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Nature inspired optimization algorithms or simply variations of metaheuristics?

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Abstract

In the last decade, we observe an increasing number of nature-inspired optimization algorithms, with authors often claiming their novelty and their capabilities of acting as powerful optimization techniques. However, a considerable number of these algorithms do not seem to draw inspiration from nature or to incorporate successful tactics, laws, or practices existing in natural systems, while also some of them have never been applied in any optimization field, since their first appearance in literature. This paper presents some interesting findings that have emerged after the extensive study of most of the existing nature-inspired algorithms. The need for irrationally introducing new nature inspired intelligent (NII) algorithms in literature is also questioned and possible drawbacks of NII algorithms met in literature are discussed. In addition, guidelines for the development of new nature-inspired algorithms are proposed, in an attempt to limit the misleading appearance of variation of metaheuristics as nature inspired optimization algorithms.

Keywords Nature-inspired intelligent (NII) algorithms · Guidelines for nature-inspired algorithms · AI and optimization · Evaluation of algorithm's innovation

1 Introduction

Computational intelligence (CI) (Chen 1999) as an important and continuously emerging sub-field of artificial intelligence (AI) (Nilsson and Nilsson 1998) focuses on the setup of computational systems that can take decisions based on some rules or models and that are also able to generalize effectively from the analysis of available collections of data. The term Computational Intelligence includes different areas of related research like machine learning, evolutionary computation, hybrid and adaptive intelligence, etc. A newer "branch" of those Computational Intelligence approaches called nature-inspired algorithms

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are becoming popular during the last decade, due to their ability of providing solutions of higher quality in difficult optimization tasks, in contrary to classical OR-approaches, such as mathematical programming. Most of nature inspired intelligent (NII) Algorithms are in fact intelligent meta-heuristic optimization methods. The main advantage of meta-heuristics compared to heuristic techniques is the ability to improve the population of candidate solutions based on intelligence collected during the algorithmic procedure.

Specifically, Holland in the very beginning of evolutionary computation (Holland 1975) paved the way for NII, by introducing the first Genetic Algorithm in literature. Although Genetic Algorithms are-strangely-not considered usually NII approaches but an Evolutionary Algorithms, they made scientists question themselves if there are other concepts in nature that could be possibly modeled within high-performance optimization algorithms. A few years later, in 1983, the first nature-inspired method was proposed by Kirkpatrick et al. (1983). Based on the annealing procedure used in metallurgy, the authors named their algorithm "Simulated Annealing" which has nowadays become one of the most known computational approaches in optimization.

Another nature-inspired algorithm of the early years was developed in 1989 (Bishop 1989), that later on was referred as Stochastic Diffusion Search (Bishop and Torr 1992). This approach maps the solution space, where agents are moving towards good solutions and as a result the local optima are surrounded by many agents. In 1992, M. Dorigo presented in his Ph.D. Thesis (Dorigo 1992) a new approach named Ant Colony Optimization (ACO). This approach used a utility-alike model to emphasize into specific solutions, avoiding at the same time low quality ones. The smart operator presented in the ACO method was pheromone, where every agent updates the pheromone magnitude for each discovered solution path, just like the way ants mark the paths that lead to food sources. Solution paths that are followed by higher numbers of agents are "marked" with larger amounts of pheromone, building strong pheromone trails, and thus the final best solution found might consist of parts of these paths. ACO approach was applied in the known Travelling Salesman Problem initially by Colorni et al. (1992).

Then, in 1995 (Eberhart and Kennedy 1995) proposed the widely known Particle Swarm Optimization (PSO) approach, based on the rules followed in nature by large swarms and flocks of animals when move and act as a group. This has been the first population-based method of nature-inspired intelligent algorithms appeared in literature, in the sense that it is based on the collective intelligence of many agents and not on the improvement of one single solution (e.g. like Simulated Annealing did). Two years later (Storn and Price 1997) proposed Differential Evolution being inspired by the work of Holland (1992) and Genetic Algorithms. Although NII algorithms are considered meta-heuristics, authors mentioned that their approach is a heuristic one. All the above schemes appeared in AI literature prior to year 2000. Since then, the number of published new algorithms keeps increasing without exception every year (Tzanetos and Dounias 2017, 2020).

A question that steadily concerns researchers is if there is an actual need for the existence of so many nature-inspired approaches in literature. Are all these emerging algorithms necessary for solving efficiently different existing problems? And the most important; what is the meaning of characterizing an algorithm as nature-inspired? This paper is trying to take a position to all the above considerations. The work by Fister et al. (2016) focused mostly on population-based nature-inspired algorithms where some interesting observations were given, that contributed to the authors' motivation to further investigate the issue.

The rest of this paper is organized as follows. Section 2 discusses matters related to the use of the term "nature-inspired", investigates the origins of the nature-inspired inspiration (if any) of related existing algorithms, while it also discusses their necessity and suggests when they should be used. The overcrowding of existing and newcomer nature-inspired algorithmic schemes is discussed in Sect. 3, while also the conceptual blocks of NI approaches are analyzed. Suggestions on the development of Nature Inspired Intelligent algorithms are provided in Sect. 4. Finally, Sect. 5 concludes with a synopsis of this work's main findings, along with suggestions for future research.

2 What is a nature-inspired algorithm?

The main issues of a Nature Inspired Intelligent algorithm are provided by Yang (2014), but a proper terminology is provided by Steer et al. (2009), where the criteria for inclusion or exclusion for selecting such schemes are given. In this work is mentioned that "the reference to nature is to any part of the physical universe, which is not a product of intentional human design". Based on the aforementioned definition, there are algorithms that shouldn't be considered as nature-inspired. Such algorithms are those inspired by concepts of human ideas that are intentionally produced. For example League Championship Algorithm (Kashan 2009), Volleyball Premier League algorithm (Moghdani and Salimifard 2018) and some others, should not be considered as nature-inspired, but they should form a new category of algorithms, instead. Anywise, some of them work as post-processing methods or components for other hybrid intelligent approaches.

