

Comprehensive Taxonomies of Nature- and Bio-inspired Optimization: Inspiration *versus* Algorithmic Behavior, Critical Analysis and Recommendations (from 2020 to 2024)

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Abstract

In recent years, bio-inspired optimization has garnered significant attention in the literature. This algorithmic family mimics various biological processes observed in nature to effectively tackle complex optimization problems. The proliferation of nature- and bio-inspired algorithms, accompanied by a plethora of applications, tools, and guidelines, underscores the growing interest in this field. However, the exponential rise in the number of bio-inspired algorithms poses a challenge to the future trajectory of this research domain. Along the five versions of this document, the number of approaches grows incessantly, and where having a new biological description takes precedence over real problem-solving. This document, in its fifth revision since the original published version in [1], presents two comprehensive taxonomies. One is based on principles of biological similarity, and the other one is based on operational aspects associated with the iteration of population models that initially have a biological inspiration. Therefore, these taxonomies enable researchers to categorize existing algorithmic developments into well-defined classes, considering two criteria: the source of inspiration and the behavior exhibited by each algorithm. Using these taxonomies, we classify 518 algorithms based on nature-inspired and bio-inspired principles. Each algorithm within these categories is thoroughly examined, allowing for a critical synthesis of design trends and similarities, and identifying the most analogous classical algorithm for each proposal. 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-fourth of the reviewed bio-inspired solvers are versions of classical algorithms. The conclusions from the analysis of the algorithms lead to several learned lessons.

Moreover, in this new update we have decided to take a brief tour of literature towards three broad directions, providing a more extensive approach to the original document:

- First, we offer a critical perspective on the field following our insights in [2], highlighting the *good* (a present and future plenty of exciting applications), the *bad* (novel metaphors not leading to innovative solvers), and the *ugly* (poor methodological practices) in metaheuristic optimization, with an expansion of these perspectives.
- Second, we revisit evolutionary and bio-inspired algorithms from a threefold approach: i) where we stand and what's next in evolutionary algorithms and population-based nature and bio-inspired optimization, based on a structured proposal of challenges that were discussed in 2020, but still exist today [3]; ii) a prescription of methodological guidelines for comparing bio-inspired optimization algorithms [4]; and iii) a tutorial on the design, experimentation, and application of metaheuristic algorithms to real-world optimization problems [5].
- Third, we perform a brief review of recent studies that propose good practices for designing metaheuristic algorithms, alongside a few highlighted taxonomies, overviews, and general approaches that, far from without attempting to be exhaustive with the literature, showcase the rich activity and attention received by this field in recent years.

This updated study ends with an analysis that exposes the double vision of the wide range of proposals that contributed to the field of metaheuristic optimization after five years of analysis: on one hand, we note a lack of analysis of the real

optimization challenges and useful proposals instead of new metaheuristics only focused on a basic comparison with very classical problems versus algorithms. On the other hand, we offer a positive vision of the crucial role that population-based optimization models can take in the design of modern Artificial Intelligence algorithms.

This document is an update as of April 2024, and contains 518 algorithms as opposed to the originally published version which amounted to 323 revised metaheuristics. This arXiv document corresponds with an extension (already mentioned) of the 2 following papers, with references:

- Molina, D., Poyatos, J., Del Ser, J., García, S., Hussain, A., & Herrera, F. (2020). Comprehensive taxonomies of nature-and bio-inspired optimization: Inspiration versus algorithmic behavior, critical analysis recommendations. *Cognitive Computation*, 12, 897-939. DOI: <https://doi.org/10.1007/s12559-020-09730-8>
- Molina-Cabrera, D., Poyatos, J., Osaba, E., Del Ser, J., Herrera, F. (2022). Nature- and Bio-inspired Optimization: the Good, the Bad, the Ugly and the Hopeful. *DYNA*, 97(2). 114-117. DOI: <https://doi.org/10.6036/10331>

Keywords – Nature-inspired algorithms, bio-inspired optimization, taxonomy, critical analysis.

1 Introduction

Traditional optimization techniques are motivated by the complexity of the problem and the mathematical properties of its fitness function and constraints. However, in many real-world optimization problems, no exact solver can be applied to solve them at an affordable computational cost or within a reasonable time. Moreover, in some cases, there is no analytical form for the problem's objective and constraints. Under such circumstances, 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 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 on 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 simulates 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.

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 problems [6] to large-scale optimization [7], evolutionary deep learning [8] 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, increasing the 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 Figure 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 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 at their time. From this rising number of nature and bio-inspired algorithms, one can easily conclude that it would be convenient to organize them into a taxonomy with well-defined criteria

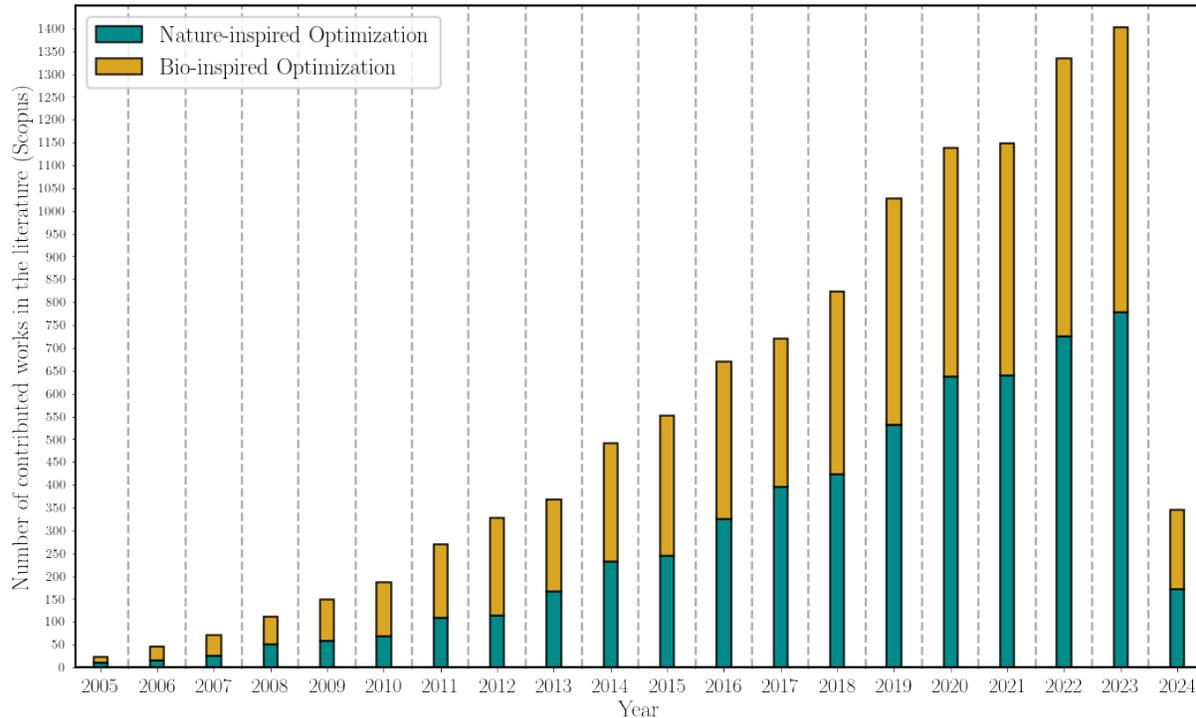


Figure 1: Number of papers with *bio-inspired optimization* and *nature-inspired optimization* in the title, abstract and/or keywords, over the period 2005–April 2024 (Scopus database).

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 concerning 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 underscored in several contributions [9, 10], which have unleashed hot debates around specific meta-heuristic schemes that remain unresolved to date [11, 12]. This problem gets exacerbated when important challenges are overseen and if more and more biological inspirations are used as the primary driver for research, as we can observe in 2024 with more than 500 proposals. 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 fifth version of the original study published in [1], we have classified 518 works proposing different types of meta-heuristic algorithms. Building upon this knowledge, we herein propose two different taxonomies for nature- and bio-inspired optimization algorithms:

- The first taxonomy classifies algorithms based on their 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 easy grouping 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 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 their 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 an 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 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 the same category in one taxonomy and their classification in the other taxonomy. Next, similarities detected among algorithms will allow discovering the most influential meta-heuristic algorithms, whose behavior has inspired many other nature- and bio-inspired proposals.

These previous research tasks provide several insights to conduct a comprehensive two-fold analysis of the field:

- The first analysis focuses on taxonomies. Specifically, we provide several recommendations to improve research practices in this area. 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 evidence in practical problems.
- The second analysis delves into a critical perspective on bio-inspired optimization. It discusses the strengths, weaknesses, and challenges that have been identified in the field in recent years, while it also highlights the potential held for future developments in bio-inspired optimization.

Both taxonomies and the analysis provide a full overview of the situation of the bio-inspired optimization field. However, Figure 1 reflects the interest of research in this field, as the number of papers is in continuous growth of interest. We believe that it is essential to highlight and reflect on what is expected from this field in the coming years, in terms of where it is currently being used and how researchers are proposing methodologies to properly design and apply bio-inspired algorithms not in real-world applications, but also in other emerging areas of Artificial Intelligence (AI). As a consequence, an analysis of the field in terms of *Bio-inspired Optimization*, *Evolutionary Computation*, *Guidelines*, *Comparison Methodology* and *Benchmarking* are found in this report.

As we have mentioned in the abstract, in this final version of the report we have decided to take a brief tour of literature from three broad perspectives with a more extensive approach to the document:

In Section 7, we pay attention from a triple critical position as it was pointed out in [2], highlighting the *good* (a present and future plenty of exciting applications), the *bad* (novel metaphors not leading to innovative solvers, going deeper into the group of works that criticize the lack of novelty of the new proposals [13, 9, 11, 10, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25]), and the *ugly* (poor methodological practices) as it was pointed out in [2], with an expansion of these analyses. As we have mentioned, we must emphasize that in these new algorithms, there exists a lack of justification together with the lack of comparison with the state of the art and of real interest in achieving reasonable levels of quality from the point of view of the optimization of well-known problems in recent competitions. Good methodological practices must be followed in forthcoming studies when designing, describing, and comparing new algorithms.

The analysis of the issues undergone by the field enables us to provide potential solutions and an analysis toward best practices. Hence, in Section 8, we introduce three previous works, outlined as follows:

- Bio-inspired computation: Where we stand and what's next [3].
- A prescription of methodological guidelines for comparing bio-inspired optimization algorithms [4].
- A tutorial on the design, experimentation, and application of metaheuristic algorithms to real-world optimization problems [5].

Lastly, Section 9 presents an analysis of metaheuristics based on studies, guidelines, and other works of a more theoretical nature that help to solve the problems of the field. We perform a brief review of recent studies that address good practices for designing metaheuristics and discussions from this perspective, and a short review of references – without attempting to be exhaustive – that address taxonomies, overviews, and general approaches in bio-inspired optimization. Therefore, this section considers such studies from a double vision:

- Good practices for designing metaheuristics: It gathers several works that are guidelines for good practices related to research orientation to measure novelty [26], to measure similarity in metaheuristics [27], Metaheuristics “In the Large”

(to support the development, analysis, and comparison of new approaches) [28], to design manual or automatic new metaheuristics [29], to guide the learning strategy in design and improvement of metaheuristics [30], to use statistical test in metaheuristics [31], and to detect the novelties in metaphor-based algorithms [32].

- Latest metaheuristics based studies which include, non-exhaustively, a dozen of recent studies about taxonomies [33, 34, 35], overviews [15, 36, 37, 38, 39, 40] and general approaches [41].

This work has been updated almost every year with several improvements, as shown in the trace of changes shown in Table 1. The latest version includes both novel bio-inspired proposals up to April 2024 and several analyses of the field, ranging from the situation of the field to the vision towards the future of this field.

Table 1: Updates of the manuscript via arXiv.

Update	Date	Contribution
Version # 1	Feb. 2020	Initial version of the manuscript with 323 reviewed algorithms.
Version # 2	Feb. 2020	Changes in title and figures for better quality.
Version # 3	Apr. 2021	Update with +31 new algorithms (up to 361), figures and tables changed.
Version # 4	May 2022	Update with +51 new algorithms (up to 412), figures and tables changed.
Version # 5	Apr. 2024	Update with +88 new algorithms (up to 518); figures and tables changed, and three analyses included as Sections 7, 8 and 9.

As we have mentioned in the abstract, this fifth and last version of this series of documents ends with an analysis that addresses the double vision of a wide range of proposals, which after five years of analysis must be indicated that they border on a lack of analysis of the real problems and useful proposals, and on the other hand, a positive vision of the role that population-based optimization models can contribute in the design of AI systems, in a new scenario of continuous emergence of AI.

The rest of this paper is organized as follows. In Section 2, we examine previous surveys, taxonomies, and reviews of nature- and bio-inspired algorithms reported so far in the literature. Section 3 delves into the taxonomy based on the inspiration of the algorithms. In Section 4, we present and populate the taxonomy based on the behavior of the algorithm. In Section 5, we analyze similarities and differences found between both taxonomies, ultimately identifying the most influential algorithms in our reviewed papers. In Section 6, we report several lessons learned and recommendations as the result of the previous analysis. In addition, as novel contributions of this version over its preceding ones, Section 7 provides an extended critical analysis of the state of the art in the field, highlighting the aforementioned *good*, the *bad*, and the *ugly* in the metaheuristic landscape [2]. In Section 8, we discuss future directions in bio-inspired optimization algorithms, and prescribe potential solutions and analysis toward ensuring good practices and correct experimental procedures with these algorithms. Section 9 shows studies and guidelines for good practices, together with recent studies including taxonomies, overviews, and general approaches related to metaheuristics. Finally, in Section 10, we summarize our current main conclusions and reflections on the field, with builds upon a five-year reflection and literature study.

2 Related Literature Studies (before 2020 according to the first version of this report, Feb. 2020)

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 [42, 43], including continuous [44], combinatorial [6], or multi-objective optimization problems [45]. For specific real-world problems, the prolific literature about nature- and bio-inspired algorithms has sparked specific state-of-the-art studies revolving around their application to different fields, such as Telecommunications [46], Robotics [47], Data Mining [48], Structural Engineering [45] or Transportation [49]. Even specific real-world problems have been dedicated exclusive overviews due to the vast research reported around the topic, like power systems [50], the design of computer networks [51], automatic clustering [52], face recognition [53], molecular docking [54], or intrusion detection [55], to mention a few.

Seen from the algorithmic perspective, many particular bio-inspired solvers have been modified over the years to yield different versions analyzed in surveys devoted to that type of algorithms, from classical approaches such as PSO [56] and DE [57, 58, 59] to more modern ones, e.g., ABC [60, 61], Bacterial Foraging Optimization Algorithm (BFOA, [62]) or the Bat Algorithm [63]. From a more general albeit still algorithmic point of view, [9] explains how the metaphor and the biological idea are 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 [64] or [65] 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 aims at deciding which approach to use for solving a problem. In [66], the popular PSO and DE versions are compared. This research line is followed by [67], which compared the performance of different bio-inspired algorithms, again with prescribing which one to use as its primary goal. More recently, [68] 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 [69], 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 [70], 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 [71], foraging algorithms (such as the aforementioned BFOA) are compared against other evolutionary algorithms. In that paper, algorithms are classified into two large groups: algorithms *with* and *without* cooperation. In [72, 73], 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 that the community has embraced the need for arranging the myriad of existing bio-inspired algorithms and classifying them under principled, coherent criteria. In 2013, [74] 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 [75, 76], 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 by human behavior. The classification criteria underneath these categories are used to build up a catalog of more than 50 algorithmic proposals, obtaining similar groups in size. In this case, there is no *miscellaneous* category as in the previous classification. Similarly to [74], categories are disjoint groups without subcategories.

Recently, [77] 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 [78], 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, 29 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. This aspect is considered in [78], 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 between classical and modern meta-heuristics. There lies the novelty and core contribution of our study, along with the aforementioned

novel behavior-based taxonomy.

3 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 518 papers over different years, starting from the most classical proposals in the late 80's (such as Simulated Annealing [79] or PSO [80]) to more novel techniques appearing in the literature until 2024 [81]. Thus, to our knowledge, this exercise can be considered the most exhaustive review in the area to date.

Taking into 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 lying at the same level are disjoint sets, which means 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 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. To keep 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 into 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 518 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 (more than a half of the proposed, 53%), inspired in the Swarm Intelligence concept [64], followed by the *Physics and Chemistry* category, inspired by different physical behaviors or chemical reactions (almost 15% of proposals). Other relevant categories are *Social Human Behavior Algorithms* (11%), inspired by human aspects, and *Breeding-based Evolution* (near 7%), 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 the 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 Figure 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.

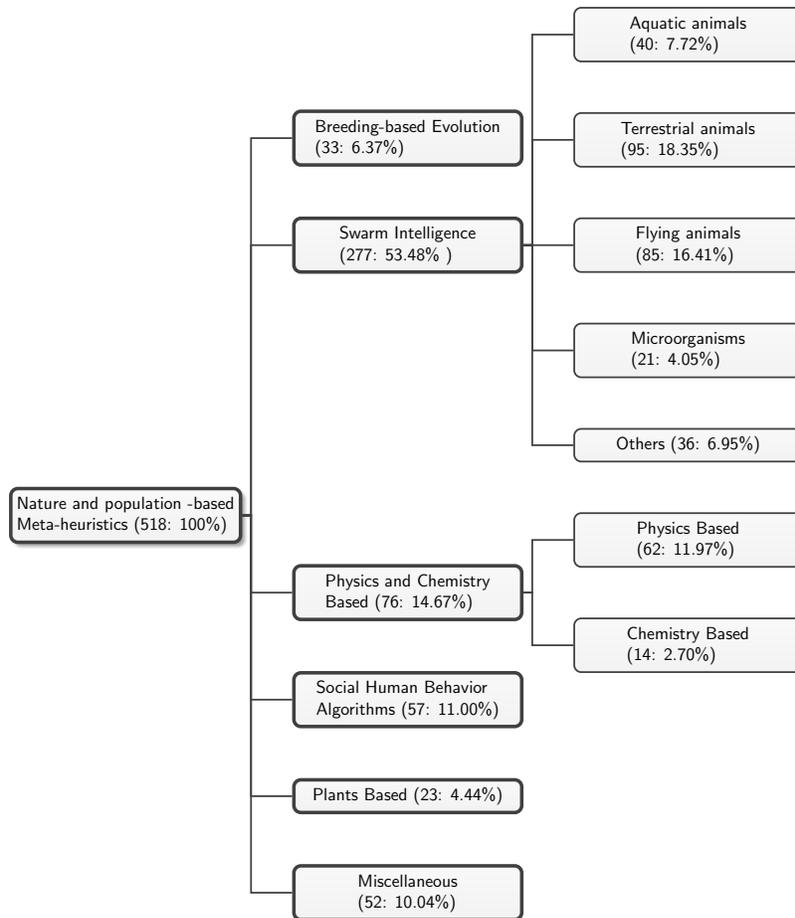


Figure 2: Classification of the reviewed papers using the *inspiration source* based taxonomy.

