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Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications

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Abstract

Bio-inspired computing represents the umbrella of different studies of computer science, mathematics, and biology in the last years. Bio-inspired computing optimization algorithms is an emerging approach which is based on the principles and inspiration of the biological evolution of nature to develop new and robust competing techniques. In the last years, the bio-inspired optimization algorithms are recognized in machine learning to address the optimal solutions of complex problems in science and engineering. However, these problems are usually nonlinear and restricted to multiple nonlinear constraints which propose many problems such as time requirements and high dimensionality to find the optimal solution. To tackle the problems of the traditional optimization algorithms, the recent trends tend to apply bio-inspired optimization algorithms which represent a promising approach for solving complex optimization problems. This paper presents state-of-art of nine of recent bio-inspired algorithms, gap analysis, and its applications namely; Genetic Bee Colony (GBC) Algorithm, Fish Swarm Algorithm (FSA), Cat Swarm Optimization (CSO), Whale Optimization Algorithm (WOA), Artificial Algae Algorithm (AAA), Elephant Search Algorithm (ESA), Chicken Swarm Optimization Algorithm (CSOA), Moth flame optimization (MFO), and Grey Wolf Optimization (GWO) algorithm. The previous related works are collected from Scopus databases are presented. Also, we explore some key issues in optimization and some applications for further research. We also analyze in-depth discussions the essence of these algorithms and their connections to self-organization and its applications in different areas of research are presented. As a result, the proposed analysis of these algorithms leads to some key problems that have to be addressed in the future.

Keywords: Genetic bee colony algorithms; Fish swarm algorithm; Artificial algae algorithm; Chicken swarm optimization; Grey wolf algorithm; Cat swarm optimization

1. Introduction

Nowadays, computational intelligence techniques are applied in many science and engineering applications for information processing, decision-making, and optimization objectives. In the last decades, there are many techniques and algorithms that are developed in different fields such as genetic algorithms, artificial neural networks, evolutionary and fuzzy algorithms. It is expected in the next few years that the intelligent optimization algorithms will be more effective in solving different problems in engineering, scientific, medical, space and artificial satellites for anomaly and failure detection areas.

The behavior of some insects or groups of animals in the nature such as colonies of ant's flocks of birds, swarms of bees, and schools of fish have attracted the attention of computer science researchers to solve several problems in science and engineering. Swarm intelligence is a subfield of artificial intelligence which is concerned with the intelligent behavior of biological swarms by the interaction of individuals in such environments to solve real-world problems by simulating such biological behaviors. In particular, animal and insect colonies

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groups provide a rich environment to develop optimization algorithms. Swarm intelligence is defined as the designing of intelligent algorithms which are simulated by the behavior of different animal societies [1]. Also, it has several characteristics such as adaptation, scalability, speed, autonomy, parallelism and fault tolerance. There are some key important characteristics of swarm intelligence such as self-organization and working division. As animals and birds biological behavior, each in the group is responsible for a specific task individually, and sometimes they work together to achieve a given task.

In computer science, a metaheuristic is developed to find optimization algorithms that can solve given complex problems. Metaheuristics optimization algorithms which are simulated or inspired by biological behaviors of animal or birds and have been used to find the optimal solution to a given problem. A meta-heuristic is a strategy for heuristics to solve complex optimization problems. In mathematical programming, a metaheuristic refers to a procedure that searches a solution to an optimization problem. Metaheuristics use a heuristic function to help the search process. The heuristic search can be either blind search or informed search. Metaheuristic optimization algorithms are turning out to be increasingly well known in different applications because of their nature since they are: (i) based on simple ideas to be easy for implementation; (ii) no need to use inclination of data; (iii) can find optimal neighborhood solution; (iv) finally, it can be applied in different areas of applications.

The optimization process is concerned with finding the optimal solution (s) to a specific problem. To perform this purpose, the choosing of the adequate algorithm is an important issue. However, there are some problems that have a complexity which makes difficult to search for all possible solutions. In the literature, there are several metaheuristic algorithms developed to mimic the biological behavior of animal or insect groups by defining deterministic or random rules to be applied in solving different optimization problems. This paper focuses on recent nine optimization algorithms of the literature that have been developed recently which are based only on the behavior of some animals to simulate the biological behavior of animals in fighting for food and mates. Also, to mimic their behavior and reaction in a different situation in nature as in getting their foods to introduce an alternative method to develop solutions to the complicated problems by stimulating analogical reasoning and thinking of these animals. Therefore, people can learn from the behaviors of such animals to design optimization algorithms to solve complicated. For example, Artificial Bee Colony (ABC) algorithm [2] simulates the collaborative behavior of bee colonies, the Particle Swarm Optimization (PSO) algorithm [3] simulates the biological behavior of fish schooling and bird flocking, the Krill Herd (KH) method [4,5], which mimic the mating behavior of firefly insects, WOA [6,7], which emulates the behavior of humpback whales, grey wolf optimizer (GWO) [8,9], which mimic the hunting technique and social leadership of grey wolves, the Social Spider Optimization (SSO) Algorithm [10] and Lion Optimization Algorithm (LOA) [2] that mimic the behavior of lions and their characteristics of cooperation.