Fister et al. (2016) proposed a taxonomy for NI algorithms, dividing them in four categories based on the concept idea that they were inspired from: (a) Swarm Intelligent algorithms, (b) Bio-inspired algorithms, (c) Physics and Chemistry-based and (d) Others. However, two main issues came up; the Bio-inspired category is confused with nature-inspired parent-category of algorithms and many of the techniques that were added in the category labeled as "Others", do not exactly fall within the terminology given above. Thus, the Bio-inspired category has been renamed into Organisms-based, while Swarm Intelligence algorithms are distinguished from Organisms-based algorithms, despite the fact that they have been proposed as Swarm Intelligence algorithms (Tzanetos and Dounias 2020). In addition, algorithms that are inspired by Physical Phenomena and Laws of Science were collected (Tzanetos and Dounias 2017), adding up to the taxonomy proposed by Fister et al. (2013).

Techniques that belong to the category labeled as "Others" can form a new category of NII, such as Social Theory approaches. In literature, some research reports have been published on this direction collecting sports-based algorithms (Alatas 2017) or referring to some related algorithms as human-based (Rajakumar et al. 2016). This field could be further investigated.

2.1 Does the physical analogue exist?

Steer et al. (2009) also divide the inspiration of NI algorithms into two categories. The first category consists of 'strong' inspiration algorithms, which model mechanisms that solve problems of the real world. Typical example of this category is the Ant Colony Optimization approach, as the "ants" (agents) do find their way to food sources via pheromone paths.

The second category includes algorithms with 'weak' inspiration, which do not strictly follow the rules of a phenomenon. There are multiple examples for this category, like Moth-flame Optimization (Mirjalili 2015a) or various Swarm Intelligent algorithms, where authors usually propose an algorithm that models a behavior which is not met by the referred-to species that gave its name to the algorithm. For example, cats do not form swarms or at least they do not seem to cooperate in any way. What is more, the update function in Cat Swarm Optimization (Chu et al. 2006) is similar to the corresponding equation proposed in Particle Swarm Optimization. Similarly, algorithms considered having 'weak' inspiration are:

- Coyote optimization algorithm (Pierezan and Dos Santos Coelho 2018),
- Dolphin swarm optimization algorithm (Yong et al. 2016),
- Dolphin pod optimization (Serani and Diez 2017),
- Monkey algorithm (Zhao and Tang 2008) and
- Penguins search optimization algorithm (Gheraibia and Moussaoui 2013).

What is more, a significant number of these algorithms are very similar to other already existing ones. Usually, algorithms with weak inspiration hold their names to differentiate from other popular NI-approaches that work in the same way.

2.2 Similar inspiration or duplicate methods?

In literature, often enough, new algorithms appear under different names, but citing a similar source of inspiration. The same concept on which Central Force Optimization (Formato 2007) was based, has influenced the introduction of Gravitational Search Algorithm (GSA) (Rashedi et al. 2009). GSA influenced in its turn Gravitational Interactions Optimization (Flores et al. 2011). The Electromagnetism-like optimization approach (Birbil and Fang 2003) inspired the creation of Charged System Search (Kaveh and Talatahari 2010), then the Electromagnetic Field Optimization (Abedinpourshotorban et al. 2016) and finally the Artificial Electric Field Algorithm (Yadav 2019). In the same sense, Spiral Optimization (Nasir et al. 2013) is similar to Galaxy-based Search Algorithm (Shah-Hosseini 2011), but also shares the same inspiration with Hurricane-based Optimization (Rbouh and Imrani 2014) and also with Whirlpool Algorithm (Zou 2019), which all four are based on spiral movement around the best solution. Note that none of them has been widely used until today in real world applications. At last, River Formation Dynamics (Rabanal et al. 2007) and Intelligent Water Drops (Shah-Hosseini 2009) were introduced in the same year by different authors, but are based on the same phenomenon.

Two methods are inspired by the movement of waves, i.e. Circular Water Waves (Colak and Varol 2015) and Water Wave Optimization (Zheng 2015), which both were presented in the same year. The cycle of evaporation and rainfall of water in nature, had inspired both Water Cycle Algorithm (Eskandar et al. 2012) and Water Evaporation Optimization (Kaveh and Bakhshpoori 2016). What is more, Artificial Raindrop Algorithm (Jiang et al. 2014), Artificial Showering Algorithm (Ali et al. 2015) and Rainfall Optimization Algorithm (Aghay-Kaboli et al. 2017) have all been based on the rainfall phenomenon. The explosion phenomenon is used to scatter agents all over the solution space in both Grenade Explosion Method (Ahrari and Atai 2010) and Mine Blast Optimization (Sadollah et al. 2012).

The foraging and mating of Bees was inspirational for many authors, resulting in ten different algorithms:

- Marriage in honey bees (Abbass 2001),

- Bee-hive algorithm (Wedde et al. 2004),
- Bee colony optimization (Teodorovic and Dell'Orco 2005),
- The bees algorithm (Pham et al. 2006),
- Honey bees mating optimization (Haddad et al. 2006),
- Artificial bee colony (Karaboga and Basturk 2007),
- Bee pollen collecting algorithm (Lu and Zhou 2008),
- Bumblebees algorithm (Comellas and Martinez-Navarro 2009),
- Bee swarm optimization (Akbari et al. 2010),
- Bumblebees mating optimization (Marinakis and Marinaki 2011), and
- Opt-bees algorithm (Maia et al. 2012).