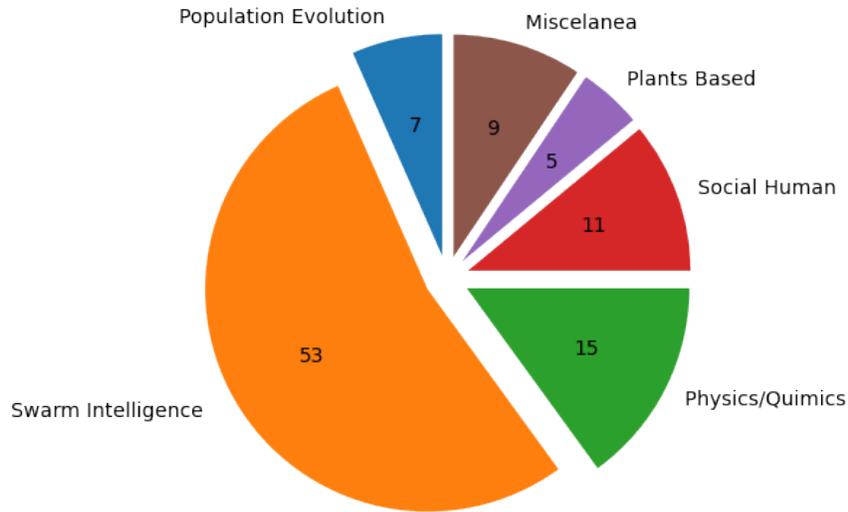


Figure 3: Ratio of reviewed algorithms by its category (first taxonomy).

3.1 Breeding-based Evolutionary Algorithms

This category comprises population-based algorithms inspired by 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 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 introduces some variety with respect to their parents. These characteristics allow them to adapt to the environment which, translated to the optimization realm, permits them 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 2 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 on the reproduction of different biological organisms are also notable, such as queen bees and weeds.

3.2 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 [47]. 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,

Table 2: Nature- and bio-inspired meta-heuristics within the *Breeding-based Evolution* category.

Breeding-based Evolution			
Algorithm Name	Acronym	Year	Reference
Artificial Ecosystem Algorithm	AEA	2014	[82]
Artificial Ecosystem Optimizer	AEO	2020	[83]
Artificial Infections Disease Optimization	AIDO	2016	[84]
Asexual Reproduction Optimization	ARO	2010	[85]
Biogeography Based Optimization	BBO	2008	[86]
Bird Mating Optimization	BMO	2014	[87]
Bean Optimization Algorithm	BOA	2011	[88]
Coronavirus Mask Protection Algorithm	CMPA	2023	[89]
Coronavirus Disease Optimization Algorithm	COVIDOA	2022	[90]
Coral Reefs Optimization	CRO	2014	[91]
Dendritic Cells Algorithm	DCA	2005	[92]
Differential Evolution	DE	1997	[93]
Ecogeography-Based Optimization	EBO	2014	[94]
Eco-Inspired Evolutionary Algorithm	EEA	2011	[95]
Earthworm Optimization Algorithm	EOA	2018	[96]
Evolution Strategies	ES	2002	[97]
Genetic Algorithms	GA	1989	[98]
Gene Expression	GE	2001	[99]
Hybrid Rice Optimization	HRO	2016	[100]
Immune-Inspired Computational Intelligence	ICI	2008	[101]
Improved Genetic Immune Algorithm	IGIA	2017	[102]
Weed Colonization Optimization	IWO	2006	[103]
Marriage In Honey Bees Optimization	MHBO	2001	[104]
Mushroom Reproduction Optimization	MRO	2018	[105]
Queen-Bee Evolution	QBE	2003	[106]
SuperBug Algorithm	SuA	2012	[107]
Stem Cells Algorithm	SCA	2011	[108]
Sheep Flock Heredity Model	SFHM	2001	[109]
Swine Influenza Models Based Optimization	SIMBO	2013	[110]
Self-Organizing Migrating Algorithm	SOMA	2004	[111]
T-Cell Immune Algorithm	TCIA	2023	[112]
Variable Mesh Optimization	VMO	2012	[113]
Virulence Optimization Algorithm	VOA	2016	[114]

bio-inspired meta-heuristics based on Swarm Intelligence are those inspired by 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 [80], followed shortly thereafter by ACO [115]. These early findings around SI concepts applied to optimization spurred many SI-based algorithms in subsequent years, such as ABC [116] and more recently, Firefly Algorithm (FA, [117]) and Grasshopper Optimization Algorithm (GOA, [118]).

Reviewed algorithms that fall under the Swarm Intelligence umbrella are shown in Tables 3, 4, 5, 6, 7 and 8. This is the most populated category of all our study, characterized by a first category that relates to the type of animal that has 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 [119] – or, instead, by its movement patterns in general. When the behavior of the algorithm is inspired by 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.

3.2.1 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 type of animals. Between the possible categories stemming from this criteria, we have grouped them according to the environmental medium inhabited by the inspiring animal (aquatic, terrestrial or aerial). This criterion is not only very intuitive since it inherits a criterion already applied in animal taxonomies, but it 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 flying insects. The most well-known algorithms in this subcategory are PSO [80] and ABC [116].
- **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 [115], which replicates the stigmergic mechanism used by ants to locate food sources and inform of the existence of their counterparts in the colony. This category also includes other popular algorithms like Grey Wolf Optimization (GWO, [240]), inspired in the wild wolf hunting strategy, Lion Optimization Algorithm (LOA, [267]), which imitates hunting methods used by these animals, or the more recent Grasshopper Optimization Algorithm (GOA, [118]), which finds its motivation in the jumping motion of grasshoppers.
- **Aquatic animals:** This type of meta-heuristic algorithm focuses on aquatic animals. The aquatic ecosystem in which they live has inspired different exploration mechanisms. It contains popular algorithms such as Krill Herd (KH, [259]), Whale Optimization Algorithm (WOA, [380]), and algorithms based on the echolocation used by dolphins to detect fish like Dolphin Partner Optimization (DPO, [201]) and Dolphin Echolocation [195].
- **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, [148]).

3.2.2 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 3-6, classifying each algorithm as belonging to one of the following behavioral patterns:

Table 3: 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	[120]
Artificial Beehive Algorithm	ABA	Flying	Foraging	2009	[121]
Artificial Bee Colony	ABC	Flying	Foraging	2007	[116]
Animal Behavior Hunting	ABH	Other	Foraging	2014	[122]
African Buffalo Optimization	ABO	Terrestrial	Foraging	2016	[123]
Andean Condor Algorithm	ACA	Flying	Foraging	2019	[124]
Ant Colony Optimization	ACO	Terrestrial	Foraging	1996	[115]
Artificial Feeding Birds	AFB	Flying	Movement	2018	[125]
Artificial Hummingbird Algorithm	AHA	Flying	Foraging	2022	[126]
Archerfish Hunting Optimizer	AHO	Aquatic	Foraging	2022	[127]
Animal Migration Optimization	AMO	Other	Movement	2014	[128]
Aphid Metaheuristic Optimization	AMO.1	Micro	Movement	2022	[129]
Ant Lion Optimizer	ALO	Terrestrial	Foraging	2015	[130]
Aquila Optimizer	AO	Flying	Foraging	2021	[131]
Anglerfish Algorithm	AOA	Aquatic	Movement	2019	[132]
Arithmetic Optimization Algorithm	AOA.2	Other	Movement	2021	[133]
Artificial Rabbits Optimization	ARO.1	Terrestrial	Foraging	2022	[134]
Artificial Searching Swarm Algorithm	ASSA	Other	Movement	2009	[135]
Artificial Tribe Algorithm	ATA	Other	Movement	2009	[136]
African Wild Dog Algorithm	AWDA	Terrestrial	Foraging	2013	[137]
American Zebra Optimization Algorithm	AZOA	Terrestrial	Movement	2023	[138]
Bald Eagle Search	BES	Flying	Foraging	2019	[139]
Bees Algorithm	BA	Flying	Foraging	2006	[140]
Bumblebees	BB	Flying	Foraging	2009	[141]
Bison Behavior Algorithm	BBA	Terrestrial	Movement	2019	[142]
Bee Colony-Inspired Algorithm	BCIA	Flying	Foraging	2009	[143]
Bee Colony Optimization	BCO	Flying	Foraging	2005	[144]
Bacterial Colony Optimization	BCO.1	Micro	Foraging	2012	[145]
Bacterial Chemotaxis Optimization	BCO.2	Micro	Foraging	2002	[146]
Border Collie Optimization	BCO.3	Terrestrial	Movement	2020	[147]
Biomimicry Of Social Foraging Bacteria for Distributed Optimization	BFOA	Micro	Foraging	2002	[148]
Bacterial Foraging Optimization	BFOA.1	Micro	Foraging	2009	[62]
Bacterial-GA Foraging	BGAF	Micro	Foraging	2007	[149]
BeeHive Algorithm	BHA	Flying	Foraging	2004	[150]
Bees Life Algorithm	BLA	Flying	Foraging	2018	[151]
Bat Intelligence	BI	Flying	Foraging	2012	[152]
Bat Inspired Algorithm	BIA	Flying	Foraging	2010	[153]
Biology Migration Algorithm	BMA	Other	Movement	2019	[154]
Barnacles Mating Optimizer	BMO.1	Micro	Movement	2019	[155]
Blind, Naked Mole-Rats Algorithm	BNMR	Terrestrial	Foraging	2013	[156]
Butterfly Optimizer	BO	Flying	Movement	2015	[157]
Bonobo Optimizer	BO.1	Terrestrial	Movement	2019	[158]
Bull Optimization Algorithm	BOA.1	Terrestrial	Movement	2015	[159]
Bee System	BS	Flying	Foraging	1997	[160]
Bee System	BS.1	Flying	Foraging	2002	[161]
Bird Swarm Algorithm	BSA	Flying	Movement	2016	[162]
Bee Swarm Optimization	BSO	Flying	Foraging	2010	[163]

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

Swarm Intelligence (II)							
Algorithm Name	Acronym	Subcategory	Type	Year	Reference		
Bioluminescent Swarm Optimization Algorithm	BSO.1	Flying	Foraging	2011	[164]		
Biological Survival Optimizer	BSO.4	Other	Movement	2023	[165]		
Bees Swarm Optimization Algorithm	BSOA	Flying	Foraging	2005	[166]		
Buzzard Optimization Algorithm	BUZOA	Flying	Foraging	2019	[167]		
Black Widow Optimization Algorithm	BWO	Terrestrial	Movement	2020	[168]		
Beluga Whale Optimization	BWO.1	Aquatic	Foraging	2022	[169]		
Binary Whale Optimization Algorithm	BWOA	Aquatic	Foraging	2019	[170]		
Collective Animal Behavior	CAB	Other	Foraging	2012	[171]		
Cheetah Based Algorithm	CBA	Terrestrial	Movement	2018	[172]		
Catfish Optimization Algorithm	CAO	Aquatic	Movement	2011	[173]		
Cricket Behavior-Based Algorithm	CBBE	Terrestrial	Movement	2016	[174]		
Cultural Coyote Optimization Algorithm	CCOA	Terrestrial	Movement	2019	[175]		
Chaotic Crow Search Algorithm	CCSA	Flying	Foraging	2018	[176]		
Chaotic Dragonfly Algorithm	CDA	Flying	Foraging	2018	[177]		
Cuttlefish Algorithm	CFA	Aquatic	Movement	2013	[178]		
Consultant Guide Search	CGS	Other	Movement	2010	[179]		
Camel Herd Algorithm	CHA	Terrestrial	Foraging	2017	[180]		
Chimp Optimization Algorithm	ChOA	Terrestrial	Foraging	2020	[181]		
Cuckoo Optimization Algorithm	COA	Flying	Foraging	2011	[182]		
Camel Travelling Behavior	COA.1	Terrestrial	Movement	2016	[183]		
Coyote Optimization Algorithm	COA.2	Terrestrial	Movement	2018	[184]		
COOT Optimization Algorithm	COA.5	Flying	Movement	2021	[185]		
Coati Optimization Algorithm	COA.6	Terrestrial	Foraging	2023	[186]		
Crested Porcupine Optimizer	CPO	Terrestrial	Movement	2024	[187]		
Cuckoo Search	CS	Flying	Foraging	2009	[188]		
Crow Search Algorithm	CSA	Flying	Movement	2016	[189]		
Chameleon Swarm Algorithm	CSA.2	Terrestrial	Foraging	2021	[81]		
Circle Search Algorithm	CSA.3	Other	Movement	2022	[190]		
Cat Swarm Optimization	CSO	Terrestrial	Movement	2006	[191]		
Chicken Swarm Optimization	CSO.1	Terrestrial	Movement	2014	[192]		
Dragonfly Algorithm	DA	Flying	Foraging	2016	[193]		
Dragonfly Swarm Algorithm	DA.1	Flying	Foraging	2020	[194]		
Dolphin Echolocation	DE.1	Aquatic	Foraging	2013	[195]		
Dynamic Hunting Leadership	DHL	Other	Foraging	2023	[196]		
Deer Hunting Optimization Algorithm	DHOA	Terrestrial	Foraging	2019	[197]		
Dwarf Mongoose Optimization	DMO	Terrestrial	Foraging	2022	[198]		
Dandelion Optimizer	DO	Other	Movement	2022	[199]		
Dingo Optimizer	DOX	Terrestrial	Foraging	2021	[200]		
Dolphin Partner Optimization	DPO	Aquatic	Movement	2009	[201]		
Donkey Theorem Optimization	DTO	Terrestrial	Foraging	2019	[202]		
Enriched Coati Osprey Algorithm	ECOA	Other	Foraging	2024	[203]		
Electric Eel Foraging Optimization	EEFO	Aquatic	Foraging	2024	[204]		
Electric Fish Optimization	EFO.1	Aquatic	Foraging	2020	[205]		
Elephant Herding Optimization	EHO	Terrestrial	Movement	2016	[206]		
Elk Herd Optimizer	EHO.1	Terrestrial	Movement	2024	[207]		
Ebola Optimization Search Algorithm	EOSA	Micro	Movement	2022	[208]		
Emperor Penguins Colony	EPC	Terrestrial	Movement	2019	[209]		

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

Swarm Intelligence (III)					
Algorithm Name	Acronym	Subcategory	Type	Year	Reference
Emperor Penguin Optimizer	EPO	Terrestrial	Movement	2018	[210]
Eagle Strategy	ES.1	Flying	Foraging	2010	[211]
Elephant Search Algorithm	ESA	Terrestrial	Foraging	2015	[212]
Elephant Swarm Water Search Algorithm	ESWSA	Terrestrial	Movement	2018	[213]
Egyptian Vulture Optimization Algorithm	EV	Flying	Foraging	2013	[214]
Firefly Algorithm	FA	Flying	Foraging	2009	[117]
Flocking Base Algorithms	FBA	Flying	Movement	2006	[215]
Fast Bacterial Swarming Algorithm	FBSA	Micro	Foraging	2008	[216]
Frog Call Inspired Algorithm	FCA	Terrestrial	Movement	2009	[217]
Fire Hawk Optimizer	FHO	Flying	Foraging	2023	[218]
Flock by Leader	FL	Flying	Movement	2012	[219]
Frilled Lizard Optimization	FLO	Terrestrial	Foraging	2024	[220]
Fruit Fly Optimization Algorithm	FOA	Flying	Foraging	2012	[221]
Falcon Optimization Algorithm	FOA.2	Flying	Foraging	2019	[222]
FOX-inspired Optimization Algorithm	FOX	Terrestrial	Foraging	2023	[223]
Fish-Swarm Algorithm	FSA	Aquatic	Foraging	2002	[224]
Fish Swarm Algorithm	FSA.1	Aquatic	Foraging	2011	[225]
Fish School Search	FSS	Aquatic	Foraging	2008	[226]
Green Anaconda Optimization	GAO	Terrestrial	Foraging	2023	[227]
Giant Armadillo Optimization	GAO.1	Terrestrial	Foraging	2023	[228]
Group Escape Behavior	GEB	Aquatic	Movement	2011	[229]
Golden Eagle Optimizer	GEO	Flying	Foraging	2021	[230]
Golden Jackal Optimization Algorithm	GJO	Terrestrial	Foraging	2023	[231]
Genghis Khan Shark Optimizer	GKSO	Aquatic	Foraging	2023	[232]
Good Lattice Swarm Optimization	GLSO	Other	Movement	2007	[233]
Grasshopper Optimisation Algorithm	GOA	Terrestrial	Foraging	2017	[118]
Gazelle Optimization Algorithm	GOA.1	Terrestrial	Movement	2023	[234]
Goat Search Algorithms	GSA.2	Terrestrial	Movement	2022	[235]
Glowworm Swarm Optimization	GSO	Micro	Movement	2013	[236]
Group Search Optimizer	GSO.1	Other	Movement	2009	[237]
Goose Team Optimization	GTO	Flying	Movement	2008	[238]
Gorilla Troops Optimizer	GTO.1	Terrestrial	Movement	2021	[239]
Grey Wolf Optimizer	GWO	Terrestrial	Foraging	2014	[240]
Hitchcock Birds-Inspired Algorithm	HBIA	Flying	Movement	2020	[241]
Honey-Bees Mating Optimization Algorithm	HBMO	Flying	Movement	2006	[242]
Hunger Games Search	HGS	Other	Foraging	2021	[243]
Harry's Hawk Optimization Algorithm	HHO	Flying	Foraging	2019	[244]
Hoopoe Heuristic Optimization	HHO.1	Flying	Foraging	2012	[245]
Horned Lizard Optimization Algorithm	HLOA	Terrestrial	Movement	2024	[246]
Horse Optimization Algorithm	HOA	Terrestrial	Movement	2020	[247]
Hunting Search	HuS	Other	Foraging	2010	[248]
Honeybee Social Foraging	HSF	Flying	Foraging	2007	[249]
Hierarchical Swarm Model	HSM	Other	Movement	2010	[250]
Hammerhead Shark Optimization Algorithm	HSOA	Aquatic	Foraging	2019	[251]
Humboldt Squid Optimization Algorithm	HSOA.1	Aquatic	Foraging	2023	[252]
Hypercube Natural Aggregation Algorithm	HYNAA	Other	Movement	2019	[253]
Improved Raven Roosting Algorithm	IRRO	Flying	Movement	2018	[254]
Invasive Tumor Optimization Algorithm	ITGO	Micro	Movement	2015	[255]

Table 6: Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (IV).

