the art, new nature- and bio-inspired solvers will not be used in practice either will attract enough attention of the research community.

- *Many proposals have a very limited influence:* By examining in depth the historical trajectory followed by each reviewed algorithm, an intriguing trend is revealed: a fraction of the proposals has a very limited influence in new papers after the original publication. For them, there is almost no new papers with improved versions, or applying it to new problems. Fortunately, other few algorithms have a stronger influence. In view of this dichotomy, the researchers should evaluate their proposals to diverse problems, including widely acknowledged benchmark functions and real-world practical problems, to grasp the interest of the community in considering their proposed algorithms for tackling other applications.
- *The interest of making source code available:* Related to the previous one, it is very interesting, in order to gain more visibility, to make the source code of the proposed algorithm available for the community. It is true that the paper presenting the new algorithm should be detailed enough to allow for a clean implementation of the proposal from the provided specification. However, it is widely acknowledged that, in many occasions, there are important details that even though they have a strong influence on the results, are not remarked in the description [373, 374]. A publicly available reference implementation could not only improve its visibility, but could also offer other researchers the chance to undertake more thorough performance comparisons. In addition, there are a huge number of software frameworks for Evolutionary Computation and Swarm Intelligence programmed in different languages (such as C++, Java, MATLAB, or Python), some of them very popular in the current research landscape. To cite a few: Evolutionary Computation Framework (ECF)[1] and ParadisEO [375] in C++; jMetal [376] and MOEA[2] in Java; NiaPy[377], jMetalPy [378] and PyGMO[3] in Python; or PlatEMO [379] in MATLAB, among others. Each of them implements the most popular algorithms (GA, DE, PSO, ABC, ...). A reference implementation could also favor the inclusion of the proposal in frameworks as the ones exemplified previously. Otherwise, different implementations of the allegedly same algorithm could produce diverging results from the original proposal (in part due to the ambiguity of the description).
- *The role of bio-inspired algorithms in competitions:* Finally, we also stress on the fact that meta-heuristic algorithms that have scored best in many competitions are far from being biologically inspired, although some of them retain their nature-inspired roots (mostly, DE) [38]. This fact was expected for the lack of good methodological practices when comparing nature- and bio-inspired algorithms, which was pointed out previously in our analysis. This issue has not encouraged participants in competitions to embrace them as reference algorithms to design better solvers. The rising trend of the community to generate an ever-growing number of bio-inspired proposals can be counterproductive and deviate efforts towards developments of a reduced number of proposals but with a better performance.
- *Work in more specific challenges:* Most proposals aim to address general single-objective optimization problems. However, other types of optimization problems still deserve further attention from the community, unfolding vast opportunities for the development of special flavors of nature- and bio-inspired algorithms as the ones collected in our taxonomies:

    – Dynamic and stochastic optimization, problems in which the problem definition varies over time.
    – Multi- and many-objective optimization, wherein the goal is to simultaneously optimize several conflicting objectives.
    – Multimodal optimization, in which there may be several global optima to be found and retained during the search.
    – Large-Scale Global Optimization, in which the number of variables (dimensionality of the search space) is huge, in the order of thousands.
    – Memetic Algorithms, where the algorithmic proposal is combined with other search techniques to further improve its performance.
    – Parameter tuning, which refers to the search for the values of the parameters of the optimization algorithm itself that lead to its best search performance.
    – Parameter adaptation, i.e., the design of adaptive parameters that allow solver to adapt themselves to the problem during the search.

[1] http://ecf.zemris.fer.hr/
[2] http://moeaframework.org/
[3] http://esa.github.io/pygmo/index.html

We suggest [32] to the reader interested in further information and prospects on the future of the above type of problems.