The majority of these approaches have been used in real-world applications. Bee-Hive algorithm was presented to solve routing problems (Wang et al. 2008; Kiran et al. 2014). Bee Colony Optimization, except for Traveling Salesman Problems (TSP), has been applied also in assignment and scheduling problems. The Bees Algorithm and Marriage in Honey Bees are applied mostly on engineering optimization problems. Honey Bees Mating Optimization is also a successful optimization approach with various implementations on energy problems. The well-known Artificial Bee Colony is considered an established method and thus it cannot be compared with the other bee algorithms. Bee Swarm Optimization, Opt-Bees and Bumblebees Mating Optimization can be found in some application papers. Contrary to the rest bee-inspired approaches, Bumblebees algorithm and Bee Pollen Collecting Algorithm have no application even though they were published in 2009 and 2008, respectively.

Bacteria's foraging strategy inspired Bacteria Foraging Optimization (Passino 2002), Bacterial Chemotaxis (Muller et al. 2002) and Bacterial Swarming Algorithm (Tang et al. 2007). Dolphins have been the inspiration for the proposition of Dolphin Partner Optimization (Y. Shiqin et al. 2009), Dolphin Echolocation (Kaveh and Farhoudi 2013), Dolphin Swarm Algorithm (Wu et al. 2016), Dolphin Swarm Optimization Algorithm (Yong et al. 2016) and Dolphin Pod Optimization (Serani and Diez 2017). Mosquitos oviposition inspired the homonym algorithm (Minhas and Arif 2011), while their flying strategy inspired Mosquito Flying Optimization (Alauddin 2016). Lion's Algorithm (Rajakumar 2012), Lion Pride Optimizer (Wang et al. 2012), Lion Optimization Algorithm (Yazdani and Jolai 2016) and Lion Pride Optimization (Kaveh and Mahjoubi 2018) are based on features of lion's life.

Penguin species have been the main inspiration source of Penguins Search Optimization Algorithm (Gheraibia and Moussaoui 2013), Emperor Penguin Optimizer (Dhiman and Kumar 2018) and Emperor Penguins Colony (Harifi et al. 2019). Spider species made researchers come up with Social Spider Optimization (Cuevas et al. 2013) and Black Widow Optimization Algorithm (Hayyolalam and Pourhaji Kazem 2020). Also, different species of beetles inspired Beetle Antennae Search Algorithm (Jiang and Li 2017), Pity Beetle Algorithm (Kallioras et al. 2018) and Beetle Swarm Optimization Algorithm (Wang et al. 2018b). Shuffled Frog Leaping Algorithm (Eusuff et al. 2006), Jumping Frogs Optimization (Garcia and Pérez 2008) and Japanese Tree Frogs (Hernández and Blum 2011) are based on the same strategy of frogs but in different species of them. Ants have been the inspiration for two successful methods, i.e. Ant Colony Optimization (Dorigo 1992) and Ant Lion Optimization (Mirjalili 2015b). The way that spider monkeys form a group, inspired Spider Monkey Optimization (Bansal et al. 2014), but the climbing strategy of monkeys was modeled in Monkey Algorithm (Zhao and Tang 2008) and Monkey Search (Mucherino and Seref 2007). Blue Monkey algorithm (Mahmood and Al-Khateeb 2019) was added recently in the monkey-based techniques, but is based on Particle Swarm Optimization.

Wolf Search (Tang et al. 2012) has affected Grey Wolf Optimizer (Mirjalili et al. 2014) and Wolf Pack Algorithm (Wu and Zhang 2014), but Grey Wolf Optimizer has become way more known method than the other two. On the other hand, Bat Algorithm (Yang 2010) influenced Bat Sonar Algorithm (Tawfeeq 2012), but Bat Algorithm seems to be an established approach already. Roach Infestation Algorithm (Havens et al. 2008) and Cockroach Swarm Optimization (Zhaohui and Haiyan 2011) model the foraging strategy of cockroaches, while Artificial Social Cockroaches algorithm (Bouarara et al. 2015), Cockroach Swarm Evolution (Wu and Wu 2015) and Cockroach Colony Optimization (Cheng et al. 2015) are based on the social features of cockroaches.

The differences of applications sharing the same inspiration techniques are presented in Tzanetos and Dounias (2017) and Tzanetos and Dounias (2020).

2.3 Do authors propose multiple techniques based on the same idea?

In related literature, several cases can be found where the same authors propose multiple algorithms, which are based on the same nature-inspired idea. For example, Carlos Klein and Leandro dos Santos Coelho proposed Meerkats-inspired algorithm (Klein and dos Santos Coelho 2018) and Cheetah based optimization algorithm (Klein et al. 2018) at the same conference. These two algorithms have the same optimization strategy (newborns follow the male or female members of the clan) and the difference is found on the parameters used on the movement function of candidates or solutions. Furthermore, Leandro dos Santos Coelho worked also on Coyote Optimization algorithm (Pierezan and Dos Santos Coelho 2018) and Rhino Herd Algorithm (Wang et al. 2018a). Both can be considered alterations of Genetic Algorithms because of the “death” of solutions and the population size update, correspondingly. Another example is Elephant Herding Optimization (Wang et al. 2015) and Elephant Search Algorithm (Deb et al. 2015), both introduced by the same authors within the same year.