Swarm Intelligence (IV)					
Algorithm Name	Acronym	Subcategory	Type	Year	Reference
Jaguar Algorithm	JA	Terrestrial	Foraging	2015	[256]
Jellyfish Search	JS	Aquatic	Movement	2021	[257]
Japanese Tree Frogs Calling Algorithm	JTFCA	Terrestrial	Movement	2012	[258]
Krill Herd	KH	Aquatic	Foraging	2012	[259]
Kookaburra Optimization Algorithm	KOA	Flying	Foraging	2023	[260]
Krestrel Search Algorithm	KSA	Flying	Foraging	2016	[261]
Killer Whale Algorithm	KWA	Aquatic	Foraging	2017	[262]
Lion Algorithm	LA	Terrestrial	Foraging	2012	[263]
Seven-Spot Labybird Optimization	LBO	Flying	Foraging	2013	[264]
Lyrebird Optimization Algorithm	LBO.1	Flying	Movement	2023	[265]
Laying Chicken Algorithm	LCA	Terrestrial	Movement	2017	[266]
Lion Optimization Algorithm	LOA	Terrestrial	Foraging	2016	[267]
Lion Pride Optimizer	LPO	Terrestrial	Movement	2012	[268]
Locust Swarms Optimization	LSO	Aquatic	Foraging	2009	[269]
Leopard Seal Optimization	LSO.1	Terrestrial	Foraging	2023	[270]
Locust Swarms Search	LSS	Aquatic	Movement	2015	[271]
Mayfly Optimization Algorithm	MA.1	Flying	Movement	2020	[272]
Magnetotactic Bacteria Optimization Algorithm	MBO	Micro	Movement	2013	[273]
Monarch Butterfly Optimization	MBO.1	Flying	Movement	2017	[274]
Migrating Birds Optimization	MBO.2	Flying	Movement	2012	[275]
Mouth Breeding Fish Algorithm	MBF	Aquatic	Foraging	2018	[276]
Migration-Crossover Algorithm	MCA	Other	Movement	2024	[277]
Modified Cuckoo Search	MCS	Flying	Foraging	2009	[278]
Modified Cockroach Swarm Optimization	MCSO	Terrestrial	Foraging	2011	[279]
Moth Flame Optimization Algorithm	MFO	Flying	Movement	2015	[280]
Mosquito Flying Optimization	MFO.1	Flying	Foraging	2016	[281]
Meerkats Inspired Algorithm	MIA	Terrestrial	Movement	2018	[282]
Mycorrhiza Optimization Algorithm	MOA	Micro	Movement	2023	[283]
Mox Optimization Algorithm	MOX	Flying	Movement	2011	[284]
Marine Predators Algorithm	MPA	Aquatic	Foraging	2020	[285]
Monkey Search	MS	Terrestrial	Foraging	2007	[286]
Moth Search Algorithm	MS.2	Flying	Movement	2018	[287]
Mantis Search Algorithm	MSA	Terrestrial	Foraging	2023	[288]
Natural Aggregation Algorithm	NAA	Other	Movement	2016	[289]
Naked Moled Rat	NMR	Terrestrial	Movement	2019	[290]
Nutcracker Optimization Algorithm	NOA	Flying	Movement	2023	[291]
Nomadic People Optimizer	NPO	Other	Movement	2019	[292]
Orcas Intelligence Algorithm	OA	Aquatic	Foraging	2020	[293]
OptBees	OB	Flying	Foraging	2012	[294]
Optimal Foraging Algorithm	OFA	Other	Foraging	2017	[295]
Owls Optimization Algorithm	OOA	Flying	Movement	2019	[296]
Osprey Optimization Algorithm	OOA.1	Flying	Foraging	2023	[297]
Orca Predation Algorithm	OPA	Aquatic	Foraging	2022	[298]
Pity Beetle Algorithm	PBA	Terrestrial	Foraging	2018	[299]
Polar Bear Optimization Algorithm	PBOA	Terrestrial	Foraging	2017	[300]
Physarum-inspired Competition Algorithm	PCA.1	Micro	Movement	2023	[301]
Prairie Dog Optimization Algorithm	PDO	Terrestrial	Foraging	2022	[302]

Table 7: Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (V).

Swarm Intelligence (V)					
Algorithm Name	Acronym	Subcategory	Type	Year	Reference
Pigeon Inspired Optimization	PIO	Flying	Movement	2014	[303]
Population Migration Algorithm	PMA	Other	Movement	2009	[304]
Puma Optimizer	PO.1	Terrestrial	Movement	2024	[305]
Pelican Optimization Algorithm	POA.1	Flying	Foraging	2022	[306]
Pufferfish Optimization Algorithm	POA.2	Aquatic	Movement	2024	[307]
Prey Predator Algorithm	PPA	Other	Foraging	2015	[308]
Particle Swarm Optimization	PSO	Flying	Movement	1995	[80]
Penguins Search Optimization Algorithm	PSOA	Aquatic	Foraging	2013	[309]
Regular Butterfly Optimization Algorithm	RBOA	Flying	Foraging	2019	[310]
Red Deer Algorithm	RDA	Terrestrial	Movement	2016	[311]
Red Fox Optimization Algorithm	RFO	Terrestrial	Foraging	2021	[312]
Rhino Herd Behavior	RHB	Terrestrial	Movement	2018	[313]
Rock Hyraxes Swarm Optimization	RHSO	Terrestrial	Foraging	2021	[314]
Roach Infestation Problem	RIO	Terrestrial	Foraging	2008	[315]
Raccoon Optimization Algorithm	ROA	Terrestrial	Foraging	2018	[316]
Reincarnation Concept Optimization Algorithm	ROA.1	Other	Movement	2010	[317]
Red Piranha Optimization	RPO	Aquatic	Foraging	2023	[318]
Red Panda Optimization Algorithm	RPO.1	Terrestrial	Foraging	2023	[319]
Raven Roosting Optimization Algorithm	RROA	Flying	Foraging	2015	[320]
Red-tailed Hawk Algorithm	RTH	Flying	Foraging	2023	[321]
Reptile Search Algorithm	RSA	Terrestrial	Foraging	2022	[322]
Rat Swarm Optimizer	RSO	Terrestrial	Foraging	2021	[323]
Ringed Seal Search	RSS	Aquatic	Movement	2015	[324]
Shark Search Algorithm	SA	Aquatic	Foraging	1998	[325]
Swarm Bipolar Algorithm	SBA	Other	Movement	2024	[326]
Simulated Bee Colony	SBC	Flying	Foraging	2009	[327]
Satin Bowerbird Optimizer	SBO	Flying	Movement	2017	[328]
Sine Cosine Algorithm	SCA.2	Other	Movement	2016	[329]
Sand Cat Swarm Optimization	SCSO	Terrestrial	Movement	2023	[330]
Snap-Drift Cuckoo Search	SDCS	Flying	Foraging	2016	[331]
Shuffled Frog-Leaping Algorithm	SFLA	Terrestrial	Movement	2006	[332]
Spotted Hyena Optimizer	SHO	Terrestrial	Foraging	2017	[333]
Selfish Herds Optimizer	SHO.1	Terrestrial	Movement	2017	[334]
Sea-horse Optimizer	SHO.2	Aquatic	Movement	2023	[335]
Swarm Inspired Projection Algorithm	SIP	Flying	Foraging	2009	[336]
Slime Mould Algorithm	SMA	Micro	Foraging	2008	[337]
Sperm Motility Algorithm	SMA.1	Other	Movement	2017	[338]
Spider Monkey Optimization	SMO	Terrestrial	Foraging	2014	[339]
Starling Murmuration Optimizer	SMO.1	Flying	Movement	2022	[340]
Seeker Optimization Algorithm	SOA	Other	Movement	2007	[341]
Seagull Optimization Algorithm	SOA.1	Flying	Foraging	2019	[342]
Sandpiper Optimization Algorithm	SOA.2	Flying	Foraging	2020	[343]
Sailfish Optimizer Algorithm	SOA.3	Aquatic	Foraging	2019	[344]
Serval Optimization Algorithm	SOA.4	Terrestrial	Foraging	2022	[345]
Symbiosis Organisms Search	SOS	Other	Movement	2014	[346]
Sooty Tern Optimization Algorithm	STOA	Flying	Movement	2019	[347]
Social Spider Algorithm	SSA	Terrestrial	Foraging	2015	[348]

Table 8: Nature- and bio-inspired meta-heuristics within the *Swarm Intelligence* category (VI).

Swarm Intelligence (VI)					
Algorithm Name	Acronym	Subcategory	Type	Year	Reference
Squirrel Search Algorithm	SSA.1	Flying	Movement	2019	[349]
Salp Swarm Algorithm	SSA.2	Aquatic	Foraging	2017	[350]
Sparrow Search Algorithm	SSA.3	Flying	Foraging	2020	[351]
Sling-shot Spider Optimization	S ² SO	Terrestrial	Foraging	2023	[352]
Shark Smell Optimization	SSO	Aquatic	Foraging	2016	[353]
Swallow Swarm Optimization	SSO.1	Flying	Foraging	2013	[354]
Social Spider Optimization	SSO.2	Terrestrial	Foraging	2013	[355]
Sperm Swarm Optimization Algorithm	SSOA	Other	Movement	2018	[356]
See-See Partidge Chicks Optimization	SSPCO	Flying	Movement	2015	[357]
Surface-Simplex Swarm Evolution Algorithm	SSSE	Other	Movement	2017	[358]
Siberian Tiger Optimization	STO	Terrestrial	Foraging	2022	[359]
Sperm Whale Algorithm	SWA	Aquatic	Movement	2016	[360]
Spider Wasp Optimizer	SWO.1	Terrestrial	Foraging	2023	[361]
Termite Hill Algorithm	TA	Terrestrial	Foraging	2012	[362]
Termite Alate Optimization Algorithm	TAOA	Terrestrial	Movement	2023	[363]
Termite Colony Optimization	TCO	Terrestrial	Foraging	2010	[364]
Tasmanian Devil Optimization	TDO	Terrestrial	Foraging	2022	[365]
Tomtit Flock Optimization Algorithm	TFOA	Flying	Foraging	2022	[366]
The Great Salmon Run Algorithm	TGSR	Aquatic	Movement	2013	[367]
Termite Life Cycle Optimizer	TLCO	Terrestrial	Movement	2023	[368]
Tyrannosaurus Optimization Algorithm	TROA	Terrestrial	Foraging	2023	[369]
Tunicate Swarm Algorithm	TSA.1	Micro	Foraging	2020	[370]
Tangent Search Algorithm	TSA.2	Other	Movement	2022	[371]
Virtual Ants Algorithm	VAA	Flying	Foraging	2006	[372]
Virtual Bees Algorithm	VBA	Flying	Foraging	2005	[373]
Virus Colony Search	VCS	Micro	Movement	2016	[374]
Virus Optimization Algorithm	VOA.1	Micro	Movement	2009	[375]
Viral Systems Optimization	VSO	Micro	Movement	2008	[376]
Wasp Colonies Algorithm	WCA	Flying	Foraging	1991	[377]
Wolf Colony Algorithm	WCA.1	Terrestrial	Foraging	2011	[378]
Worm Optimization	WO	Micro	Foraging	2014	[379]
Whale Optimization Algorithm	WOA	Aquatic	Foraging	2016	[380]
Walrus Optimization Algorithm	WaOA	Terrestrial	Movement	2023	[381]
Wolf Pack Search	WPS	Terrestrial	Foraging	2007	[382]
Weightless Swarm Algorithm	WSA	Other	Movement	2012	[383]
Wolf Search Algorithm	WSA.1	Terrestrial	Foraging	2012	[384]
Wasp Swarm Optimization	WSO	Flying	Foraging	2005	[385]
White Shark Optimizer	WSO.1	Aquatic	Foraging	2022	[386]
Yellow Saddle Goldfish	YSGA	Aquatic	Foraging	2018	[387]
Zebra Optimization Algorithm	ZOA	Terrestrial	Foraging	2022	[388]
Zombie Survival Optimization	ZSO	Other	Foraging	2012	[389]

- **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 [80], jumping actions as in Shuffled Frog-Leaping Algorithm, SFLA [332], or by aquatic movements as in DPO [201]), or by the movement of the population (correspondingly, swarming movements as in Bird Swarm Algorithm, BSA [162], the migration of populations like Population Migration Algorithm, PMA [304], or the migration of particular animals like salmon [367], 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 [240] and LA [263]), inspired in breeding nutrition (as Cuckoo Search [188, 390]), 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 [115]), or other exploration strategies such as the echolocation in dolphins [195], or the flashing attraction between partners observed in fireflies [117]. 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.

3.3 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 to 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 9 and 10 (physics-based algorithms) and Table 11 (chemistry-based methods). In this category we can find some well-known algorithms reported in the last century such as Simulated Annealing [79], or one of the most important algorithms in physics-based meta-heuristic optimization, Gravitational Search Algorithm, GSA [391]. Interestingly, a variety of space-based algorithms are rooted in GSA, such as Black Hole optimization (BH, [392]) or Galaxy Based Search Algorithm (GBSA, [393]). Other algorithms such as Harmony Search (HS, [394]) 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.

3.4 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, [466]), or political concepts such as the Imperialist Colony Algorithm (ICA, [467]). This category also includes algorithms that emulate sports competitions such as the Soccer League Competition Algorithm (SLC, [468]). Brainstorming processes have also laid the inspirational foundations of several algorithms such as Brain Storm Optimization algorithm (BSO.2, [469]) and Global-Best Brain Storm Optimization algorithm (GBSO, [470]). The complete list of algorithms in this category is given in Table 12 and in Table 13.

3.5 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, [523]), inspired by the process of plant reproduction. Table 14 details the specific algorithms classified in this category.

3.6 Algorithms with Miscellaneous Sources of Inspiration

In this category there are included 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, [546]). Although this defined category

Table 9: 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	[395]
Archimedes Optimization Algorithm	AOA.1	2021	[396]
Artificial Physics Optimization	APO	2009	[397]
Atom Search Optimization	ASO.1	2019	[398]
Big Bang Big Crunch	BBBC	2006	[399]
Black Hole Optimization	BH	2013	[392]
Colliding Bodies Optimization	CBO	2014	[400]
Crystal Energy Optimization Algorithm	CEO	2016	[401]
Central Force Optimization	CFO	2008	[402]
Charged Systems Search	CSS	2010	[403]
Electromagnetic Field Optimization	EFO	2016	[404]
Electromagnetism Mechanism Optimization	EMO	2003	[405]
Electimize Optimization Algorithm	EOA.1	2011	[406]
Electron Radar Search Algorithm	ERSA	2020	[407]
Galaxy Based Search Algorithm	GBSA	2011	[393]
Gravitational Clustering Algorithm	GCA	1999	[408]
Gravitational Emulation Local Search	GELS	2009	[409]
Gravitational Field Algorithm	GFA	2010	[410]
Geysers Inspired Algorithm	GIA	2023	[411]
Gravitational Interactions Algorithm	GIO	2011	[412]
General Relativity Search Algorithm	GRSA	2015	[413]
Gravitational Search Algorithm	GSA	2009	[391]
Galactic Swarm Optimization	GSO.2	2016	[414]
Hydrological Cycle Algorithm	HCA	2017	[415]
Harmony Elements Algorithm	HEA	2009	[416]
Hysteresis for Optimization	HO	2002	[417]
Hurricane Based Optimization Algorithm	HO.2	2014	[418]
Harmony Search	HS	2005	[394]
Intelligent Gravitational Search Algorithm	IGSA	2012	[419]
Intelligence Water Drops Algorithm	IWD	2009	[420]
Light Ray Optimization	LRO	2010	[421]
Lightning Search Algorithm	LSA	2015	[422]
Magnetic Optimization Algorithm	MFO.2	2008	[423]
Method of Musical Composition	MMC	2014	[424]
Melody Search	MS.1	2011	[425]
Multi-Verse Optimizer	MVO	2016	[426]
Newton-Raphson-Based Optimizer	NRBO	2024	[427]
Optics Inspired Optimization	OIO	2015	[428]
Particle Collision Algorithm	PCA	2007	[429]
PopMusic Algorithm	PopMusic	2002	[430]
Quantum Superposition Algorithm	QSA	2015	[431]
Rain-Fall Optimization Algorithm	RFOA	2017	[432]
Rain Water Algorithm	RWA	2017	[433]
River Formation Dynamics	RFD	2007	[434]
Radial Movement Optimization	RMO	2014	[435]
Ray Optimization	RO	2012	[436]

Table 10: Nature- and bio-inspired meta-heuristics within the *Physics based* category (II).

Physics based (II)			
Algorithm Name	Acronym	Year	Reference
Snow Ablation Optimizer	SAO	2023	[437]
Space Gravitational Algorithm	SGA	2005	[438]
Sonar Inspired Optimization	SIO	2017	[439]
States Matter Optimization Algorithm	SMS	2014	[440]
Spiral Dynamics Optimization	SO	2011	[441]
Spiral Optimization Algorithm	SPOA	2010	[442]
Self-Driven Particles	SPP	1995	[443]
Solar System Algorithm	SSA.4	2021	[444]
Turbulent Flow of Water-based Optimization	TFWO	2020	[445]
Vibrating Particle Systems Algorithm	VPO	2017	[446]
Vortex Search Algorithm	VS	2015	[447]
Water Cycle Algorithm	WCA.2	2012	[448]
Water Evaporation Optimization	WEO	2016	[449]
Water Flow-Like Algorithms	WFA	2007	[450]
Water Flow Algorithm	WFA.1	2007	[451]
Water-Flow Algorithm Optimization	WFO	2011	[452]
Water Wave Optimization Algorithm	WWA	2015	[453]

Table 11: Nature- and bio-inspired meta-heuristics within the *Chemistry based* category.

Chemistry based			
Algorithm Name	Acronym	Year	Reference
Artificial Chemical Process	ACP	2005	[454]
Artificial Chemical Reaction Optimization Algorithm	ACROA	2011	[455]
Artificial Reaction Algorithm	ARA	2013	[456]
Chemical Reaction Optimization Algorithm	CRO.1	2010	[457]
Gases Brownian Motion Optimization	GBMO	2013	[458]
Heat Transfer Search Algorithm	HTS	2015	[459]
Ions Motion Optimization Algorithm	IMO	2015	[460]
Integrated Radiation Optimization	IRO	2007	[461]
Kinetic Gas Molecules Optimization	KGMO	2014	[462]
Photosynthetic Algorithm	PA	1999	[463]
Simulated Annealing	SA.1	1989	[79]
Synergistic Fibroblast Optimization	SFO	2017	[464]
Thermal Exchange Optimization	TEO	2017	[465]

Table 12: Nature- and bio-inspired meta-heuristics within the *Social Human Behavior* based category.

Social Human Behavior (I)			
Algorithm Name	Acronym	Year	Reference
Adolescent Identity Search Algorithm	AISA	2020	[471]
Anarchic Society Optimization	ASO	2012	[472]
Alpine Skiing Optimization	ASO.2	2022	[473]
Brain Storm Optimization Algorithm	BSO.2	2011	[469]
Bus Transportation Behavior	BTA	2019	[474]
Collective Decision Optimization Algorithm	CDOA	2017	[475]
Cognitive Behavior Optimization Algorithm	COA.3	2016	[476]
Competitive Optimization Algorithm	COOA	2016	[477]
Community of Scientist Optimization Algorithm	CSOA	2012	[478]
Cultural Algorithms	CA	1999	[479]
Duelist Optimization Algorithm	DOA	2016	[480]
Election Algorithm	EA	2015	[481]
Football Game Inspired Algorithms	FCA.1	2009	[482]
FIFA World Cup Competitions	FIFAAO	2016	[483]
Golden Ball Algorithm	GBA	2014	[484]
Global-Best Brain Storm Optimization Algorithm	GBSO	2017	[470]
Group Counseling Optimization	GCO	2010	[485]
Group Leaders Optimization Algorithm	GLOA	2011	[486]
Greedy Politics Optimization Algorithm	GPO	2014	[487]
Gaining-sharing Knowledge	GSK	2023	[488]
Group Teaching Optimization Algorithm	GTOA	2020	[489]
Human Evolutionary Model	HEM	2007	[490]
Human Group Formation	HGF	2010	[491]
Human-Inspired Algorithms	HIA	2009	[492]
Human Urbanization Algorithm	HUA	2020	[493]
Ideology Algorithm	IA	2016	[466]
Imperialist Competitive Algorithm	ICA	2007	[467]
Kho-Kho optimization Algorithm	KKOA	2020	[494]
League Championship Algorithm	LCA.1	2014	[495]
Life Choice Based Optimizer	LCBO	2020	[496]
Leaders and Followers Algorithm	LFA	2015	[497]
Old Bachelor Acceptance	OBA	1995	[498]
Oriented Search Algorithm	OSA	2008	[499]
Political Optimizer	PO	2020	[500]
Parliamentary Optimization Algorithm	POA	2008	[501]
Poor and Rich Optimization Algorithm	PRO	2019	[502]
Queuing Search Algorithm	QSA.1	2018	[503]
Search and Rescue Algorithm	SAR	2019	[504]
Social Behavior Optimization Algorithm	SBO.1	2003	[505]
Social Cognitive Optimization	SCO	2002	[506]
Social Cognitive Optimization Algorithm	SCOA	2010	[507]
Social Emotional Optimization Algorithm	SEA	2010	[508]
Stock Exchange Trading Optimization	SETO	2022	[509]
Stochastic Focusing Search	SFS	2008	[510]
Soccer Game Optimization	SGO	2012	[511]
Soccer League Competition	SLC	2014	[468]
Student Psychology Optimization Algorithm	SPBO	2020	[512]

Table 13: Nature- and bio-inspired meta-heuristics within the *Social Human Behavior* based category.