- *Hybridization might produce new algorithmic behaviors:* In our bibliographic study we have noted the tendency in the literature to propose combinations (hybridizations) of two or more nature- and bio-inspired algorithms into a single solver [380, 381]. However, in the different proposals a solid proof is required to verify that the results compensate for the increase in complexity when compared with existing approaches. When this proof is eventually achieved, the community should gradually incorporate these new hybrid approaches into existing taxonomies. This could require widening the criteria followed in taxonomies to also account for the mixture of algorithmic behaviors present in hybrid search techniques. Taxonomies reported to date do not explicitly take into account this possibility. Once hybrid schemes are verified to provide significant gains over traditional methods, it will be time for the research community to start modifying the existing taxonomies to reflect their importance in the field.

Conclusions

Nature and biological organisms have been a source of inspiration of many optimization algorithms. During the last years, this family of solvers has grown considerably in size, achieving unseen levels of diversity in regards to their source of inspiration. This explosion of literature has made it difficult for the community to appraise the general trajectory followed by the field, which is a necessary step towards identifying research trends and challenges of scientific value and practical impact. Some efforts have been dedicated so far towards classifying the state of the art on nature- and bio-inspired optimization in a taxonomy with well-defined criteria, allowing researchers to classify existing algorithms and newly proposed schemes. Unfortunately, the few attempts at furnishing this desired taxonomy have not succeeded through the years, relying mostly on the source of inspiration (*metaphor*) or in taxonomies with narrow algorithmic coverage.

In this work, we have reviewed more than three hundred nature- and bio-inspired algorithms, and classified them in two taxonomies that group the different proposals in categories and subcategories. The first proposed taxonomy considers its source of inspiration, whereas the second taxonomy discriminates among algorithm by their algorithmic behavior, namely, by the procedure by which new candidate solutions to the optimization problem are generated. Remarkably, our second taxonomy leaves aside any aspect related to the source of inspiration behind the design of the algorithm to strictly focus on algorithmic aspects of its search procedure. We have provided clear descriptions of the classification criterion, illustrative examples and an enumeration of the reviewed nature- and bio-inspired approaches that fall within each of the categories of both proposed taxonomies.

Once the taxonomies have been presented and populated, our study has also critically examined the reviewed literature by identifying and discussing on the similarities and differences among them. We have concluded that a very loose connection exists between the natural inspiration of an algorithm and its algorithmic behavior. Likewise, many algorithms, even if claiming to be inspired by very different natural and biological phenomena, result to be algorithmically more similar than one could expect as per their design rationale. Even more serious is the noted fact that more than 50% of all proposals follow a very similar behavior, namely, the exploration of the search space by moving a reference solution with a differential vector towards the current best solution. Yet another finding that goes in this line of discussion: 32% of the reviewed proposals were identified to be versions of classical algorithms such as PSO, DE, or GA. Specially PSO, with more than 17% of the nature- and bio-inspired algorithms proposed in the last years that can be regarded as versions of this solver. To a lesser albeit also illustrative extent, 7% of the studied proposals were versions of GA. These findings bring light to the longstanding discussion held within the nature- and bio-inspired community around the questionable algorithmic contributions of recent advances in the field.

On a note summarizing our above challenges and recommendations, we stress on our main three conclusions:

1. The growing number of nature- and bio-inspired proposals must be regarded as a symptomatic fact of the vivid status of this field [32], as well as a clear exponent of the possibilities brought by Nature to solve complex optimization problems.
2. Its evolution suggest that research efforts should aim at devising new algorithms with truly new behavioral differences with respect to the state of the art, providing verifiable evidences of a superior performance in practical problems.
3. Good methodological practices must be followed in forthcoming studies when designing, describing, and comparing new algorithms.

All in all, there are exciting times for research on nature- and bio-inspired optimization, which should depart from a consensus on which research avenues should be pursued collectively by the community. We hope that the double taxonomy proposed in this overview and the critical analysis made thereafter take a sensible step in this direction, and contribute to achieving the scientific soundness and technical rigor that this field deserves.

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Compliance with Ethical Standards

Conflict of Interest AH is Editor-in-Chief, and FH is editorial board member of Cognitive Computation. They had no involvement in any aspect of the decision-making on this paper.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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