What especially attracted our interest is the existence of numerous different algorithms proposed by a research group, namely:

- Charged system search (Kaveh and Talatahari 2010),
- Ray optimization (Kaveh and Khayatazad 2012),
- Dolphin echolocation (Kaveh and Farhoudi 2013),
- Colliding bodies optimization (Kaveh and Mahdavi 2014),
- Water evaporation optimization (Kaveh and Bakhshpoori 2016),
- Natural forest regeneration (Moez et al. 2016),
- Thermal exchange optimization (Kaveh and Dadras 2017),
- Vibration particles system optimization (Kaveh and Ilchi Ghazaan 2017),
- Cyclical parthenogenesis algorithm (Kaveh and Zolghadr 2017),
- Lion pride optimization (Kaveh and Mahjoubi 2018) and
- Artificial coronary circulation system (Kaveh and Kooshkebaghi 2019).

All these algorithms have been applied in the same engineering problems, except of Dolphin Echolocation.

This phenomenon is met also in two algorithms proposed by another research group, which correspond to the same modelling idea; hunting preys. The first one was Grey Wolf

Optimizer (Mirjalili et al. 2014) and the second one was the Whale Optimization algorithm (Mirjalili and Lewis 2016). Both algorithms make use of the same encircling hunting method which is performed through the same parameters, except one; the radius that affects the movements around the best solution. What is more, Moth-flame Optimization Algorithm (Mirjalili 2015a) adopts the same calculation of the aforementioned radius. In other words, seems like an attempt is made to break down GWO into two parts, for creating a new algorithm by each part.

The "repulsion" and "attraction" forces of Ions Motion Algorithm (Javidy et al. 2015) look similar to the forces described in Dragonfly Algorithm (Mirjalili 2016a) and even less with the repulsion phase of Grasshopper Optimization Algorithm (Mirjalili et al. 2018). Other techniques proposed by the same author are Ant Lion Optimizer (Mirjalili 2015b), Multi-verse Optimizer (Mirjalili et al. 2016), Sine Cosine Algorithm (Mirjalili 2016b), Salp Swarm Algorithm (Mirjalili et al. 2017), Harris Hawks Optimization (Heidari et al. 2019), Henry Gas Solubility Algorithm (Hashim et al. 2019).

The existence of so many nature-inspired algorithmic approaches brings up the instigation of Fister et al. (2015) to hybridize and adapt an existing algorithm, rather than introduce a new one. On the other hand, algorithms of both Kaveh and Mirjalili have been widely used in literature since their first appearance. However, as it is stated later on in this paper, there is no obvious need to propose a new technique if it does not prove superior to previous existing techniques, unless substantiated properly by the authors initially proposing each technique. Skepticism increases, since the results of each new algorithm are equivalent to those of the rest of the similar algorithms proposed by the same authors.

2.4 When should a new NI-algorithm be introduced?

Despite the name of the algorithm and the nature-inspired principle incorporated into it, what actually matters is the ability of the algorithm to perform well in specific applications. There is a general belief that in some cases heuristic methods are adequate and easier to implement in contrast with Nature-inspired meta-heuristics. However, as the size of the problem increases, so does the difficulty of the problem. Given the fact that as many dimensions the problem has, as much time would be needed to check all possible solutions, we conclude that exhaustive search is not an option. Thus, optimization is a difficult process (Weise et al. 2009), because the goal is to find one of the possible sub-optimal solutions existing in the search space, without knowing either the global optimum, or if there is already a better sub-optimal solution that has not been discovered yet.

As it is stated by Yang (2018), traditional algorithms are usually problem-specific, cannot solve highly nonlinear multimodal problems effectively, most of them are local search tools and the majority of them belongs to the deterministic techniques. On the contrary, NI meta-heuristics do not need to be given specific knowledge on the problem, can deal with high dimensional and nonlinear problems, are useful global optimizers covering larger areas of the solution space in their search routines and the most important is that they are stochastic, meaning that no identical solutions will be found starting by the same initial points. All the above conclude to the fact that NI techniques should be used when traditional methods prove to be of low performance.

Because of their global searching feature, NI algorithms are capable of investigating a larger number of possible solutions. Thus, in cases where there is a feeling that better solutions could exist, a NI meta-heuristic would perhaps be capable to provide more promising solutions. What would make the difference in this case, is the stochastic nature of NI techniques. Even if the known solution of a traditional or heuristic technique is given as initial point, the NI algorithm will end up in different points of the search space in each independent search process.

Furthermore, NI algorithms are useful in hybrid intelligent approaches. 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 NI method. In many cases, however, NI algorithms have been used as optimizers for other well-known intelligent methods such as Artificial Neural Networks (Aljarah et al. 2018) and Support Vector Machines (Zhang et al. 2010). Also, NI algorithms have been widely used in hybrid approaches with Machine Learning and Deep Learning methods (Kazem et al. 2013; Valdez et al. 2014).

3 Is there a need for new optimization approaches?

By now, according to our exhaustive literature search on the matter, at least 256 published nature-inspired algorithms can be found, while there are a few more that are considered nature-inspired but we believe they are not. The authors have recently performed comprehensive surveys around nature inspired intelligence (Tzanetos and Dounias 2017, 2020). In these surveys, the application areas of Nature Inspired Algorithms have been investigated.

First of all, as can be seen in Fig. 1, the rate of proposed NI approaches is rapidly growing since 2005 and beyond. The majority of the proposed NI algorithms are inspired by animals, insects, microorganisms and plants, forming the Organisms-based category. An interesting question arising is what has forced so many researchers to come up with new algorithms.