Social Human Behavior (II)			
Algorithm Name	Acronym	Year	Reference
Stadium Spectators Optimizer	SSO.3	2024	[513]
Tiki-Taka Algorithm	TTA	2020	[514]
Team Game Algorithm	TGA	2018	[515]
Teaching-Learning Based Optimization Algorithm	TLBO	2011	[516]
Thieves and Police Optimization Algorithm	TPOA	2021	[517]
Tactical Unit Algorithm	TUA	2024	[518]
Tug Of War Optimization	TWO	2016	[519]
Unconscious Search	US	2012	[520]
Volleyball Premier League Algorithm	VPL	2017	[521]
Wisdom of Artificial Crowds	WAC	2011	[522]

Table 14: Nature- and bio-inspired meta-heuristics within the *Plants based* category.

Plants based			
Algorithm Name	Acronym	Year	Reference
Artificial Flora Optimization Algorithm	AFO	2018	[524]
Artificial Plants Optimization Algorithm	APO.1	2013	[525]
Brunsvigia Flower Optimization Algorithm	BVOA	2018	[526]
Carnivorous Plant Algorithm	CPA	2021	[527]
Discrete Mother Tree Optimization	DMTO	2020	[528]
Forest Optimization Algorithm	FOA.1	2014	[523]
Flower Pollination Algorithm	FPA	2012	[529]
Lotus Effect Algorithm	LEA	2023	[530]
Natural Forest Regeneration Algorithm	NFR	2016	[531]
Plant Growth Optimization	PGO	2008	[532]
Plant Propagation Algorithm	PPA.1	2009	[533]
Paddy Field Algorithm	PFA	2009	[534]
Root Growth Optimizer	RGO	2015	[535]
Root Tree Optimization Algorithm	RTOA	2016	[536]
Runner Root Algorithm	RRA	2015	[537]
Saplings Growing Up Algorithm	SGA.1	2007	[538]
Self-Defense Mechanism Of The Plants Algorithm	SDMA	2018	[539]
Seasons Optimization	SO.1	2022	[540]
Strawberry Plant Algorithm	SPA	2014	[541]
Smart Root Search	SRS	2020	[542]
Tree Growth Algorithm	TGA.1	2019	[543]
Tree Physiology Optimization	TPO	2018	[544]
Tree Seed Algorithm	TSA	2015	[545]

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 ultimate goal of reflecting 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 Tables 15 and 16. In this regard, we stress this pressing need for grouping assorted algorithms in years to come 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.

Table 15: Nature- and bio-inspired meta-heuristics within the *Miscellaneous* category.

Miscellaneous (II)			
Algorithm Name	Acronym	Year	Reference
Scientifics Algorithms	SA.2	2014	[547]
Social Engineering Optimization	SEO	2017	[548]
Stochastic Fractal Search	SFS.1	2015	[549]
Snow Flake Optimization Algorithm	SFO.1	2023	[550]
Search Group Algorithm	SGA.2	2015	[551]
Simple Optimization	SOPT	2012	[552]
Ship Rescue Optimization	SRO	2024	[553]
Small World Optimization	SWO	2006	[554]
The Great Deluge Algorithm	TGD	1993	[555]
Wind Driven Optimization	WDO	2010	[556]
Ying-Yang Pair Optimization	YYOP	2016	[546]

Table 16: Nature- and bio-inspired meta-heuristics within the *Miscellaneous* category.

Miscellaneous (I)			
Algorithm Name	Acronym	Year	Reference
Atmosphere Clouds Model	ACM	2013	[557]
Artificial Cooperative Search	ACS	2012	[558]
Innovative Gunner Algorithm	AIG	2019	[559]
Across Neighbourhood Search	ANS	2016	[560]
Botox Optimization Algorithm	BOA.2	2024	[561]
Battle Royale Optimization Algorithm	BRO	2020	[562]
Bar Systems	BS.2	2008	[563]
Backtracking Search Optimization	BSO.3	2012	[564]
Cloud Model-Based Algorithm	CMBDE	2012	[565]
Chaos Optimization Algorithm	COA.4	1998	[566]
Clonal Selection Algorithm	CSA.1	2000	[567]
COVID-19 Optimizer Algorithm	CVA	2020	[568]
Dice Game Optimizer	DGO	2019	[569]
Dialectic Search	DS	2009	[570]
Differential Search Algorithm	DSA	2012	[571]
Exchange Market Algorithm	EMA	2014	[572]
Extremal Optimization	EO	2000	[573]
Equilibrium Optimizer	EO.1	2020	[574]
Fireworks Algorithm Optimization	FAO	2010	[575]
Farmland Fertility Algorithm	FFA	2018	[576]
Grenade Explosion Method	GEM	2010	[577]
Golden Sine Algorithm	GSA.1	2017	[578]
Golf Sport Inspired Search	GSIS	2024	[579]
Heart Optimization	HO.1	2014	[580]
Hyper-parameter Dialectic Search	HDS	2020	[581]
Ideological Sublations	IS	2017	[582]
Interior Search Algorithm	ISA	2014	[583]
Keshtel Algorithm	KA	2014	[584]
Kidney-Inspired Algorithm	KA.1	2017	[585]
Kaizen Programming	KP	2014	[586]
Liver Cancer Algorithm	LCA.2	2023	[587]
Literature Research Optimizer	LRO.1	2024	[588]
Membrane Algorithms	MA	2005	[589]
Mine Blast Algorithm	MBA	2013	[590]
Neuronal Communication Algorithm	NCA	2017	[591]
Nizar Optimization Algorithm	NOA.1	2024	[592]
Plasma Generation Optimization	PGO.1	2020	[593]
Pearl Hunting Algorithm	PHA	2012	[594]
Passing Vehicle Search	PVS	2016	[595]
Artificial Raindrop Algorithm	RDA.1	2014	[596]
Reactive Dialectic Search	RDS	2017	[597]

4 Taxonomy by Behavior for Population based Nature- and Bio-inspired Optimization

We now proceed with our second proposed taxonomy for population-based metaheuristics. In this case, we sort the different algorithmic proposals reported by the community by their behavior, without any regard 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 into 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 [80], 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 [59], 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 (Figure 4.a); ii) only the significant/relevant solutions, e.g., the best and/or the worst candidates in the population (Figure 4.b); 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 (Figure 4.c).
- **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 (Figure 4.d). The classical GA [98] is the most straightforward example of this type. Another approach is by stigmergy (Figure 4.e), in which there is 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 [598], 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, Figure 5 shows the classification reached after our literature analysis. The plot indicates, for the 518 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 (69% vs 31%). Among them, the search process is mainly guided by representative solutions (almost 60% in global, 86% 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 movement vectors oriented towards the best solution is the search mechanism found in more than half (almost 60%) of all the 518 reviewed proposals.

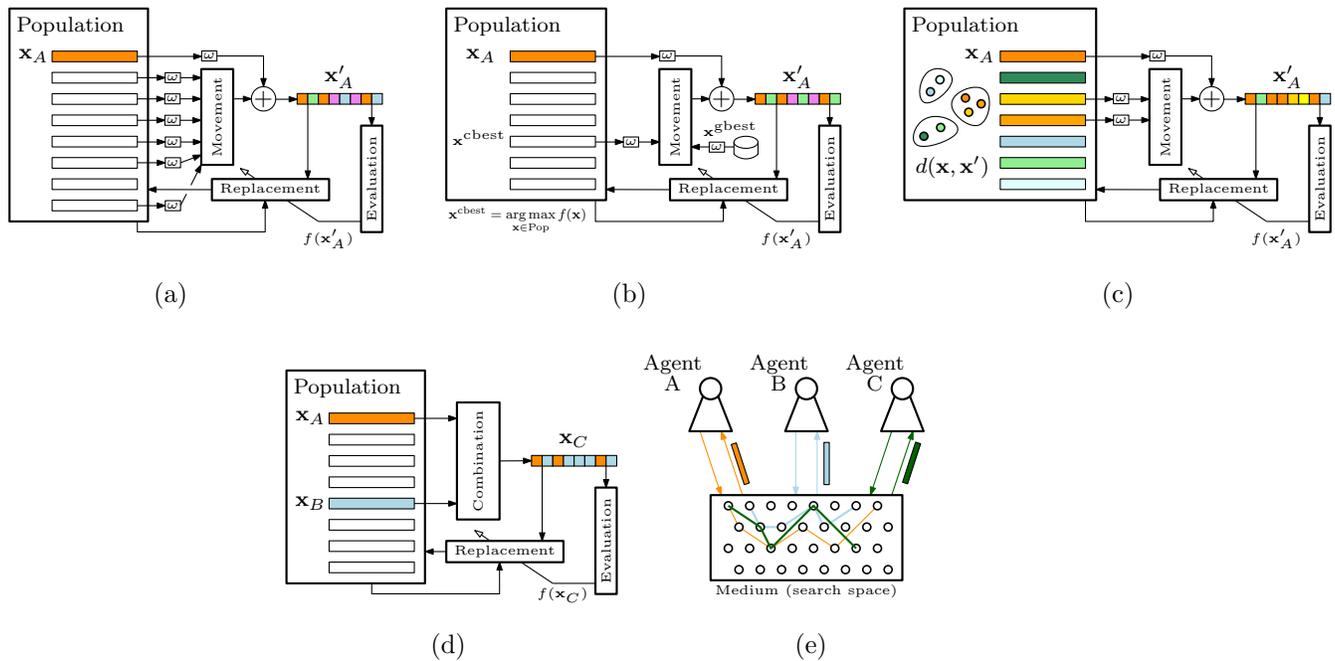


Figure 4: Schematic diagrams of the different algorithmic behaviors on which our second taxonomy relies. The upper plots illustrate the process of generating new solutions by *Differential Vector Movement* from a given solution x_A , using (a) the entire population; (b) relevant individuals (in the example, 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.

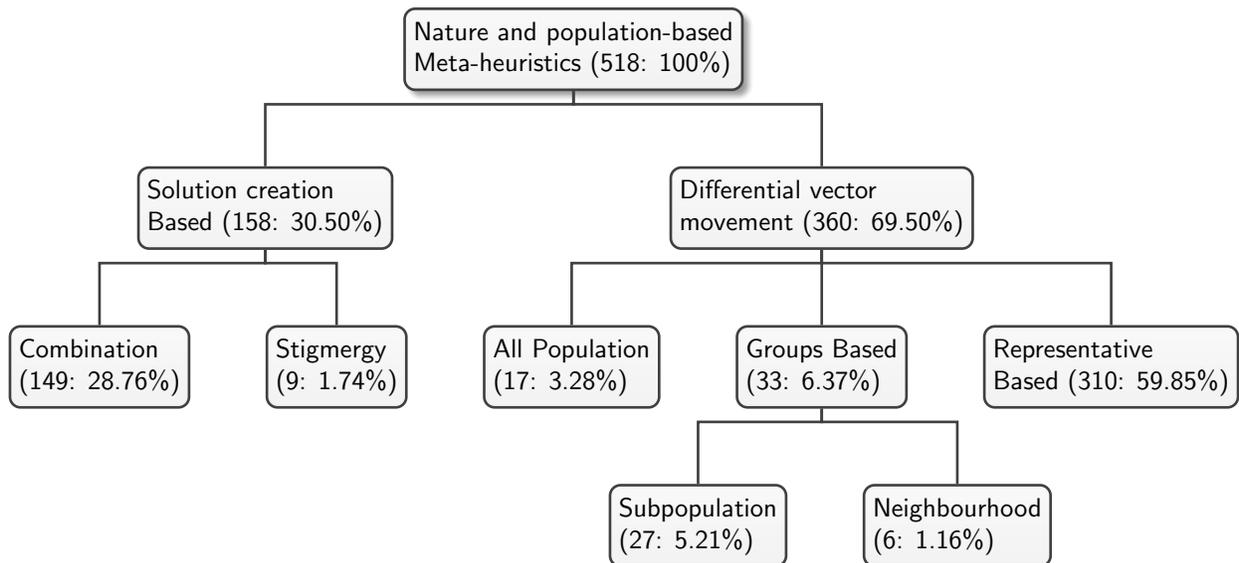


Figure 5: Classification of the reviewed papers using the *behavior* taxonomy.

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.

4.1 Differential Vector Movement

This category of our behavior-based taxonomy amounts up to 69% 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 (toward the best solutions) 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.

4.1.1 Differential Vector as a Function of the Entire Population

One possible criterion is to use 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 [117], 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 17, algorithms in this subcategory belong to different categories in the previous *inspiration source* based taxonomy.

4.1.2 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 the 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 18, 19, 20, 21, 22, 23 and 24 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 [80]. 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 [59]. 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 toward random individuals for the sake of increased diversity along the search. However, this subcategory also includes many other algorithms with differences in considering nearly better solutions (as in the Bat Inspired Algorithm [153] or the Brain Storm Optimization Algorithm [469]) or the worse solutions (to avoid less promising regions), as in the Grasshopper Optimization Algorithm (GOA, [118]). More than half of all algorithmic proposals dwell in this subcategory, with a prominence of Swarm Intelligence solvers due to their behavioral inspiration in PSO and DE. We will revolve around these identified similarities in Section 5.

4.1.3 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

Table 17: 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	[395]
Artificial Plants Optimization Algorithm	APO.1	2013	[525]
Botox Optimization Algorithm	BOA.2	2024	[561]
Chaotic Dragonfly Algorithm	CDA	2018	[177]
Central Force Optimization	CFO	2008	[402]
Charged Systems Search	CSS	2010	[403]
Dwarf Mongoose Optimization	DMO	2022	[198]
Electromagnetism Mechanism Optimization	EMO	2003	[405]
Firefly Algorithm	FA	2009	[117]
Gravitational Clustering Algorithm	GCA	1999	[408]
Group Counseling Optimization	GCO	2010	[485]
Gravitational Search Algorithm	GSA	2009	[391]
Human Group Formation	HGF	2010	[491]
Hoopoe Heuristic Optimization	HHO.1	2012	[245]
Intelligent Gravitational Search Algorithm	IGSA	2012	[419]
Integrated Radiation Optimization	IRO	2007	[461]
Locust Swarms Search	LSS	2015	[271]

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:

- **Subpopulation based differential vector:** In algorithms belonging to this subcategory (listed in Table 25) 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 [263] or the Monarch Butterfly Optimization algorithm (MBO, [274]).
- **Neighborhood based differential vector:** In this subcategory, each solution is affected only by solutions in its local neighborhood. Table 26 compiles all algorithms that are classified in this subcategory. A notable example in this list is BFOA [148], 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).

4.2 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 (almost 31%) of all proposals, and includes many classical algorithms like GA [98]. 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 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.

4.2.1 Creation by Combination

The most common option to generate a new solution is to combine existing ones. In these algorithms, different solutions are selected and combined using a crossover operator or combining method to give rise to new solutions. The underlying idea

Table 18: 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	[120]
Artificial Bee Colony	ABC	2007	[116]
Animal Behavior Hunting	ABH	2014	[122]
African Buffalo Optimization	ABO	2016	[123]
Atmosphere Clouds Model	ACM	2013	[557]
Artificial Ecosystem Optimizer	AEO	2020	[83]
Artificial Feeding Birds	AFB	2018	[125]
Artificial Hummingbird Algorithm	AHA	2022	[126]
Archerfish Hunting Optimizer	AHO	2022	[127]
Adolescent Identity Search Algorithm	AISA	2020	[471]
Ant Lion Optimizer	ALO	2015	[130]
Animal Migration Optimization	AMO	2014	[128]
Aphid Metaheuristic Optimization	AMO.1	2022	[129]
Across Neighbourhood Search	ANS	2016	[560]
Aquila Optimizer	AO	2021	[131]
Archimedes Optimization Algorithm	AOA.1	2021	[396]
Arithmetic Optimization Algorithm	AOA.2	2021	[133]
Artificial Rabbits Optimization	ARO.1	2022	[134]
Anarchic Society Optimization	ASO	2012	[472]
Atom Search Optimization	ASO.1	2019	[398]
Alpine Skiing Optimization	ASO.2	2022	[473]
Artificial Searching Swarm Algorithm	ASSA	2009	[135]
Artificial Tribe Algorithm	ATA	2009	[136]
African Wild Dog Algorithm	AWDA	2013	[137]
Bison Behavior Algorithm	BBA	2019	[142]
Big Bang Big Crunch	BBBC	2006	[399]
Bacterial Chemotaxis Optimization	BCO.2	2002	[146]
Bacterial Colony Optimization	BCO.1	2012	[145]
Border Collie Optimization	BCO.3	2020	[147]
Bald Eagle Search Optimization	BES	2019	[139]
Black Hole Optimization	BH	2013	[392]
Bat Intelligence	BI	2012	[152]
Bat Inspired Algorithm	BIA	2010	[153]
Biology Migration Algorithm	BMA	2019	[154]
Blind, Naked Mole-Rats Algorithm	BNMR	2013	[156]
Butterfly Optimizer	BO	2015	[157]
Bonobo Optimizer	BO.1	2019	[158]
Battle Royale Optimization Algorithm	BRO	2020	[562]
Bird Swarm Algorithm	BSA	2016	[162]
Bee Swarm Optimization	BSO	2010	[163]
Bioluminescent Swarm Optimization Algorithm	BSO.1	2011	[164]
Brain Storm Optimization Algorithm	BSO.2	2011	[469]
Biological Survival Optimizer	BSO.4	2023	[165]
Buzzard Optimization Algorithm	BUZOA	2019	[167]
Beluga Whale Optimization	BWO.1	2022	[169]
Binary Whale Optimization Algorithm	BWOA	2019	[170]
Collective Animal Behavior	CAB	2012	[171]

Table 19: 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
Catfish Optimization Algorithm	CAO	2011	[173]
Cheetah Based Algorithm	CBA	2018	[172]
Cricket Behavior-Based Algorithm	CBBE	2016	[174]
Chaotic Crow Search Algorithm	CCSA	2018	[176]
Collective Decision Optimization Algorithm	CDOA	2017	[475]
Camel Herd Algorithm	CHA	2017	[180]
Chimp Optimization Algorithm	ChOA	2020	[181]
Cloud Model-Based Algorithm	CMBDE	2012	[565]
Camel Traveling Behavior	COA.1	2016	[183]
Coyote Optimization Algorithm	COA.2	2018	[184]
Cognitive Behavior Optimization Algorithm	COA.3	2016	[476]
Chaos Optimization Algorithm	COA.4	1998	[566]
COOT Optimization Algorithm	COA.5	2021	[185]
Coati Optimization Algorithm	COA.6	2023	[186]
Competitive Optimization Algorithm	COOA	2016	[477]
Crested Porcupine Optimizer	CPO	2024	[187]
Crow Search Algorithm	CSA	2016	[189]
Chameleon Swarm Algorithm	CSA.2	2021	[81]
Circle Search Algorithm	CSA.3	2022	[190]
Cat Swarm Optimization	CSO	2006	[191]
Community of Scientist Optimization Algorithm	CSOA	2012	[478]
Dragonfly Algorithm	DA	2016	[193]
Differential Evolution	DE	1997	[93]
Dynamic Hunting Leadership	DHL	2023	[196]
Deer Hunting Optimization Algorithm	DHOA	2019	[197]
Dandelion Optimizer	DO	2022	[199]
Dingo Optimizer	DOX	2021	[200]
Dolphin Partner Optimization	DPO	2009	[201]
Differential Search Algorithm	DSA	2012	[571]
Donkey Theorem Optimization	DTO	2019	[202]
Enriched Coati Osprey Algorithm	ECOA	2024	[203]
Electric Eel Foraging Optimization	EEFO	2024	[204]
Elephant Herding Optimization	EHO	2016	[206]
Elk Herd Optimizer	EHO.1	2024	[207]
Ebola Optimization Search Algorithm	EOSA	2022	[208]
Emperor Penguin Optimizer	EPO	2018	[210]
Electron Radar Search Algorithm	ERSA	2020	[407]
Elephant Search Algorithm	ESA	2015	[212]
Eagle Strategy	ES.1	2010	[211]
Elephant Swarm Water Search Algorithm	ESWSA	2018	[213]
Fireworks Algorithm Optimization	FAO	2010	[575]
Flocking Base Algorithms	FBA	2006	[215]
Fast Bacterial Swarming Algorithm	FBSA	2008	[216]
Football Game Inspired Algorithms	FCA.1	2009	[482]
Farmland Fertility Algorithm	FFA	2018	[576]
Fire Hawk Optimizer	FHO	2023	[218]
FIFA World Cup Competitions	FIFAAO	2016	[483]

Table 20: 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
Flock by Leader	FL	2012	[219]
Frilled Lizard Optimization	FLO	2024	[220]
Fruit Fly Optimization Algorithm	FOA	2012	[221]
Falcon Optimization Algorithm	FOA.2	2019	[222]
Flower Pollination Algorithm	FPA	2012	[529]
Fish-Swarm Algorithm	FSA	2002	[224]
Fish Swarm Algorithm	FSA.1	2011	[225]
Fish School Search	FSS	2008	[226]
Green Anaconda Optimization	GAO	2023	[227]
Giant Armadillo Optimization	GAO.1	2023	[228]
Gases Brownian Motion Optimization	GBMO	2013	[458]
Global-Best Brain Storm Optimization Algorithm	GBSO	2017	[470]
Group Escape Behavior	GEB	2011	[229]
Golden Eagle Optimizer	GEO	2021	[230]
Grenade Explosion Method	GEM	2010	[577]
Gravitational Field Algorithm	GFA	2010	[410]
Geyser Inspired Algorithm	GIA	2023	[411]
Gravitational Interactions Algorithm	GIO	2011	[412]
Golden Jackal Optimization Algorithm	GJO	2023	[231]
Genghis Khan Shark Optimizer	GKSO	2023	[232]
Good Lattice Swarm Optimization	GLSO	2007	[233]
Grasshopper Optimisation Algorithm	GOA	2017	[118]
Gazelle Optimization Algorithm	GOA.1	2023	[234]
General Relativity Search Algorithm	GRSA	2015	[413]
Golden Sine Algorithm	GSA.1	2017	[578]
Glowworm Swarm Optimization	GSO	2013	[236]
Galactic Swarm Optimization	GSO.2	2016	[414]
Goose Team Optimization	GTO	2008	[238]
Gorilla Troops Optimizer	GTO.1	2021	[239]
Group Teaching Optimization Algorithm	GTOA	2020	[489]
Grey Wolf Optimizer	GWO	2014	[240]
Hitchcock Birds-Inspired Algorithm	HBIA	2020	[241]
Hydrological Cycle Algorithm	HCA	2017	[415]
Hunger Games Search	HGS	2021	[243]
Harry's Hawk Optimization Algorithm	HHO	2019	[244]
Horned Lizard Optimization Algorithm	HLOA	2024	[246]
Heart Optimization	HO.1	2014	[580]
Hurricane Based Optimization Algorithm	HO.2	2014	[418]
Hybrid Rice Optimization	HRO	2016	[100]
Hunting Search	HuS	2010	[248]
Honeybee Social Foraging	HSF	2007	[249]
Humboldt Squid Optimization Algorithm	HSOA.1	2023	[252]
Heat Transfer Search Algorithm	HTS	2015	[459]
Human Urbanization Algorithm	HUA	2020	[493]
Ideology Algorithm	IA	2016	[466]
Imperialist Competitive Algorithm	ICA	2007	[467]
Ideological Sublations	IS	2017	[582]

Table 21: 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
Interior Search Algorithm	ISA	2014	[583]
Jaguar Algorithm	JA	2015	[256]
Jellyfish Search	JS	2021	[257]
Kidney-Inspired Algorithm	KA.1	2017	[585]
Kinetic Gas Molecules Optimization	KGMO	2014	[462]
Krill Herd	KH	2012	[259]
Kho-Kho optimization Algorithm	KKOA	2020	[494]
Kookaburra Optimization Algorithm	KOA	2023	[260]
Krestrel Search Algorithm	KSA	2016	[261]
Killer Whale Algorithm	KWA	2017	[262]
Seven-Spot Ladybird Optimization	LBO	2013	[264]
Lyrebird Optimization Algorithm	LBO.1	2023	[265]
League Championship Algorithm	LCA.1	2014	[495]
Lotus Effect Algorithm	LEA	2023	[530]
Leaders and Followers Algorithm	LFA	2015	[497]
Literature Research Optimizer	LRO.1	2024	[588]
Lightning Search Algorithm	LSA	2015	[422]
Locust Swarms Optimization	LSO	2009	[269]
Leopard Seal Optimization	LSO.1	2023	[270]
Membrane Algorithms	MA	2005	[589]
Mayfly Optimization Algorithm	MA.1	2020	[272]
Mine Blast Algorithm	MBA	2013	[590]
Magnetotactic Bacteria Optimization Algorithm	MBO	2013	[273]
Mouth Breeding Fish Algorithm	MBF	2018	[276]
Modified Cuckoo Search	MCS	2009	[278]
Modified Cockroach Swarm Optimization	MCSO	2011	[279]
Moth Flame Optimization Algorithm	MFO	2015	[280]
Magnetic Optimization Algorithm	MFO.2	2008	[423]
Meerkats Inspired Algorithm	MIA	2018	[282]
Marine Predators Algorithm	MPA	2020	[285]
Mushroom Reproduction Optimization	MRO	2018	[105]
Monkey Search	MS	2007	[286]
Moth Search Algorithm	MS.2	2018	[287]
Mantis Search Algorithm	MSA	2023	[288]
Multi-Verse Optimizer	MVO	2016	[426]
Naked Moled Rat	NMR	2019	[290]
Nutcracker Optimization Algorithm	NOA	2023	[291]
Nizar Optimization Algorithm	NOA.1	2024	[592]
Nomadic People Optimizer	NPO	2019	[292]
Newton-Raphson-Based Optimizer	NRBO	2024	[427]
Orcas Intelligence Algorithm	OA	2020	[293]
OptBees	OB	2012	[294]
Optimal Foraging Algorithm	OFA	2017	[295]
Optics Inspired Optimization	OIO	2015	[428]
Owls Optimization Algorithm	OOA	2019	[296]
Osprey Optimization Algorithm	OOA.1	2023	[297]
Orca Predation Algorithm	OPA	2022	[298]

Table 22: 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
Oriented Search Algorithm	OSA	2008	[499]
Prairie Dog Optimization Algorithm	PDO	2022	[302]
Paddy Field Algorithm	PFA	2009	[534]
Pigeon Inspired Optimization	PIO	2014	[303]
Population Migration Algorithm	PMA	2009	[304]
Political Optimizer	PO	2020	[500]
Puma Optimizer	PO.1	2024	[305]
Parliamentary Optimization Algorithm	POA	2008	[501]
Pelican Optimization Algorithm	POA.1	2022	[306]
Pufferfish Optimization Algorithm	POA.2	2024	[307]
Prey Predator Algorithm	PPA	2015	[308]
Plant Propagation Algorithm	PPA.1	2009	[533]
Poor and Rich Optimization Algorithm	PRO	2019	[502]
Particle Swarm Optimization	PSO	1995	[80]
Penguins Search Optimization Algorithm	PSOA	2013	[309]
Passing Vehicle Search	PVS	2016	[595]
Queuing Search Algorithm	QSA.1	2018	[503]
Regular Butterfly Optimization Algorithm	RBOA	2019	[310]
Artificial Raindrop Algorithm	RDA.1	2014	[596]
Red Fox Optimization Algorithm	RFO	2021	[312]
Root Growth Optimizer	RGO	2015	[535]
Roach Infestation Problem	RIO	2008	[315]
Radial Movement Optimization	RMO	2014	[435]
Ray Optimization	RO	2012	[436]
Red Piranha Optimization	RPO	2023	[318]
Red Panda Optimization Algorithm	RPO.1	2023	[319]
Runner Root Algorithm	RRA	2015	[537]
Raven Roosting Optimization Algorithm	RROA	2015	[320]
Red-tailed Hawk Algorithm	RTH	2023	[321]
Reptile Search Algorithm	RSA	2022	[322]
Rat Swarm Optimizer	RSO	2021	[323]
Root Tree Optimization Algorithm	RTOA	2016	[536]
Rain Water Algorithm	RWA	2017	[433]
Snow Ablation Optimizer	SAO	2023	[437]
Search and Rescue Algorithm	SAR	2019	[504]
Swarm Bipolar Algorithm	SBA	2024	[326]
Satin Bowerbird Optimizer	SBO	2017	[328]
Stem Cells Algorithm	SCA	2011	[108]
Sine Cosine Algorithm	SCA.2	2016	[329]
Social Cognitive Optimization	SCO	2002	[506]
Social Cognitive Optimization Algorithm	SCOA	2010	[507]
Sand Cat Swarm Optimization	SCSO	2023	[330]
Social Emotional Optimization Algorithm	SEA	2010	[508]
Stock Exchange Trading Optimization	SETO	2022	[509]
Synergistic Fibroblast Optimization	SFO	2017	[464]
Stochastic Focusing Search	SFS	2008	[510]
Stochastic Fractal Search	SFS.1	2015	[549]

Table 23: Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (VI).

Influenced by representative solutions (VI)			
Algorithm Name	Acronym	Year	Reference
Space Gravitational Algorithm	SGA	2005	[438]
Soccer Game Optimization	SGO	2012	[511]
Spotted Hyena Optimizer	SHO	2017	[333]
Selfish Herds Optimizer	SHO.1	2017	[334]
Sea-horse Optimizer	SHO.2	2023	[335]
Swarm Inspired Projection Algorithm	SIP	2009	[336]
Soccer League Competition	SLC	2014	[468]
Slime Mould Algorithm	SMA	2008	[337]
Sperm Motility Algorithm	SMA.1	2017	[338]
Spider Monkey Optimization	SMO	2014	[339]
Starling Murmuration Optimizer	SMO.1	2022	[340]
States Matter Optimization Algorithm	SMS	2014	[440]
Spiral Dynamics Optimization	SO	2011	[441]
Student Psychology Optimization Algorithm	SPBO	2020	[512]
Spiral Optimization Algorithm	SPOA	2010	[442]
Self-Driven Particles	SPP	1995	[443]
Seeker Optimization Algorithm	SOA	2007	[341]
Seagull Optimization Algorithm	SOA.1	2019	[342]
Sandpiper Optimization Algorithm	SOA.2	2020	[343]
Sailfish Optimizer Algorithm	SOA.3	2019	[344]
Serval Optimization Algorithm	SOA.4	2022	[345]
Symbiosis Organisms Search	SOS	2014	[346]
Ship Rescue Optimization	SRO	2024	[553]
Siberian Tiger Optimization	STO	2022	[359]
Sooty Tern Optimization Algorithm	STOA	2019	[347]
Social Spider Algorithm	SSA	2015	[348]
Squirrel Search Algorithm	SSA.1	2019	[349]
Sparrow Search Algorithm	SSA.3	2020	[351]
Solar System Algorithm	SSA.4	2021	[444]
Shark Smell Optimization	SSO	2016	[353]
Swallow Swarm Optimization	SSO.1	2013	[354]
Social Spider Optimization	SSO.2	2013	[355]
Stadium Spectators Optimizer	SSO.3	2024	[513]
Sperm Swarm Optimization Algorithm	SSOA	2018	[356]
See-See Partridge Chicks Optimization	SSPCO	2015	[357]
Surface-Simplex Swarm Evolution Algorithm	SSSE	2017	[358]
Spider Wasp Optimizer	SWO.1	2023	[361]
Termite Alate Optimization Algorithm	TAOA	2023	[363]
T-Cell Immune Algorithm	TCIA	2023	[112]
Termite Colony Optimization	TCO	2010	[364]
Tasmanian Devil Optimization	TDO	2022	[365]
Tomtit Flock Optimization Algorithm	TFOA	2022	[366]
Team Game Algorithm	TGA	2018	[515]
The Great Salmon Run Algorithm	TGSR	2013	[367]
Teaching-Learning Based Optimization Algorithm	TLBO	2011	[516]
Termite Life Cycle Optimizer	TLCO	2023	[368]
Tree Physiology Optimization	TPO	2018	[544]

Table 24: Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by representative solutions (VII).

Influenced by representative solutions (VII)			
Algorithm Name	Acronym	Year	Reference
Thieves and Police Optimization Algorithm	TPOA	2021	[517]
Tyrannosaurus Optimization Algorithm	TROA	2023	[369]
Tree Seed Algorithm	TSA	2015	[545]
Tuncate Swarm Algorithm	TSA.1	2020	[370]
Tangent Search Algorithm	TSA.2	2022	[371]
Tiki-Taka Algorithm	TTA	2020	[514]
Tactical Unit Algorithm	TUA	2024	[518]
Tug Of War Optimization	TWO	2016	[519]
Unconscious Search	US	2012	[520]
Virus Colony Search	VCS	2016	[374]
Variable Mesh Optimization	VMO	2012	[113]
Volleyball Premier League Algorithm	VPL	2017	[521]
Vibrating Particle Systems Algorithm	VPO	2017	[446]
Vortex Search Algorithm	VS	2015	[447]
Wolf Colony Algorithm	WCA.1	2011	[378]
Water Cycle Algorithm	WCA.2	2012	[448]
Wind Driven Optimization	WDO	2010	[556]
Water Evaporation Optimization	WEO	2016	[449]
Whale Optimization Algorithm	WOA	2016	[380]
Walrus Optimization Algorithm	WaOA	2023	[381]
Wolf Pack Search	WPS	2007	[382]
Weightless Swarm Algorithm	WSA	2012	[383]
Wolf Search Algorithm	WSA.1	2012	[384]
White Shark Optimizer	WSO.1	2022	[386]
Water Wave Optimization Algorithm	WWA	2015	[453]
Yellow Saddle Goldfish	YSGA	2018	[387]
Zebra Optimization Algorithm	ZOA	2022	[388]
Zombie Survival Optimization	ZSO	2012	[389]

Table 25: 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	[454]
Artificial Cooperative Search	ACS	2012	[558]
Artificial Physics Optimization	APO	2009	[397]
Bee Colony-Inspired Algorithm	BCIA	2009	[143]
Colliding Bodies Optimization	CBO	2014	[400]
Cuttlefish Algorithm	CFA	2013	[178]
Cuckoo Optimization Algorithm	COA	2011	[182]
Carnivorous Plant Algorithm	CPA	2021	[527]
Chicken Swarm Optimization	CSO.1	2014	[192]
COVID-19 Optimizer Algorithm	CVA	2020	[568]
Dice Game Optimizer	DGO	2019	[569]
Exchange Market Algorithm	EMA	2014	[572]
Greedy Politics Optimization Algorithm	GPO	2014	[487]
Gaining-sharing Knowledge	GSK	2023	[488]
Group Search Optimizer	GSO.1	2009	[237]
Horse Optimization Algorithm	HOA	2020	[247]
Hierarchical Swarm Model	HSM	2010	[250]
Ions Motion Optimization Algorithm	IMO	2015	[460]
Life Choice Based Optimizer	LCBO	2020	[496]
Lion Optimization Algorithm	LOA	2016	[267]
Monarch Butterfly Optimization	MBO.1	2017	[274]
Social Behavior Optimization Algorithm	SBO.1	2003	[505]
Sperm Whale Algorithm	SWA	2016	[360]
Thermal Exchange Optimization	TEO	2017	[465]
Turbulent Flow of Water-based Optimization	TFWO	2020	[445]
Wisdom of Artificial Crowds	WAC	2011	[522]
Worm Optimization	WO	2014	[379]

Table 26: Nature- and bio-inspired meta-heuristics within the *Differential Vector Movement* category, wherein the differential vector is influenced by neighborhoods.

Influenced by neighbourhoods			
Algorithm Name	Acronym	Year	Reference
Bees Algorithm	BA	2006	[140]
Biomimicry Of Social Foraging Bacteria for Distributed Optimization	BFOA	2002	[148]
Bacterial Foraging Optimization	BFOA.1	2009	[62]
Gravitational Emulation Local Search	GELS	2009	[409]
Neuronal Communication Algorithm	NCA	2017	[591]
Physarum-inspired Competition Algorithm	PCA.1	2023	[301]

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 [98]. 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, [479]) (in the Social Human Behavior category), LA [267] (in the Swarm Intelligence category), Particle Collision Algorithm (PCA, [429], in the chemistry-based category) or Light Ray Optimization (LRO, [421], in the physics-based category). Tables 27, 28, 29, and 30 show the algorithms that rely on combination when creating new solutions along their search.

4.2.2 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 [598], 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 the most promising values for each dimension.

Table 31 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 stigmergic behavior when producing new solutions, such as methods inspired by water flow dynamics [452] and the natural formation of rivers [434].

5 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.

5.1 Comparison Between both Taxonomies

Comparing the two taxonomies to each other and the algorithms falling into each of their categories, it can be observed that there is not a strong relationship between 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, [410]) or animal evolution (ABO, [123]) exhibit a significant similarity with PSO [80]. 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, [195]) and the Dolphin Partner Optimization [201]. Both are inspired by 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 than half of the reviewed algorithms (almost 60%), but it also comprises algorithms from all the different categories in the first taxonomy: Social Human Behavior (as Anarchic Society Optimization, ASO, [472]), microorganisms (Bacterial Colony Optimization, [145]), Physics/Chemistry category (correspondingly, Fireworks Algorithm Optimization, FAO, [575]), Breeding-based Evolution (as Variable Mesh Optimization, VMO [113]), or even Plants-Based (such as Flower Pollination Algorithm, FPA [529]). This inspirational diversity is not exclusive to this subcategory. Others, such as Solution Creation, also include algorithms relying on the heterogeneity of natural concepts.