For the construction of a new algorithm, two possible things might have motivated the corresponding authors:

- either the new NI algorithm manages to solve a problem in a way superior to the way it was solved by previous competitive approaches,

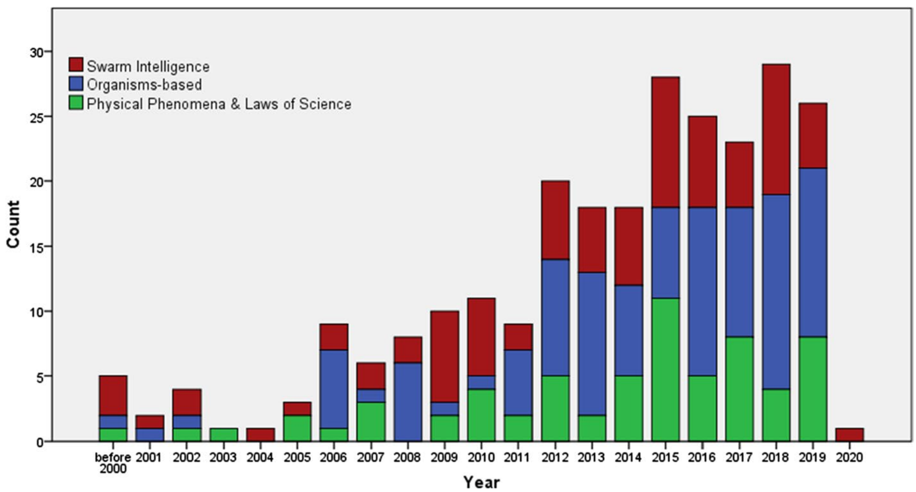

Fig. 1 Number of published algorithms by year

- or a more intelligent mechanism has been incorporated within this new NI algorithm that seems to render it more efficient than others.

The second bullet point inspired the authors of Grammatical Evolution (Ryan et al. 1998) and Differential Evolution (Storn and Price 1997), as well as the built up of Stochastic Diffusion Search (Bishop and Torr 1992). The first question was the main influence for the presentation of Ant Colony Optimization (Dorigo 1992). To answer these questions, we have to investigate if NI algorithms were applied in a problem or they were simply tested in benchmark functions in their initial work. This can be seen in Fig. 2.

In (Tzanetos and Dounias 2020) all NI algorithms proposed for a specific application have been gathered, including all those that were at least applied in a specific field when first introduced. Figure 2, above gives a better depict of the findings of the aforementioned report. Hopefully a small percentage (2.73%) of these algorithms has not been applied in any real-world problem when it was first introduced. However, nearly half of these algorithms (47.27%) were tested only in benchmark functions instead of any real problem. Most of the times, they are compared with GA, PSO and other established methods. The interesting thing here is that each author programs these algorithms by himself and the results are sometimes questionable since the code is not published.

The construction of a repository containing selected benchmark datasets for performance comparison of NI algorithms seems to be a necessary next step, for been able to get information on the capabilities of new NI algorithms [similar benchmark data collections with special characteristics and properties exist for other domains related to machine learning algorithms to classification and/or clustering problems (Dua and Graff 2017; Olson et al. 2017) and also for optimization and other typical OR applications (Beasley 1990)].

What is more, from the 256 existing NI algorithms mentioned above, 128 were proposed for solving a specific real world problem. A comprehensive list with algorithms that have been proposed to tackle real world applications is presented in Tzanetos and Dounias (2019). Most of these algorithms, although they have been proposed for a specific problem, profited from this fact and they have been used in several different real-world problems, either within the same application field or also in other areas. However, a high percentage of them (approximately 30%) have not been applied in any problem since it was initially proposed and beyond.

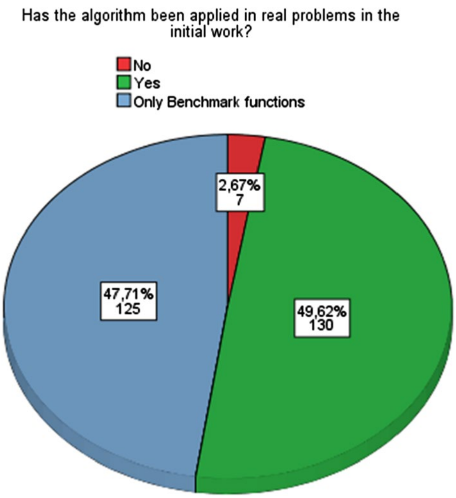

Fig. 2 Percentages of NI algorithms tested in benchmark functions and/or applied in real world applications when first appeared in literature

This is not surprising for algorithms that have appeared recently (e.g. in the last 1 or 2 years), but it is observed also in older NI algorithms. Luckily, only a few NI algorithms have been proposed more than a decade ago and have not been used since then for dealing with real-world applications, as it can be seen in Fig. 3.

There are papers introducing new NI algorithms and at the same time successfully applying them to real-world problems, like the Electromagnetism-like Optimization (Birbil and Fang 2003; Birbil and Feyzioğlu 2003) and the Gravitational Search Algorithm (Rashedi et al. 2009). In addition, a publication in an established journal helps every new proposed NI algorithm to quickly gain popularity and gives a chance to other researchers for further testing in other domains of application.

In Fig. 4 it is observed that no NI algorithms appear in recent literature without demonstrating a successful application in real world problems in the paper where they first appear. This also depicts the importance of an NI algorithm to tackle actual problems. A comprehensive list of the algorithms that belong to each category of the pie chart, shown in Fig. 2, is given in Tzanetos and Dounias (2019).

Below, we discuss and analyze the first nature-inspired intelligence idea that influenced all others subsequently, in introducing other new NI algorithms.

3.1 The swarm model

The work of Eberhard and Kennedy (1995) inspired many others to build swarm intelligence algorithms. The main concept is that all the members of a swarm move together or based on the movement of the other members of the swarm. The movement equation that Eberhard and Kennedy proposed is:

$$x_{k+1}^{i} = x_{k}^{i} + v_{k+1}^{i} \tag{3.1}$$

where x_k^i is the position of the i-th agent in the current iteration k, x_{k+1}^i is the position of the i-th agent in the next iteration and v_{k+1}^i is the velocity of the i-th agent for the next iteration.