Table 27: 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	[121]
Andean Condor Algorithm	ACA	2019	[124]
Artificial Chemical Reaction Optimization Algorithm	ACROA	2011	[455]
Artificial Ecosystem Algorithm	AEA	2014	[82]
Artificial Flora Optimization Algorithm	AFO	2018	[524]
Artificial Infections Disease Optimization	AIDO	2016	[84]
Innovative Gunner Algorithm	AIG	2019	[559]
Anglerfish Algorithm	AOA	2019	[132]
Artificial Reaction Algorithm	ARA	2013	[456]
Asexual Reproduction Optimization	ARO	2010	[85]
American Zebra Optimization Algorithm	AZOA	2023	[138]
Bacterial-GA Foraging	BGAF	2007	[149]
Bumblebees	BB	2009	[141]
Biogeography Based Optimization	BBO	2008	[86]
Bee Colony Optimization	BCO	2005	[144]
BeeHive Algorithm	BHA	2004	[150]
Bees Life Algorithm	BLA	2018	[151]
Bird Mating Optimization	BMO	2014	[87]
Barnacles Mating Optimizer	BMO.1	2019	[155]
Bean Optimization Algorithm	BOA	2011	[88]
Bull Optimization Algorithm	BOA.1	2015	[159]
Bee System	BS	1997	[160]
Bar Systems	BS.2	2008	[563]
Backtracking Search Optimization	BSO.3	2012	[564]
Bees Swarm Optimization Algorithm	BSOA	2005	[166]
Bus Transportation Behavior	BTA	2019	[474]
Brunsvigia Flower Optimization Algorithm	BVOA	2018	[526]
Black Widow Optimization Algorithm	BWO	2020	[168]
Cultural Algorithms	CA	1999	[479]
Cultural Coyote Optimization Algorithm	CCOA	2019	[175]
Crystal Energy Optimization Algorithm	CEO	2016	[401]
Consultant Guide Search	CGS	2010	[179]
Coronavirus Mask Protection Algorithm	CMPA	2023	[89]
Coronavirus Disease Optimization Algorithm	COVIDOA	2022	[90]
Coral Reefs Optimization	CRO	2014	[91]
Chemical Reaction Optimization Algorithm	CRO.1	2010	[457]
Cuckoo Search	CS	2009	[188]
Clonal Selection Algorithm	CSA.1	2000	[567]
Dragonfly Swarm Algorithm	DA.1	2020	[194]
Dendritic Cells Algorithm	DCA	2005	[92]
Dolphin Echolocation	DE.1	2013	[195]
Discrete Mother Tree Optimization	DMTO	2020	[528]
Duelist Optimization Algorithm	DOA	2016	[480]
Dialectic Search	DS	2009	[570]
Election Algorithm	EA	2015	[481]
Ecogeography-Based Optimization	EBO	2014	[94]
Eco-Inspired Evolutionary Algorithm	EEA	2011	[95]
Electromagnetic Field Optimization	EFO	2016	[404]

Table 28: Nature- and bio-inspired meta-heuristics within the *Solution Creation - Combination* category (II).

Creation-Combination category (II)			
Algorithm Name	Acronym	Year	Reference
Electric Fish Optimization	EFO.1	2020	[205]
Extremal Optimization	EO	2000	[573]
Equilibrium Optimizer	EO.1	2020	[574]
Earthworm Optimization Algorithm	EOA	2018	[96]
Electimize Optimization Algorithm	EOA.1	2011	[406]
Emperor Penguins Colony	EPC	2019	[209]
Evolution Strategies	ES	2002	[97]
Egyptian Vulture Optimization Algorithm	EV	2013	[214]
Frog Call Inspired Algorithm	FCA	2009	[217]
Forest Optimization Algorithm	FOA.1	2014	[523]
FOX-inspired Optimization Algorithm	FOX	2023	[223]
Genetic Algorithms	GA	1989	[98]
Golden Ball Algorithm	GBA	2014	[484]
Galaxy Based Search Algorithm	GBSA	2011	[393]
Gene Expression	GE	2001	[99]
Group Leaders Optimization Algorithm	GLOA	2011	[486]
Goat Search Algorithms	GSA.2	2022	[235]
Golf Sport Inspired Search	GSIS	2024	[579]
Honey-Bees Mating Optimization Algorithm	HBMO	2006	[242]
Hyper-parameter Dialectic Search	HDS	2020	[581]
Harmony Elements Algorithm	HEA	2009	[416]
Human Evolutionary Model	HEM	2007	[490]
Human-Inspired Algorithms	HIA	2009	[492]
Hysteresis for Optimization	HO	2002	[417]
Harmony Search	HS	2005	[394]
Hypercube Natural Aggregation Algorithm	HYNAA	2019	[253]
Japanese Tree Frogs Calling Algorithm	JTFCA	2012	[258]
Immune-Inspired Computational Intelligence	ICI	2008	[101]
Improved Genetic Immune Algorithm	IGIA	2017	[102]
Improved Raven Roosting Algorithm	IRRO	2018	[254]
Invasive Tumor Optimization Algorithm	ITGO	2015	[255]
Weed Colonization Optimization	IWO	2006	[103]
Keshtel Algorithm	KA	2014	[584]
Kaizen Programming	KP	2014	[586]
Lion Algorithm	LA	2012	[263]
Laying Chicken Algorithm	LCA	2017	[266]
Liver Cancer Algorithm	LCA.2	2023	[587]
Lion Pride Optimizer	LPO	2012	[268]
Light Ray Optimization	LRO	2010	[421]
Migrating Birds Optimization	MBO.2	2012	[275]
Migration-Crossover Algorithm	MCA	2024	[277]
Mosquito Flying Optimization	MFO.1	2016	[281]
Marriage In Honey Bees Optimization	MHBO	2001	[104]
Method of Musical Composition	MMC	2014	[424]
Mycorrhiza Optimization Algorithm	MOA	2023	[283]
Mox Optimization Algorithm	MOX	2011	[284]
Melody Search	MS.1	2011	[425]
Natural Aggregation Algorithm	NAA	2016	[289]

Table 29: Nature- and bio-inspired meta-heuristics within the *Solution Creation - Combination* category (III).

Creation-Combination category (III)			
Algorithm Name	Acronym	Year	Reference
Natural Forest Regeneration Algorithm	NFR	2016	[531]
Old Bachelor Acceptance	OBA	1995	[498]
Photosynthetic Algorithm	PA	1999	[463]
Pity Beetle Algorithm	PBA	2018	[299]
Polar Bear Optimization Algorithm	PBOA	2017	[300]
Particle Collision Algorithm	PCA	2007	[429]
Plant Growth Optimization	PGO	2008	[532]
Plasma Generation Optimization	PGO.1	2020	[593]
Pearl Hunting Algorithm	PHA	2012	[594]
PopMusic Algorithm	PopMusic	2002	[430]
Queen-Bee Evolution	QBE	2003	[106]
Quantum Superposition Algorithm	QSA	2015	[431]
Red Deer Algorithm	RDA	2016	[311]
Reactive Dialectic Search	RDS	2017	[597]
Rain-Fall Optimization Algorithm	RFOA	2017	[432]
Rhino Herd Behavior	RHB	2018	[313]
Rock Hyraxes Swarm Optimization	RHSO	2021	[314]
Raccoon Optimization Algorithm	ROA	2018	[316]
Reincarnation Concept Optimization Algorithm	ROA.1	2010	[317]
Ringed Seal Search	RSS	2015	[324]
Shark Search Algorithm	SA	1998	[325]
Simulated Annealing	SA.1	1989	[79]
Scientifics Algorithms	SA.2	2014	[547]
SuperBug Algorithm	SuA	2012	[107]
Simulated Bee Colony	SBC	2009	[327]
Snap-Drift Cuckoo Search	SDCS	2016	[331]
Self-Defense Mechanism Of The Plants Algorithm	SDMA	2018	[539]
Social Engineering Optimization	SEO	2017	[548]
Sheep Flock Heredity Model	SFHM	2001	[109]
Shuffled Frog-Leaping Algorithm	SFLA	2006	[332]
Snow Flake Optimization Algorithm	SFO.1	2023	[550]
Saplings Growing Up Algorithm	SGA.1	2007	[538]
Search Group Algorithm	SGA.2	2015	[551]
Swine Influenza Models Based Optimization	SIMBO	2013	[110]
Sonar Inspired Optimization	SIO	2017	[439]
Seasons Optimization	SO.1	2022	[540]
Self-Organizing Migrating Algorithm	SOMA	2004	[111]
Simple Optimization	SOPT	2012	[552]
Strawberry Plant Algorithm	SPA	2014	[541]
Smart Root Search	SRS	2020	[542]
Salp Swarm Algorithm	SSA.2	2017	[350]
Sling-shot Spider Optimization	S ² SO	2023	[352]
Tree Growth Algorithm	TGA.1	2019	[543]
The Great Deluge Algorithm	TGD	1993	[555]
Small World Optimization	SWO	2006	[554]
Virulence Optimization Algorithm	VOA	2016	[114]
Virus Optimization Algorithm	VOA.1	2009	[375]
Viral Systems Optimization	VSO	2008	[376]

Table 30: Nature- and bio-inspired meta-heuristics within the *Solution Creation - Combination* category (IV).

Creation-Combination category (IV)			
Algorithm Name	Acronym	Year	Reference
Wasp Colonies Algorithm	WCA	1991	[377]
Water Flow-Like Algorithms	WFA	2007	[450]
Water Flow Algorithm	WFA.1	2007	[451]
Wasp Swarm Optimization	WSO	2005	[385]
Ying-Yang Pair Optimization	YYOP	2016	[546]

Table 31: 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	[115]
Bee System	BS.1	2002	[161]
Hammerhead Shark Optimization Algorithm	HSOA	2019	[251]
Intelligence Water Drops Algorithm	IWD	2009	[420]
River Formation Dynamics	RFD	2007	[434]
Termite Hill Algorithm	TA	2012	[362]
Virtual Ants Algorithm	VAA	2006	[372]
Virtual Bees Algorithm	VBA	2005	[373]
Water-Flow Algorithm Optimization	WFO	2011	[452]

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 518 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 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 [599, 600].

We further elaborate on the above statement: our literature analysis revealed that the majority of proposals (more than a half, 60%) generate 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: 23% of all reviewed algorithms (122 out of 518) were found to be so influenced by classical algorithms that, without their biological inspiration, they could be regarded as incremental variants. The other 396 solvers (about 77%) have enough differences to be considered a new proposal by themselves, instead of another version of existing classical algorithms. But, we must emphasize that in these new algorithms there exists a lack of originality or justification in a significant percentage of cases. We must emphasize that in these new algorithms there exists a lack of justification due to the lack of comparison with the state of the art and the lack of real interest in achieving reasonable levels of quality from the perspective of the optimization of well-known problems in recent competitions.

Table 32: Percentages of similar algorithms in the reviewed literature.

Classical algorithm	Number of papers with similar algorithms	Percentage over the total
PSO	57	11.00%
DE	24	4.63%
GA	24	4.63%
ACO	7	1.35%
ABC	7	1.35%
SA	3	0.59%
Total	122	23.55%

5.2 Identification of the Most Influential Algorithms

In order to know 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 5.2 shows the classification of each algorithm based on its behavior, and the number of proposals in each classification are summarized in Table 32.

Very insightful conclusions can be drawn from this grouping. To begin with, in Table 32 the most influential algorithm was identified to be PSO, appearing in 11% of the reviewed literature (which corresponds to almost 47% of the proposals that were clearly based on a previous algorithm). 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. [72, 73] – have inspired many authors to create new metaheuristics 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 in the evolution of a population. Both have been used by around 5% 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 linear combination of existing ones in the population, which is used by 5% of all reviewed proposals, maybe by its superior

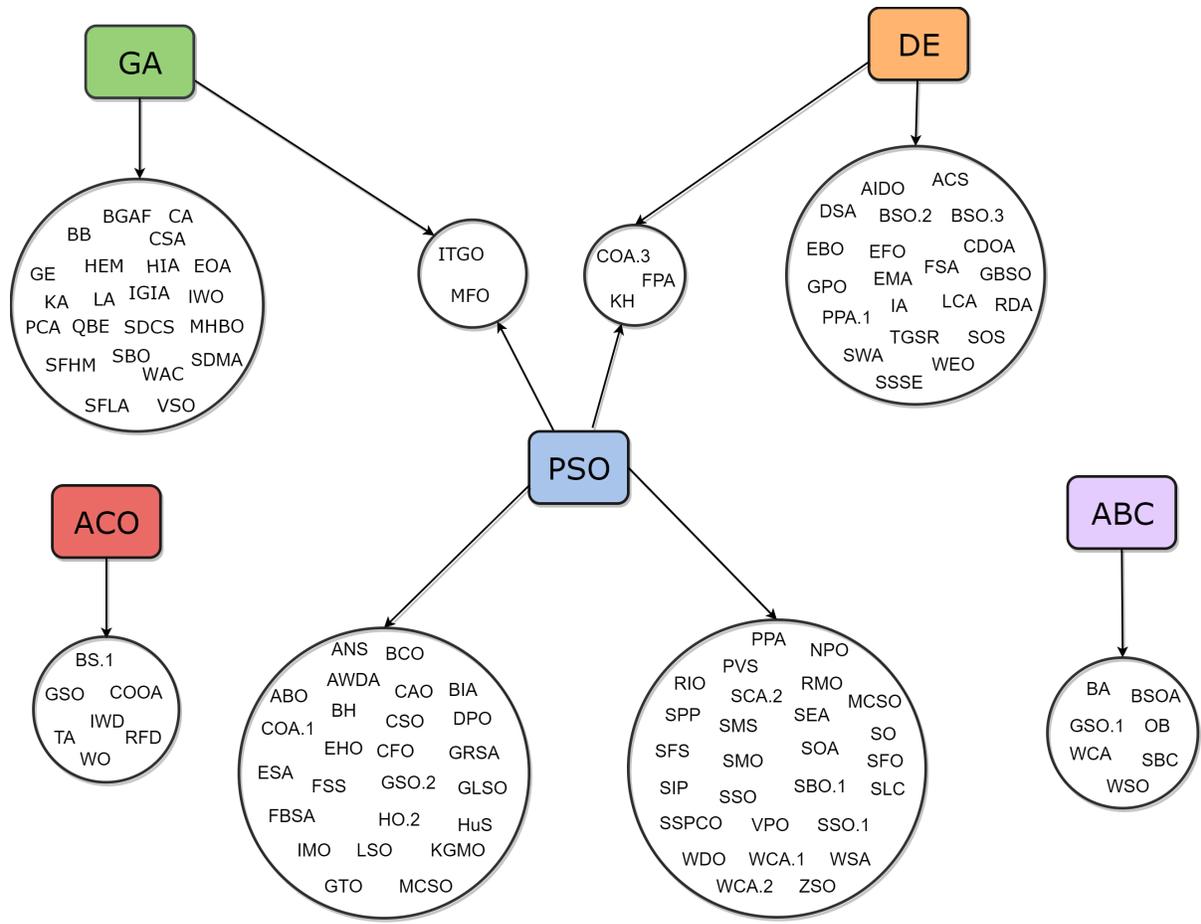


Figure 6: Classification of proposals by its original algorithm.

performance reported for many optimization problems [44].

When inspecting the influential approaches from a higher perspective, two are the categories whose algorithms have been more frequently used to create new nature-based algorithms. The first one is *Swarm Intelligence*: about 14% 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 almost 5% 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 to 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.

6 Learned Lessons and Recommendations from the Analysis of the Evolution of Bio-Inspired Optimization

After reviewing the algorithms and both taxonomies, we have identified several key learned lessons which serve as recommendations to deal with in forthcoming years for that is working on nature- and bio-inspired optimization. The learned lessons gained from the taxonomies and research outlined in [1] form the foundation of this section. In the subsequent sections, we will further expand upon them to provide a more extended analysis. We next outline them in no particular order:

1. **The behavior is more relevant than the natural inspiration:** As was exposed in Section 5, 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 results are very similar in terms of behavior. This disparity is a controversial topic in recent years [3, 599]. 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.
2. **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). 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.
3. **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 to 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 [600]. In some cases, the proposed algorithm is compared to similar algorithms but not with competitive algorithms outside that semantic niche [600, 601]. 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 proven to be competitive in 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.
4. **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 have a very limited influence in new papers after the original publication. For them, there are almost no new papers with improved versions, or applying it to new problems.

Fortunately, other algorithms have a stronger influence. In view of this dichotomy, the researchers should evaluate their proposals for 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.

5. **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 [602, 603]. 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 [604] in C++; jMetal [605] and MOEA² in Java; NiaPy[606], jMetalPy [607] and PyGMO³ in Python; or PlatEMO [608] 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).
6. **The role of bio-inspired algorithms in competitions:** Finally, we also stress on the fact that metaheuristic 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) [44]. 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 the development of a reduced number of proposals but with a better performance.

7 A Short Reflection on The *Good*, the *Bad* and the *Ugly*

This section corresponds to the integration and extension of Section 3 of the article published in [2] within this report. In Section 7.1, we extend the original analysis on the importance of applications, stressing on the numerous applications that leverage results from this research area (the *good*). In section 7.2, we have also extended the original content to more studies based on the recent problems of the area, namely, the lack of algorithmic innovation in algorithms inspired by novel metaphors and good comparisons between algorithms (the *bad*). Section 7.3 remains as in the original work, underscoring the poor practices experienced by the area in recent times (the *ugly*).

7.1 The *Good*: A Present and Future Plenty of Exciting Applications

An undeniable fact is that nature- and bio-inspired optimization algorithms have been applied to a great variety of optimization problems emerging in different disciplines. We distinguish among three different horizons of applications, without being exhaustive, nor entering into the recent horizons of general-purpose AI that we will mention in the conclusions. They are outlined shortly as follows:

- **Real-world engineering applications:** We can find many examples regarding the usage of bio-inspired techniques to solve real-world engineering processes [609]. Furthermore, structural design and civil engineering have also largely embraced the benefits of nature and bio-inspired solvers to assorted problems, including the multi-criteria design of structures [610], logistics and supply chain management [611], to cite a few. The application of Evolutionary Algorithms (EAs) has reached many areas, including works from these human competitions for the design of breakwaters [612], the evolution of antennas for Space Mission of the NASA [613], and also the discovery of new formulas in the field of physics [614], among many other important applications.

¹<http://ecf.zemris.fer.hr/>

²<http://moeaframework.org/>

³<http://esa.github.io/pygmo/index.html>

- **Academic competitions:** From the research perspective, several worldwide competitions have developed over the years to test new proposals in an unbiased and replicable way. In such competitions, DE has created a great impact as the core meta-heuristic algorithm of winning competitors in the global optimization competitions held in renowned conferences (GECCO and CEC) over the last decade [44]. The family of EAs has attracted the interest of researchers by participating in genetic and evolutionary competitions with prizes ⁴ (Annual "Humies" Awards For Human-Competitive Results), and others such as GECCO and CEC previously annotated [600].
- **Going deeper into the creation of Machine Learning (ML) and Deep Learning (DL) models:** Although most algorithms have been developed in recent years, the impact of EAs, a classical family of algorithms, has risen in the last few years. Their use in ML has been widely studied both for the design of models [615] and also as a support for the optimization of those models [616]. These algorithms have gained momentum under the evidence reported around their usage to evolve and improve other AI techniques: most notably, the optimization of the structure and training parameters of deep neural networks [8], or the creation of new data-based models from scratch (i.e. by evolving very essential data processing primitives) that has been presented in the groundbreaking work by Google [617]. With this ongoing development, the research trend of Neural Architecture Search has emerged as another important area full of EAs applications [618], which mainly focuses on the construction of the DL model via the evolution of block of layers [619, 14, 620]. Recently, we have witnessed the use of EAs to model more AI models, as in the case of POET [621] where more environments are generated to learn from the diversity created, with the merging of EAs with Large Language Model (LLM) [622], and with other areas such as Automated Machine Learning [623], Reinforcement Learning and robotics [624], and Multi-task Learning [625]. In recent years, an interesting synergy between bio-inspired optimization and modern ML systems has been observed in the literature, in particular General-Purpose Artificial Intelligence Systems (GPAIS), as we will highlight later in the report.

7.2 The *Bad*: Novel Metaphors Not Leading to Innovative Solvers

As previously mentioned, an ever-growing amount of new bio-inspired optimization techniques has been proposed in recent decades (see Figure 1). This overwhelming number of alternatives could make it difficult to choose an appropriate option for a given optimization problem. The vast number of proposals not only casts doubt on the convenience of choosing one or another algorithm but has also produced solvers that, even if relying on different metaphors, are mathematically too similar to already existing optimization algorithms. In other words, despite the diversity of methods considering their natural inspiration, such diversity does not hold as far as mathematical differences are concerned, as exposed by recent studies [13]. As we have mentioned in the introduction, this metaphor-driven research trend has been already denounced in several contributions [9, 10], which have unleashed hot debates around specific meta-heuristic schemes that remain unresolved to date [11, 12], and with a growing problem when important challenges are not addressed and if more and more biological inspirations are maintained as we can observe in 2024 with more than 500 proposals.

Particular reasons aside, some algorithms are not created to solve problems and provide a practical advantage, but mainly to be published and gain notoriety without any consideration for their lack of algorithmic novelty and innovation. Examples of this controversy can be found in [14], as authors state this problem even in the title of the work. In the previous work, authors “provide compelling evidence that the grey wolf, the firefly, and the bat algorithms are not novel, but a reiteration of ideas introduced first for particle swarm optimization and reintroduced years later using new natural metaphors”. Then, they rewrite these highly cited papers in terms of PSO, and conclude that “they create confusion because they hide their strong similarities with existing PSO algorithms ... these three algorithms are unnecessary since they do not add anything new to the tools that can be used to tackle optimization problems”.

More and more works lack variety in the field, as it was discussed in [15] (“Nature inspired optimization algorithms or simply variations of metaheuristics?”), authors discussed several matters listed as follows:

- **Does the physical analogue exist?:** The inspiration of several bio-inspired algorithms does not strictly follow the rules of a phenomenon. An example is Cat Swarm Optimization, in which cats form a swarm, but in real life, they do not seem to cooperate in any way. Authors show more examples (Coyote Optimization Algorithm, Dolphin Swarm Optimization Algorithm, among others), and claim that “ a significant number of these algorithms are very similar to other already existing ones”.

⁴<https://human-competitive.org/>

- **Similar inspiration or duplicate methods?:** Authors analyze several classes of bio-inspired algorithms such as those based on gravitational forces, water phenomena, bees, penguins, wolves, and bacteria, and conclude that not all the different variations are real contributions.
- **Do authors propose multiple techniques based on the same idea?:** Authors discuss the fact that “several cases can be found where the same authors propose multiple algorithms, which are based on the same nature-inspired idea.” They show various examples in which a research group has almost a dozen “novel” algorithms, with the same researchers at the front. Also, a relevant group of algorithms that are based on attraction and repulsion is full of works under the same researcher’s name.
- **When should a new nature-inspired algorithm be introduced?:** The authors analyze the cases in which it is necessary to create novel algorithms. In their words, “They could be used as global optimizers, while a heuristic algorithm could be added for acting as local search technique for the solutions provided by the nature-inspired method.” They also annotate the ability of these algorithms as optimizers for Artificial Neural Networks and Support Vector Machines.

Due to “useless metaphors”, “lack of novelty” and “poor experimental validation and comparison”, in [16] authors took the decision in this letter to “call upon all editors-in-chief in the field to adapt their editorial policies” to reject the publication of *novel* metaphor-based metaheuristics. More than 80 important researchers in the area signed this letter, and accept the publication of novel bio-inspired algorithms if and only if (1) present their method using the normal, standard optimization terminology; (2) show that the new method brings useful and novel concepts to the field; (3) motivate the use of the metaphor on a sound, scientific basis; and (4) present a fair comparison with other state-of-the-art methods using state-of-the-art practices for benchmarking algorithms.

In the following, we shortly describe the critical analysis that has recently been published in several articles that address this problem “not leading to innovative solvers”:

- In [17], the authors argue that metaheuristics should be simplified by eliminating the unneeded elements as in the case of two winners of the CEC2016 competition, L-SHADE-EpSin and UMOEA-II. The authors conclude that these algorithms “contain operators that structurally bias their search by favouring sampling from some parts of the decision space” and “other metaheuristics should be simplified as they contain unneeded or even harmful operators”. By doing so, metaheuristics will be easier to understand for other researchers. The authors simplify both algorithms by removing operators that are the main cause of structural bias and the experiments when testing against other metaheuristics reveal “that simplification of some metaheuristics may not only make them more transparent and easier to use, but also improve their performance.”
- In [18, 19], the authors analyze the algorithm called Intelligent Water Drops, providing several proofs that “all main algorithmic components of Intelligent Water Drops are simplifications or special cases of ant colony optimization (ACO)”. They also examine the natural metaphor of “water drops flowing in rivers removing the soil from the riverbed”, which is the source of inspiration for this algorithm. Authors conclude that it “is unnecessary, misleading and based on unconvincing assumptions of river dynamics and soil erosion that lack a real scientific rationale”.
- In [20], authors present an analysis of the Cuckoo Search, one of the most well-known algorithms in the literature. Their review of this algorithm based on its usefulness, novelty and sound motivation allow them to “conclude that neither the metaphor nor the algorithm can be considered as part of the set of useful techniques in stochastic optimization”. The Cuckoo Search is just an evolutionary strategy with some parts of DE, algorithms from the last century.
- In [21], authors perform a comparison between seven bio-inspired algorithms with various benchmarks and discovered that “these (algorithms) contain a centre-bias operator that lets them find optima in the centre of the benchmark set with ease”. The conclusion is that making more “comparison with other methods (that do not have a centre-bias) is meaningless”. This problem is similar to the appearance of harmful operators, which has already been discussed in [17]. Authors carry out experimentation with these algorithms against DE and PSO on shifted problems and encounter that “the worst one performed barely better than a random search”, which is a very serious problem.
- In [22], authors discuss the possible causes of the exponential growth of nature-inspired algorithms and the negative consequences for the field. One cause is the pressure to “publish or perish,” and authors argue that the “publishing metaphor-based method is perceived as a low-effort, low-risk process with high potential rewards” because there are authors that have built professional careers out of creating not one but often multiple metaphor-based methods. The other cause

reflected by the authors is “the lack of a well-established statistical tradition in the field compounds the problem, leading to generally poor practices by authors and, in many cases, an inability of reviewers to pick up on the main methodological problems of some papers”.

- In [23], authors aim to present some nature-inspired methods that contribute to achieving lifelike features of computing systems such as open-ended evolution, intelligence, emergence, resilience, and social awareness. In this work, authors select the algorithms of Big Bang–Big Crunch, Mine Blast Algorithm, Lightning Search Algorithm, Water Wave Optimization, Gravitational Search Algorithm, Cat Swarm Optimization, Chicken Swarm Optimization, and Roach Infestation Optimization to “investigate if the mechanisms being part of the algorithms produce qualities found in evolutionary, physical, or chemical analogues.” The conclusion is that most nature-inspired algorithms “do not contribute to achieving lifelike features” and that “the recent algorithms do not remain accurate to the behavior or the phenomenon on which they are based.”
- In [24], the authors claim that grey wolf, moth-flame, whale, firefly, bat, and antlion algorithms are not novel algorithms, and their inspiration has been in the literature for years. To assert this, the authors present a rigorous, component-based analysis of each algorithm that reveals evidences about them: these algorithms are variants of PSO and evolutionary strategies.
- In [25], authors discuss the problem of centre-bias. 47 of 90 algorithms that were compared presented a centre-bias. Also, the authors conclude that Harmony Search (HS), Cuckoo Search Algorithm, Firefly Algorithm, Moth Flame Optimization, Ant Lion Optimizer (ALO) should not be used, due to similarities to other algorithms.

7.3 The *Ugly*: Poor Methodological Practices (Questionable Reproducibility and Comparability)

An alarming issue that prevails in the area besides the number of metaphor-based proposals is the lack of a fair experimental study to prove their competitiveness when compared to existing solvers. In many research contributions, the newly introduced bio-inspired optimization algorithms are not compared to relevant techniques, but only to classical solvers already surpassed by more recent approaches. Therefore, improving their performance in a benchmark is not a reliable proof of performance competitiveness, but rather a convenient choice of comparison counterparts. Moreover, the experimental design is often not right: for example, the optima of the tested functions is often at the center of the domain search, which favors solvers that focus their search over this region of the solution space. In addition, the statistical significance of the performance gaps reported among algorithms is also frequently overlooked, despite the variability of the results imprinted by the stochastic nature of these algorithms. In this regard, in [25] the same controversy as shown in [21] is followed: several algorithms contain a centre-bias operator that makes them more suitable for certain fitness functions. As a result of such bias, these algorithms achieve better results than other algorithms in the appearance of this condition. Thus, they should not be recommended for real-world problems, because the experiments that showed their good performance are biased.

Another important concern in the area is the questionable reproducibility of published studies: the only proof that a proposal is competitive is done experimentally, so it is of utmost importance that results can be reproduced, checked, and verified by third parties, ideally by a different team to that proposing the new algorithm. Unfortunately, in the majority of cases, this is not possible because the implementation of the algorithms is not available, or because important information for the replicability of the experiments is missing or not reported whatsoever [626].

More and more researchers are advocating that a novel metaphor is not enough for a new bio-inspired algorithm to be considered a step beyond the state of the art. Instead, several factors should be proven with empirical evidence, such as superior performance to the state of the art, innovation in the design of its mathematical components and operators, or non-functional benefits that make them more appropriate for real-world optimization problems when compared to other alternatives, e.g. less computational complexity, smaller memory footprint, or faster convergence properties [5].

We strongly urge interested readers to embrace the methodological practices recommended in [4], considering proposals that have been tested against modern techniques, using standard benchmarks, and with adequate statistical testing to shed light on the relevance of performance gaps. Unfortunately, many recent proposals do not follow these guidelines, remaining as evidence of the ugly side that still prevails in this research area.

8 Three Propositional Discussions about Nature- and Bio-Inspired Optimization

As we have mentioned in the introduction, we revisit a triple study of evolutionary and bio-inspired algorithms from a triple perspective, where we stand and what’s next from a perspective published in 2020, but still valid in terms of the

need to address important problems and challenges in optimization for EAs and population-based optimization models, a prescription of methodological guidelines for comparing bio-inspired optimization algorithms, and a tutorial on the design, experimentation, and application of metaheuristic algorithms to real-world optimization problems.

8.1 Bio-inspired computation: Where we stand and what's next

We should pause and reflect on which research directions should be pursued in the future in regard to bio-inspired optimization and related areas, as there are other remarkable fields to be noted as direct applications for bio-inspired optimization. In [3], the authors show a full discussion of the status of the field from both descriptive (*where we stand*) and prescriptive (*what's next*) points of view. Here, we describe the areas in which bio-inspired optimization algorithms are used, and research niches related to them, as shown in Figure 7. The areas and their main aspects that can be studied as promising research lines are:

- **Theoretical studies:** By the hand of the fitness landscape for a better understanding of how a search algorithm can perform on a family of problem instances, of multidisciplinary theories to study the role of diversity and the balance of local search and global search required to undertake a certain problem efficiently, and of convergence, studies to identify the conditions for the convergence of the algorithm, its speed, fitness stability, and other characteristics.
- **Dynamic and stochastic optimization:** These areas need reliable modeling of real optimization scenarios where the characteristics of several of these problems hold (diversity control), and the development of change detection mechanisms relying on characteristics of the optimization algorithm (change detection).
- **Multi/Many-objective optimization:** These areas need new ideas regarding the design of multiobjective solvers because they usually use the main multi-objective solver (radically new approaches) or even the combination of different solvers to create new ones (hybridization of techniques). Another problem to be addressed is the scalability, as solvers do not scale properly with many objectives.
- **Multimodal optimization:** The incorporation of new bio-inspired multimodal solvers and the hybridization of new bio-inspired techniques with traditional strategies can contribute to the progress of this area.
- **Topologies:** A promising research direction is to jointly consider topologies and ensemble strategies to leverage the superior explorative/exploitative powers of ensembles and also topologies for population-based metaheuristics to achieve better solutions than other solvers.
- **Surrogate model-assisted optimization:** This area has promising research lines of investigation with highly dimensional search spaces and DL models, where there is a need to alleviate high computational efforts, with evaluation times that range from hours to days per experiment.
- **Distributed EAs:** These algorithms are needed in large-scale data mining to deal with expensive objective functions, which are common in real-world applications comprising multiple criteria, and also in large-scale multi-objective optimization for the development of asynchronous parallel multi-objective solvers.
- **Ensemble methods and hyper-heuristics:** Both areas have promising challenges in large-scale optimization to address problems such as the encoding strategy, the exploration capabilities of the algorithms, and the computational complexity of the proper ensembles. In real applications, these areas need to address the challenge of the appropriate selection of their low-level composing pieces.
- **Memetic algorithms:** Although these algorithms have shown great results, researchers need to investigate their hybridization with other bio-inspired optimization algorithms for the design of new algorithms, and also the derivation of self-adaptive mechanisms to tune the balance between exploration and exploitation
- **Large-scale global optimization:** For this area, it will be interesting to develop new techniques that automatically infer relationships among variables (grouping variables) that could be optimized in isolation with the minimum loss of efficiency and to study new approaches of memetic computing with this area, due to the great results of DE and large-scale global optimization.

- Parameter tuning: The assignation of proper values to the parameters of bio-inspired algorithms is crucial for obtaining the best possible results for a given problem, so the development of parametric sensitivity analysis, or robustness studies, can be very useful to identify the relevant parameters to tune. Also, when an algorithm is compared to another, it will be necessary to perform a similar parameter-tuning process to make fair comparisons.
- Parameter adaptation: Further research about self-adaptation mechanisms for very sensible parameters is necessary, as it reduces the parameters to tune, but can also yield great improvements.
- Benchmarks and comparison methodologies: The development of a novel bio-inspired solver includes the comparison to other techniques with several fitness functions. To encourage better comparison methodologies, the most promising avenues are the use of existing benchmarks and also the creation of new ones based on real-world problems. Moreover, better comparison methodologies, including more attention to scalability and new statistical testing approaches such as the use of Bayesian tests, are needed. We delve deeper into this in Subsection 8.2.

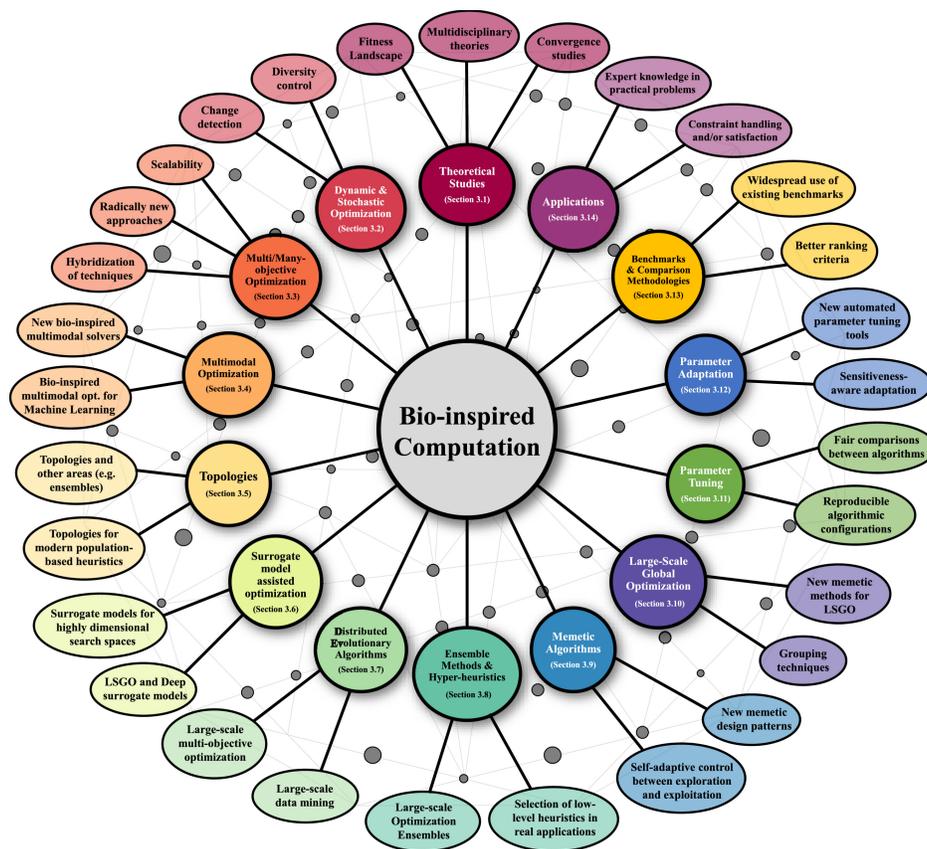


Figure 7: Bio-inspired optimization areas and promising research lines. Image taken from [3].

8.2 Separating the Wheat from the Chaff: Fair and Right Comparisons

One of the problems identified in this manuscript is the abundance of proposals with limited impact. A key aspect for these algorithms to show their strengths is the development of comparative best practices against more competitive algorithms and the state of the art.

To clarify and provide guidelines for a fair and effective comparison between bio-inspired proposals, an extended discussion of the various guidelines to be followed is presented in [4] and here it is summarized as follows:

1. **Benchmarks:** The choice of benchmarking in algorithm evaluation can vary between real-world scenarios and comparisons against existing algorithms. Selecting the right benchmark is crucial, as study conclusions heavily rely on the test environment. However, chosen benchmarks often exhibit biases that can unfairly advantage certain algorithms. Consequently, it is essential to analyze results considering the diverse characteristics of the test problems within the chosen benchmark to ensure fairness in subsequent comparisons.
2. **Validation of the results:** Today, simply presenting raw results in extensive tables falls short. Validating results statistically is imperative, complementing tables with proper statistical analyses. It is crucial to not just employ statistical tests, but to ensure they are appropriate for the data at hand. Often, parametric tests are used without verifying if the underlying assumptions are met by the results. Moreover, the use of visualization techniques in comparative analysis is crucial, as these methods condense vast amounts of data into easily comprehensible representations, also aiding quick interpretation for readers.
3. **Components analysis and parameter tuning of the proposal:** The hypotheses of the proposal should be explicitly outlined at the paper's outset and revisited upon validation of results. Furthermore, authors ought to undertake a comprehensive analysis of results, addressing key aspects such as search phase identification (balancing exploration and exploitation), component analysis (individually assessing each method component and its complexity), algorithm parameter tuning, and statistical comparison with state-of-the-art algorithms. This thorough examination ensures a robust evaluation of the proposed method and its performance relative to existing approaches.
4. **Why is my algorithm useful?:** Prospective contributors must articulate why their proposed algorithm merits attention within the community. Several reasons are proposed to show why a new proposal constitutes an advancement in knowledge, such as its competitiveness against state-of-the-art methods or methodological contributions that foster additional research. This clarity aids in understanding the significance of the proposed algorithm and its potential impact on the field.

These four guidelines form the basis of their work and are discussed in more detail inside the paper published in [4]. Finally, these guidelines are further detailed in Figure 8.

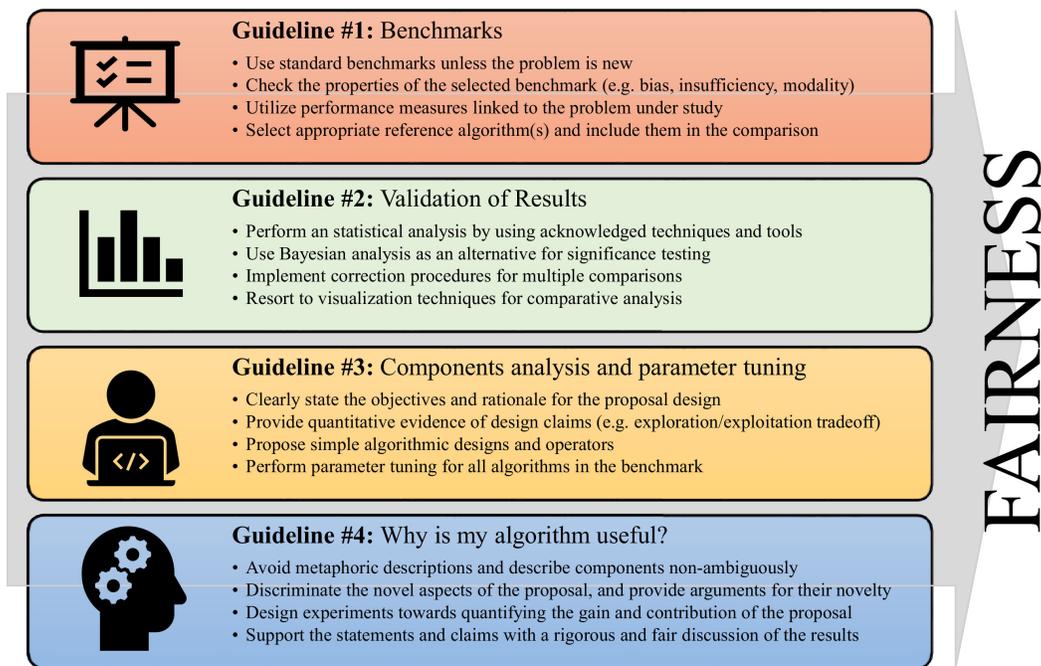


Figure 8: Summary of the guidelines for goods comparisons between bio-inspired optimization algorithms. Image taken from [4].