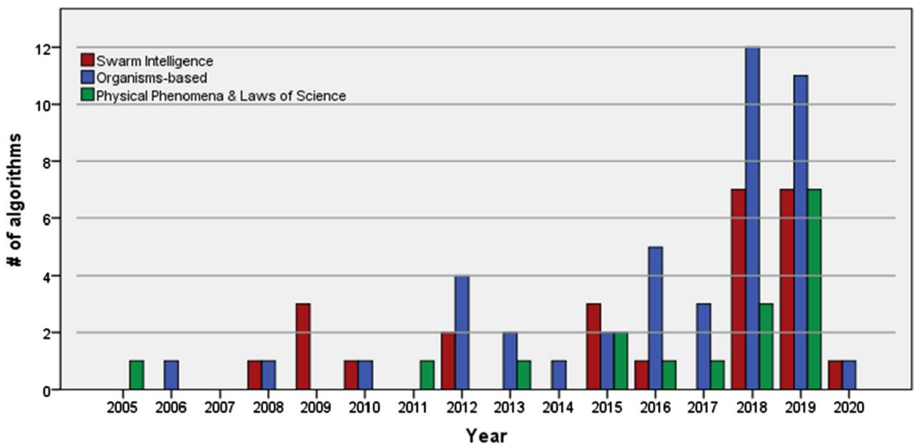

Fig. 3 Year of first appearance for NI algorithms that have not been used since then for dealing with real-world applications

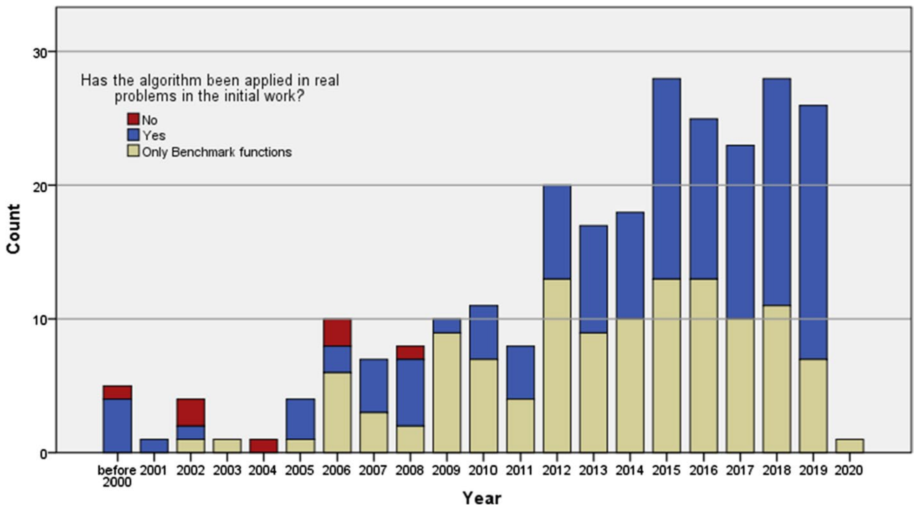

Fig. 4 Cumulative number of NI algorithms with and without application in the paper where they were initially proposed (per year)

Initially, the calculation of velocities was performed randomly. Later on, the information of the position of the best particle and the position of the local best was added in the model:

$$v_{k+1}^{i} = c_1 \cdot rand \cdot \left(x_k^{best} - x_k^{i}\right) + c_2 \cdot rand \cdot \left(x^{best} - x_k^{i}\right) \tag{3.2}$$

where *rand* is a random number between (0, 1), c_1 and c_2 are learning factors, x_k^{best} is the position of the best particle in the current iteration k and x^{best} is the global best particle, i.e. the best solution found so far.

However, many other NI algorithms that appeared in the following years just interfered with this equation and claimed to propose a new NI algorithmic approach in the absence of a "physical analogue" (i.e. a behavior observed in nature or science and which is considered a best practice or a golden standard for a specific task or activity). For example, in Animal Migration Optimization (Li et al. 2014) the movement equation is as follows:

$$x_{k+1}^{i} = x_k^{i} + \delta \cdot \left(x_k^{best} - x_k^{i}\right) \tag{3.3}$$

where δ can be altered based on the problem, nevertheless the authors have used a random number. The similarities with Eq. (3.2) are obvious, while also in the same work the movement equation is the same as Eq. (3.2) without the learning factors c_1 and c_2.

Swarm Intelligence category of NI algorithms has a variety of 46 algorithms (Tzanetos and Dounias 2020). The majority of them are a different version of Particle Swarm Optimization, or in other words they represent another viewpoint for the movement equation of the original PSO approach. This is the case in Bacterial Foraging Optimization (Das et al. 2009), Bird Swarm Algorithm (Meng et al. 2016), Krill Herd (Gandomi and Alavi 2012), Cat Swarm Optimization (Chu et al. 2006), Chicken Swarm Optimization (Meng et al. 2014) and Blue Monkey algorithm (Mahmood and Al-Khateeb 2019).

Note also that the term «swarm» is often confused with «population». All Swarm Intelligence methods are population-based, because they use the intelligence of multiple agents, either by their mutual interaction, or by their mutual collaboration. On the other hand, all population-based intelligent approaches are not swarm intelligence approaches. A robust definition of what is Swarm Intelligence is given by Blum and Li (2008): "[Swarm Intelligence is the] design of intelligent multi-agent systems by taking inspiration from the collective behavior of social insects such as ants, termites, bees, and wasps, as well as from other animal societies such as flocks of birds or schools of fish". A typical example of this misunderstanding is the Firework Algorithm (Tan and Zhu 2010), which is often referred in literature as swarm intelligent algorithm, but actually such swarm activity has never been observed in nature. In Sect. 3 a definition of a NI algorithm is given, for strengthening cases like the one of the abovementioned example of incorrect use of the term "Nature Inspired".