8.3 Bridging Theory and Practice in Bio-inspired Optimization: Application to real-world Problems

The correct design of a bio-inspired algorithm involves the execution of a series of steps in a conscientious and organized manner, both at the time of algorithm development and during subsequent experimentation and application to real-world optimization problems. In [5], a complete tutorial on the design of new bio-inspired algorithms is presented, and in this work, we make a brief introduction to the phases that are necessary for quality research.

In such work, an analysis is conducted from a critical yet constructive point of view, aiming to correct misconceptions and bad methodological habits. Each phase of the analysis includes the prescription of application guidelines and recommendations intended for adoption by the community. These guidelines are intended to promote actionable metaheuristics designed and tested in a principled manner, to achieve valuable research results and ensure their practical use in real-world applications.

Other studies have standardized key optimization concepts, though often focusing narrowly on specific phases or domains. However, this tutorial addresses this gap by offering a comprehensive approach, covering all steps from problem modeling to algorithm validation and implementation. This analysis sheds light on different issues to be solved while designing new bio-inspired algorithms and, to prevent this difficulty, a list of the steps to be performed during the creation of the algorithm is presented, ranging from the early phase of problem modeling to the validation of the developed algorithm, as follows:

- **Problem Modeling and Mathematical Formulation:** Leading by a previous conceptualization of the problem, this phase entails the modeling and mathematical formulation of the optimization problem.
- **Algorithmic Design, Solution Encoding and Search Operators:** The goal of this phase is to design and implement the bio-inspired algorithm. In order to do so, we have to avoid the metaphor and align the design of the algorithm according to the constraints of the problem at hand.
- **Performance Assessment, Comparison and Replicability:** Certain aspects of correct evaluation, applicability, and consistency of the research are studied in this phase. It should be based on good practices as he published in [4] which are resumed in the previous subsection.
- **Algorithmic Deployment for Real-World Applications:** This phase is focused on the study of the deployment of the algorithm in a real environment.

These phases are described in depth in the manuscript, but here we show in Figure 9 a summary of the main recommendations for every phase of the proposed methodology for the design of new bio-inspired optimization algorithms.

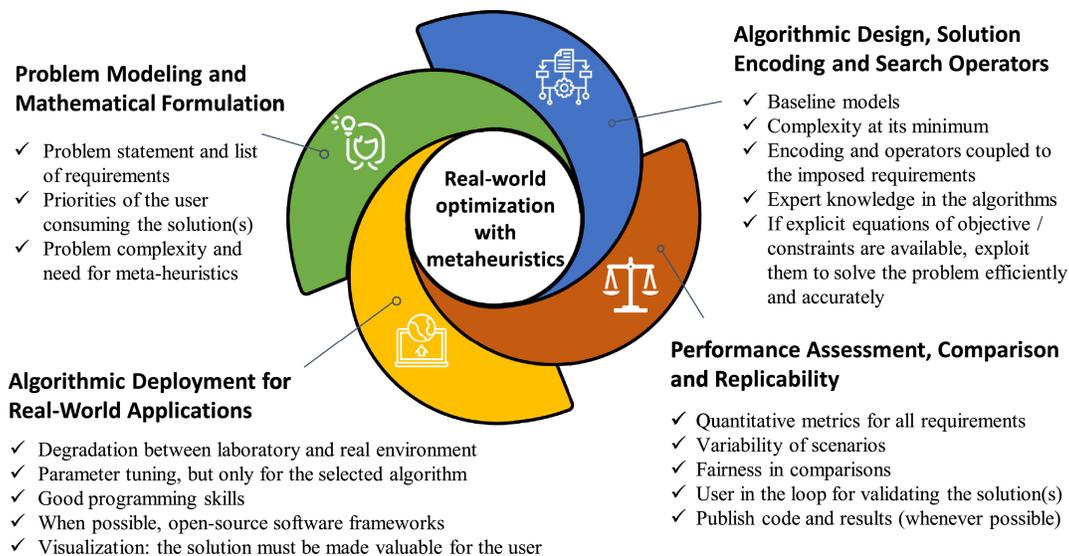


Figure 9: Summary of the recommendations in the four stages of the proposed methodology for the design of new bio-inspired algorithms. Image taken from [5].

9 A Short Recent Literature Analysis: Good Practices, Taxonomies, Overviews, and General Approaches

Since the initial version of this paper in 2020, the field of nature and bio-inspired optimization algorithms has continuously evolved. During these last years, the lack of novelty, and bad comparisons, among others, are described as problems that have to be solved to keep the field in progress. As a result, in Subsection 9.1, we show several studies and guidelines as good practices for designing metaheuristics. At the same time, researchers continue to work on new ways of classifying metaheuristics and publishing general studies on the topic. That is why in Subsection 9.2 we consider, without the intention of being exhaustive with all the studies, a summary of almost a dozen of recent studies about taxonomies [33, 34, 35], overviews [15, 36, 37, 38, 39, 40], and general approaches [41]. For each paper cited in both subsections, we provide its title, year of publication, and a very short summary of its main contents.

9.1 Good Practices for Designing Metaheuristics

The constant evolution of the field leads to a significant issue: the lack of novelty in metaheuristics. However, researchers recognize the need to address this problem and have proposed methods to evaluate the novelty of new algorithms. This section shows different studies and guidelines to measure novelty, to design new metaheuristics, and to perform statistical tests between metaheuristics. We list these approaches as follows:

- **On detecting the novelties in metaphor-based algorithms - 2021 [32]:** This work studies the comparison at the conceptual level using a mathematical formulation based on Markov's chains, and also at the experiment level using the Spearman correlation coefficient between the objective and the population diversity of the algorithms.
- **Similarity in metaheuristics: A gentle step towards a comparison methodology - 2022 [27]:** This paper uses a pool template as a framework for decomposing and analyzing metaheuristics, inspired by another previous work. This template works as a framework for decomposing and analyzing metaheuristics based on these concepts explained in such work: generation method, pool of solutions, archive of solutions, selected pool of solutions, updating mechanism, updated pool, and the archiving and output functions. The authors provide some measures and methodologies to identify their similarities and novelties based on the updating mechanism component, similar to our second taxonomy. They review 15 metaheuristics and their insights confirm that many metaheuristics are special cases of others.
- **Metaheuristics "In the Large" - 2022 [28]:** The objective of this work is to provide a useful tool for researchers. To address the lack of novelty, the authors propose a new infrastructure to support the development, analysis, and comparison of new approaches. This framework is based on (1) the use of algorithm templates for reuse without modification, (2) white box problem descriptions that provide generic support for the injection of domain-specific knowledge, and (3) remotely accessible frameworks, components, and problems. This can be considered as a step towards the improvement of the reproducibility of results.
- **Designing new metaheuristics: Manual versus automatic approaches - 2023 [29]:** This study discusses two methods for the design of new metaheuristics, manual or automatic. Although authors give credit to the manual design of metaheuristics because this development is based on the designer's *intuition* and often involves looking for inspiration in other fields of knowledge, which is a positive aspect. However, they remark that this method could involve finding a good algorithm design in a large set of options through trial and error, possibly leading to eliminating designs that, based on their knowledge, they believe would not work for the problem at hand. For this reason, the authors assure the benefits of automatic design, which seeks to reduce human involvement in the design process by harnessing recent advances in automatic algorithm configuration methods. In this work, several automatic configuration methods and metaheuristic software frameworks from the literature are presented and analyzed, some of them already mentioned in section 6, as steps towards better design of metaheuristics.
- **Research orientation and novelty discriminant for new metaheuristic algorithms - 2024 [26]:** This work proposes a discriminant method based on a mathematical formulation. It provides the division into root and homologous algorithms so that the former represent strongly innovative proposals due to the novelty of their reproduction operators, and the latter does not show any new combinatorial structure about their reproduction operator. This method shows that Harmony

Search, Backtracking Search Optimization Algorithm, Grey Prediction Evolution algorithm, Grey Wolf Optimizer, and Gaining-sharing Knowledge-based algorithm are homologous to several classical algorithms. As a consequence, they develop a research orientation for homologous algorithms to transform the nature metaphor into new structures.

- **Guided learning strategy: A novel update mechanism for metaheuristic algorithms design and improvement - 2024 [30]:** This work provides guidelines for improving the performance of metaheuristics. The authors have developed a strategy for recalling the algorithm's requirements based on the current population. Authors annotate that this novel mechanism is capable of checking that if the algorithm is biased towards exploration, it will shift towards exploitation in subsequent iterations and vice versa. This strategy obtains the dispersion degree of the population by calculating the standard deviation of the historical locations of individuals in recent generations and infers what guidance the algorithm currently needs. This method has been tested with nearly 60 algorithms, validating its effectiveness in improving performance.
- **A Simple statistical test against origin-biased metaheuristics - 2024 [31]:** The authors have developed a test to determine algorithm bias. The test is based on the idea that an unbiased algorithm can choose either direction for one of two different local optima in a function. If there is a difference in behavior between independent runs, then the algorithm is likely biased. Algorithms that are biased in terms of the fitness function can lead to undesired behavior. This paper develops and applies a test to known algorithms, including Grey Wolf Optimizer, Whale Optimization, and Harris Hawk, which fail this test. However, algorithms such as DE, GA, and PSO pass the test. This test is a useful tool to solve the centre-bias problem that has already been studied in [25].

9.2 Latest Metaheuristics based Taxonomies, Overviews, and General Approaches

This section aims to briefly analyze a summary of almost a dozen other taxonomies, overviews, and global approaches developed during these years. Sorted by year of publication, each work is shortly explained to summarize their messages and contribution to the community:

- **A new taxonomy of global optimization algorithms - 2020 [33]:** This work analyzes the four characteristic elements of optimization algorithms: how they initialize, generate, and select solutions, how these solutions are evaluated, and lastly, how these algorithms can be parametrized and controlled. By leveraging these elements, a generalized view of optimization algorithms can be created, just by identifying their specific components. The algorithms, according to those specific components, are classified in a taxonomy based on five categories: hill-climbing, trajectory, population-based, surrogate, or hybrid algorithms. Moreover, the study concludes that most algorithms and algorithm classes have a close connection and share similar components, operators, and a large part of their search strategies, which is the basis for the automated design of new algorithms. Lastly, this work provides a guide for algorithm selection, offering best practices for advanced practitioners when choosing optimization algorithms for new problems.
- **Nature inspired optimization algorithms or simply variations of metaheuristics? - 2021 [15]:** This overview focuses on the study of the frequency of new proposals that are no more than variations of old ones. The authors critique a large set of algorithms based on three criteria: (1) whether there is a physical analogy that follows the metaheuristic, (2) whether most algorithms are duplicates or similarly inspired, and (3) whether the authors propose different techniques based on the same idea. They then specify their criteria for introducing a new metaheuristic.
- **An exhaustive review of the metaheuristic algorithms for search and optimization: taxonomy, applications, and open challenges - 2023 [34]:** This taxonomy provides a large classification of metaheuristics based on the number of control parameters of the algorithm. In this work, the authors question the novelty of new proposals and discuss the fact that calling an algorithm new is often based on relatively minor modifications to existing methods. They highlight the limitations of metaheuristics, open challenges, and potential future research directions in the field.
- **Metaheuristics in a nutshell - 2023 [36]:** The purpose of this overview is to define the main terms related to the concept of metaheuristic. The text does not provide an extensive taxonomy, but it clearly distinguishes between two classes of metaheuristics: trajectory and population algorithms. It describes the most well-known algorithms for both classes and for single and multi-objective problems. Finally, quality indicators and statistical analysis are explained as good practices. This overview serves as an introduction to the main concepts, algorithms, and methodologies that every metaheuristics researcher should know.

- **Initialization of metaheuristics: comprehensive review, critical analysis, and research directions - 2023 [35]:** This review addresses a gap in the literature by developing a taxonomy of initialization methods for metaheuristics. This classification is based on the initialization of metaheuristics according to random techniques, learning methods (supervised learning, Markov models, opposition- and diversification-based learning), and other generic methods based on sampling, clustering, and cooperation. The review also examines the initialization of metaheuristics with local search approaches, offers guidance on designing a diverse and informative sequence of initial solutions, and provides insights that will help research in constrained and discrete optimization problems.
- **Metaheuristic optimization algorithms: a comprehensive overview and classification of benchmark test functions - 2024 [37]:** This work focuses on the practical scenario of developing a new metaheuristic. It reviews over 200 mathematical test functions and more than 50 real-world engineering design problems. For each function, it is described its variables and value range. Due to the design of a metaheuristic should be accompanied by a set of experiments, this paper provides researchers with a wide range of options to test the quality of their new developments.
- **A literature review and critical analysis of metaheuristics recently developed - 2024 [38]:** This review focuses on algorithms with titles containing words such as ‘new’, ‘hybrid’, or ‘improved’, in response to the growing trend of nature-based approaches. After analyzing over 100 algorithms, it was found that a significant percentage of these algorithms outperform previous techniques. From the several analyses made in this review, it is noted that most new algorithms are an improved version of some established algorithm, which reveals that the trend is no longer to propose metaheuristics based on new analogies. Moreover, they compare Black Widow Optimization and Coral Reef Optimization, which are considered new frameworks. By analyzing the components of both metaheuristics, authors evident the lack of innovation, as the operators of such algorithms are merely a combination of other evolutionary operators.
- **Metaheuristic optimization algorithms: an overview - 2024 [39]:** This paper focuses on studying the main components and concepts of optimization. More specifically, the overview provides the advantages (agnostic to the problem being solved, gradient independence, global search capability, the capability of dealing with multi-objective optimization problems, balanced exploration and exploitation, configurability and tuning, practical problem-solving, and innovation) and the limitations (absence of global optimality guarantee, convergence speed, parameter tuning, and black-box nature) of metaheuristics. The authors specifically focus on the references used by the algorithms to guide the search, and on how to achieve a good balance between exploration and exploitation. Visual representations accompany the text to illustrate the behavior of a set of metaheuristics.
- **50 years of metaheuristics - 2024 [40]:** This overview traces the last 50 years of the field, starting from the roots of the area to the latest proposals to hybridize metaheuristics with machine learning. The revision encompasses constructive (GRASP and ACO), local search (iterated local search, Tabu search, variable neighborhood search), and population-based heuristics (memetic algorithms, biased random-key genetic algorithms, scatter search, and path relinking). Each category presents its core characteristics and the description of the mentioned algorithms. This review presents metaheuristic frameworks to guide the design of heuristic optimization algorithms during the last 50 years. It discusses the role of the journal in which it is published in introducing solid heuristic papers. This work also recalls the maturity of the field, which leads to solving very complex problems, with a growing number of researchers applying them, as shown in the numerous conferences and related events. Also, they criticize the fragmentation as each group of research usually applies the same methods regardless of the type of problem being solved, the lack of theoretical foundations, the limited analytical understanding of novel proposals, the problem-specific tuning of metaheuristics, the lack of standardized benchmarking protocols and the absence of general guidelines. Several research directions are also annotated for researchers to be applied in the future.
- **Learn to optimize – A brief overview - 2024 [41]:** This paper discusses the concept of Learn to Optimize (L2O) and its application in accelerating the configuration process to obtain a good solver for unseen instances. The studies can be categorized into three main types: training a solver performance prediction model, training a single solver, and training a portfolio of solvers. The first category aims to connect problem instance features with solver performance, resulting in the selection of the best solver, as seen in Automated Algorithm Selection (AAS). The second category, training a single solver, involves finding the best solver for overall performance on the training instances, known as Automatic Algorithm Configuration (AAC). The last category, training a portfolio of solvers, is a more general case of the second category in which a set of solvers is trained, introducing a higher degree of freedom. L2O has achieved importance in general-purpose approaches and other problems like adversarial attacks.

10 Conclusions

Nature and biological organisms have been a source of inspiration for many optimization algorithms. During the last few years, this family of solvers has grown considerably in size, achieving unseen levels of diversity about 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.

We have reviewed 518 nature- and bio-inspired algorithms and grouped them into two taxonomies. The first taxonomy has considered the source of inspiration, while the second has discriminated algorithms based on their behavior in generating new candidate solutions. We have provided clear descriptions, examples, and an enumeration of the reviewed approaches within each taxonomy category. Our study has critically examined the reviewed literature and found that many algorithms claiming to be inspired by different natural and biological phenomena exhibit algorithmic similarities. Additionally, a significant percentage (24%) of the reviewed proposals have been identified as versions of classical algorithms such as PSO, DE, or GA. These findings shed light on the ongoing debate within the nature- and bio-inspired community regarding the algorithmic contributions of recent advances in the field.

A critical point of reflection associated with this explosion of proposals has been that novel metaphors do not lead to new solvers, and that comparisons undergo serious methodological problems. Although there are increasingly more bio-inspired algorithms, many of them rely on so-claimed novel metaphors that do not create any innovative bio-inspired solvers. In addition, comparisons have been often inadequate, leading to problems of reproducibility and applicability. This problem has captured the interest of other researchers, leading to several papers on various aspects related to bad comparisons and the increasing number of unoriginal proposals, even to the point of not accepting completely new proposals with quality marks. As we have mentioned, we emphasize that in these new algorithms there exists a lack of justification together with the lack of comparison with the state of the art and the lack of real interest in achieving reasonable levels of quality from the perspective of the optimization of well-known problems in recent competitions. Good methodological practices must be followed in forthcoming studies when designing, describing, and comparing new algorithms.

From a positive vision, bio-inspired algorithms have been regularly used in AI and real-world applications. These algorithms hold potential in new scientific avenues, contributing to recent advances in DL evolution [8], the design of large language models (LLM) [627], and more recently, the design and enrichment of GPAIS [628]. GPAIS (including DL evolution and generative AI, such as LLM) are capable of performing tasks beyond those for which they were originally designed. In this context, the paradigm of AI-powered AI, which involves utilizing AI algorithms to enhance other AI systems, assumes paramount importance. In this thrilling era of AI explosion and advancement, we are already witnessing the significant impact of bio-inspired algorithms on the improvement of AI systems through examples like POET [621], EUREKA [624], EvoPrompt [629], and EGANs [630], among others.

In the last update of this report, which is herein released 4 years after its original version, we note that there has been an evolution within the nature and bio-inspired optimization field. There is an excessive use of the biological approach as opposed to the real problem-solving approach to tackle real and complex optimization goals, as those discussed in Section 8.1. This issue needs to be addressed in the future by following guidelines that will allow for the definition of metaheuristics in a way that is appropriate to current challenges. This is important for the constructive design and development of proposals in response to emerging problems. For this reason, the potential impact the emerging problems and GPAIS, population-based metaheuristics as nature and bio-inspired optimization algorithms are poised to shape the future of AI, contributing to the design of continuously emerging AI systems, and serving as an inspiration for the new era of innovation and progress in AI.

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