3.2 Is there a best-of-all algorithm?

According to the so-called No-Free-Lunch Theorem (Wolpert and Macready 1995; Wolpert and Macready 1997; Igel and Toussaint 2005) it has been proven that there is no algorithm capable of solving all kinds of problems. This theorem highlights the need of building different algorithmic approaches. Usually the motivation for a researcher for introducing a new NI algorithm is to obtain a more effective solution to an existing problem. For example, A. Hatamlou proposed the Black Hole algorithm (Hatamlou 2013) and Heart optimization algorithm (Hatamlou 2014) for performing data clustering. The results proved promising enough for the Black Hole algorithm and the approach was adopted by other researchers (Li et al. 2015; Pashaei et al. 2015)—also beyond clustering problems (Bouchekara 2014). However, the existence of the Black Hole algorithm rendered the Heart optimization algorithm unnecessary. Also, in contrast with the Black Hole algorithm, the results of Heart optimization algorithm proved that there was no performance improvement. The advantage of the Black Hole approach is the ability to cope with different problems an in this sense, any new NI approach aiming at data clustering, should prove experimentally that outperforms the Black Hole approach in order to appear in related NI literature.

Therefore, there is no such best-of-all algorithm which can tackle all kind of problems. Though, it might be useful for researchers to have a global benchmark that they can refer to.

Summarizing, the naming of an intelligent metaheuristic or a slightly modified known NI technique under a new NI-oriented name, without providing related inspiration evidence, is not the proper thing to do. New NI algorithms when they first appear in literature should be accompanied by a demonstration of their successful application in a real-world problem, or by experimentally proving that they outperform other known competitive approaches in standard benchmark datasets.

4 A framework for nature inspired intelligence

Taking into consideration all the ascertainments stated during the previous section, two main issues remain unspecified; (a) what can be considered as Nature Inspired algorithm and (b) what is the utility of such an algorithm in real world problems.

4.1 Inspiration and algorithm novelty

There are a few works (Fister et al. 2015; Sörensen 2015; Fister et al. 2016) that question the existence of an actual physical analogue for the majority of NI algorithms. This issue is of high importance and should not be ignored by researchers that investigate new NI approaches. The substantiation of the strategy that is used as an inspiration is required when presenting a new NI algorithm. Otherwise, this algorithm can be referred as a meta-heuristic approach.

An essential question that has to be answered when proposing a new NI algorithm is if the inspiration comes from an optimal strategy met in nature or just a good one that simply works adequately and performs a task. Living organisms in nature follow some strategy to solve their daily problems, such as finding food. However, such strategies might be adequate but not optimal. For example, bees cooperate in a specific way to collect pollen (Lu and Zhou 2008), but this strategy followed by bees may not be the best one, while there might be additional optimal strategies which have not been discovered by bees yet. Despite this concern, the inspiration of a new approach should be at least a successful strategy met in nature, such as in finding food, in reproduction (where the strongest survive), in group movement (e.g. PSO), in hunting, in avoidance of natural enemies, in adaptation in the surrounding environment, etc.

A new swarm intelligence oriented algorithm should also be based on behavior that is also met in nature. The reproduction of a PSO-alike algorithm by changing some minor factors of the movement equation is not a new NI algorithm but a PSO modification. Let alone that the substantiation of the physical analogue in these situations is poor. "The animal X does not move in such a way, but…" or "the animal Y does not form swarms, however…" are two examples of using a name of an animal in a technique, where the physical analogue doesn't exist. For example, in the recently proposed Moth-flame optimization algorithm (Mirjalili 2015a), there is a statement for the movement equation mentioning that "…this assumption is done for designing the MFO algorithm, while possibly it is not the actual behavior of moths in nature."

4.2 Performance measurement

Usually, when proposing a new technique, it is necessary to prove its proper functioning through an adequate number of experiments. As it can be seen from Fig. 3, the number of algorithms that are tested on real problems rather than benchmark functions is growing. Thus, it is highly recommended to apply NI algorithms in real world problems, in order to highlight their usage. As it has been stated above, the utility of a new NI algorithm can be found in its capability to solve a problem for the first time, or in a superior way compared to other competitive approaches.

The comparison with other approaches, however, should take place in a fair manner, i.e. under the same conditions. If it is possible, authors should reproduce the results of the literature that they use as benchmarks. Yet still, this is not always feasible. In that case, the selection of the benchmark methods should be made according to three factors:

(a) which method has the best-so-far performance,
(b) which simple or classical methods can be used to solve the problem and
(c) which methods are considered more robust in related literature.

The best performance is needed as a norm for establishing how much better (or worse) is the proposed approach from the best one existing in literature. However, NI algorithms are stochastic optimization techniques, meaning that they may have found the best solution just once during the experimentation phase and this best solution might be an outlier in terms of statistical performance. Thus, the usage of statistical measures such as mean performance or mean error seems to be necessary. The robustness of the method can be measured with this statistical analysis.

What is more, other useful measurements of the performance could be convergence analysis, exploration and exploitation balance, number of function evaluations etc. Each one of these measures can highlight a significant characteristic of the proposed algorithm. The comparison with other methods should take place using the same experimental conditions; same number of parameters (population, generations) and same computational specifications, as it is stated above.

4.3 A metric to specify the utility of a nature-inspired algorithm

The most important factor in this case is the number of the existing published works containing real-world applications of an algorithm. The higher this number is, the greater its utility is. Established methods like Simulated Annealing, Ant Colony Optimization, Gravitational Search Algorithm and Electromagnetism-like algorithm have all been cited extensively, mostly in papers representing successful applications of these approaches to real world problems. The construction of a related database containing known benchmarks is highly recommended for this purpose. At the time, repositories exist where nature-inspired or evolutionary algorithms have been implemented, such as DEAP (Fortin et al. 2012), EvoloPy (Faris et al. 2016), NiaPy (Vrbančič et al. 2018), jMetalPy (Benítez-Hidalgo et al. 2019), PySwarms (Miranda 2018) and Inspyred (Tonda 2020). However, most of them do not include benchmark optimization functions to test these approaches. And when such a repository consists of benchmark functions, they are either only mathematical optimization functions (NiaPy, EvoloPy) or there is no plethora of different functions.

It is suggested that (either on these libraries or in a new one) benchmark problems of real world applications are added/implemented. For each category of problems, i.e. engineering design optimization, energy, finance, etc., one or more typical problems could be described and implemented. Therefore, if a new method is proposed, it can be tested on these problems and compared with the performance of other approaches. Moreover, an index of performance can be constructed based on the results derived by each method that is added in the repository. Examples of such problems for each one of the aforementioned categories of optimization problems could be the following one:

- Tension/compression spring design (engineering design optimization)
- Economic load dispatch (energy)
- Portfolio optimization (finance)
- Travelling salesman problem/vehicle routing problem (operational research)

Such an example is EvoloPy-FS (Khurma et al. 2020), where evolutionary algorithms have been implemented for Feature Selection, which is a very common problem in Machine Learning.

The type of publication where a new NI algorithm was first presented might also play an important role to the diffusion of the approach. Figure 5 shows that high readability publications tend to affect more the applicability of algorithms in the future.

Another important factor that affects the utility and the popularity of a NI algorithm is the novelty of the main idea incorporated by the algorithm. A metric to specify the utility of a nature-inspired algorithm could be related to the number of citations of the approach, as well as to the number of research reports containing applications of real-world problems.

The above details can be found in a recently published database containing nature-inspired algorithms (Tzanetos et al. 2020), where a preliminary analysis on their applications is included. Authors aim to come up with a tool that will go through literature and automatically update the number of studies containing applications of real-world problems and the fields that discriminate the application areas.

5 Synopsis

During the last decade NI algorithms have been consistently emerging. However, a number of these new approaches, although named under a NI-compatible terminology, seem not to have been inspired by any related tactic or strategy met in nature. New techniques are often either PSO-alike approaches or highly similar variations of other existing NI algorithms.

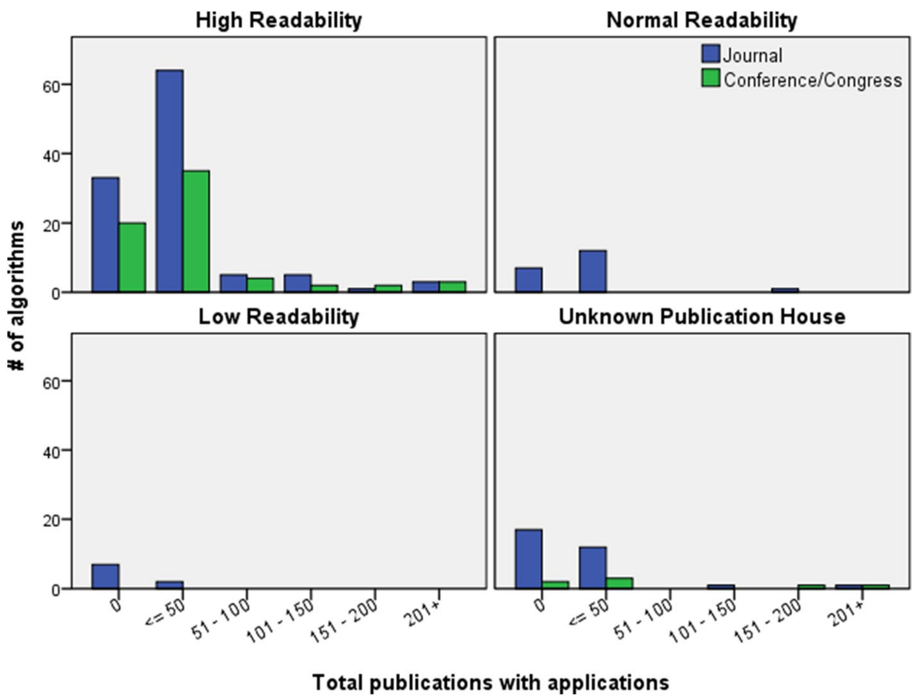

Fig. 5 Total number of publications with applications based on the readability of the journal or conference in which the algorithm initially appeared

The applications of the NI algorithms in real world problems were investigated in this paper, in order to judge the importance and the future prospects of each NI approach. The study tried to define NI algorithms and also to investigate whether there is a real need to insist on proposing new similar approaches in literature. Basic metrics were proposed for defining the utility of each NI algorithm. The necessity for the creation of metrics showing the utility of NI algorithms was recorded. A database containing known standard benchmarks for comparison of the performance of NI algorithms seems to be a necessary step in the near future and thus it was suggested in this study. Furthermore, the construction of a repository consisting of all papers referring to NI algorithms with respect to their successful application in real-world problems was proposed.

The main goal from now on should be the attempt to upgrade and fine-tune the existing NI algorithms, in order to obtain competitive solutions in real-world applications. The construction of efficient hybrid intelligent approaches containing NI algorithms as their main components could be another useful research direction in the near future.

Authors' contributions All authors contributed to the study conception and design. AT has performed the literature review needed for this work. Visualization of review results was performed also by AT. GD supervised this study. The first draft of the manuscript was written by both AT and GD, which also read and approved the final manuscript.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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