In this paper, nine of recent nature-inspired algorithms, namely GBC, FSA, CSO, WOA, AAA, ESA, CSOA, MFO, and GWO algorithms have been presented and analyzed. The application areas of each algorithm have been proposed.

The remaining of this paper is organized as follows. Section 2 presents and discusses in details nine of the most recent bio-inspired algorithms in the literature. This II describes the inspiration and mathematical model for each algorithm. In section III, we introduce the overview of the evolution of the bio-inspired algorithm over the last ten years. In section IV, we identify the application areas of the nine proposed bio-inspired algorithm in this paper. Section V concludes this paper and highlights the future work.

2. Bio-inspired swarm optimization algorithms

2.1. Genetic bee colony (GBC) algorithm

GBC is a new optimization algorithm which is designed by integrating the advantages of the Genetic Algorithms (GA) and Artificial Bee Colony (ABC) for optimizing the numerical problems. In the ABC algorithm that proposed in Ref. [11] the colony of the artificial bees is divided into three types of bees: the employed artificial bees, the onlookers' bees, and scouts artificial bees. The basic ABC has the following steps [12,13].

2.1.1. Setting ABC parameters

The main parameters of this algorithm should be first initialized. These parameters are the population size *(PS)* or solution, the number of bees that are supposed to be as twice of the size of *PS*, the *(L)* is the limit parameter.

2.1.2. Initialization of the population of solutions

The solutions with size equal to *PS* are generated randomly by the following equation:

$$u = u_{i,j}^{min} + rand[0,1]\left(u_{i,j}^{max} - u_{i,j}^{min}\right) \quad (1)$$

where i is the solution index, j is defined to be the decision variable, *rand* [0,1] generate a random value between 0 and $u_{i,j}^{min}$and $u_{i,j}^{max}$ denote the lower and upper limits of the *j-th* decision variable.

2.1.3. Evaluation of the population solutions

The objective functions can be used to determine the obtained generated solutions.

2.1.4. The employee bee

In this phase, each employed bee has a specific task to discover a new source of food in the surrounding area of its location. Then the employee bees move into candidate neighbor solutions, food sources, such that each employed bee has its food source in the surrounding environment. The nectar amount is evaluated of the detected food sources, and if the amount of the nectar of the detected source of food is greater than the amount of nectar of the current resources of food, then the detected food source is memorized. A neighborhood solution, v can be obtained by the modification of the i -th solution, x is proposed as in the following equation:

$$v_{i,j} = u_{i,j} + \theta_{i,j}\left(u_{i,j} - u_{k,j}\right) \tag{2}$$

where k is a solution which is selected randomly from PS and θ is a randomly selected between [−1, 1].

2.1.5. The onlooker bee

The information that has gained from the previous phase from the employed bees is used to detect the new source of food in the neighborhood of the selected food source by onlooker bee and then other qualified sources of food can be chosen in the exploitation process. The onlooker bees and employee bees try to improve their current solutions with exploring their neighborhood using equation (2). The (*fit*) values can be exploited by onlooker bees select the solutions according to the following equation:

$$p_i = \frac{fit_i}{\sum_{j=1}^{PS} fit_j} \tag{3}$$

2.1.6. The scout bee

When the source of food is detected, the employee bee becomes a scout to find the new source of food in the space of solutions. To control the number of scout bees, a parameter called limit can be used to represent the number of trials. Then, the new source of food needs to be randomly determined when the source of food cannot be improved. In this case, exploitation and exploration processes in the search space have to be carried out together.

2.1.7. Genetic operators

Since the basic structure of ABC is not preferred for the binary optimization; therefore, there is in the literature [14] proposed a new binary version of ABC algorithm by using some genetic operators such as swap and crossover to find the solution binary optimization problems. For this reason, the previous equations (1) and (2) of ABC algorithm should be modified, and then the initial solutions can be generated by the following equation (4) instead of equation (1);

$$U_i : i = 1, \ldots, SN \quad u_{ij} = \begin{cases} 0, \ if\ G(0,1) \le 0.5 \\ 1, \ if\ G(0,1) > 0.5 \end{cases} \tag{4}$$

where $G(0,1)$ is a generated uniformly value.

The integration of searching mechanism of the basic ABC algorithm and GA to the neighborhood will be performed in the following four steps:

(i) In the neighborhood of a food source (current), randomly we can select two other sources of food from the population and then can find a proposed solution;
(ii) Apply the first operator and two-point crossover operator between the current two neighborhoods, best and zero food sources to generate the sources of children food;
(iii) Apply the second operator, swap operator, to the sources of children of food to find grandchildren sources of food;
(iv) The best source of food can be selected as a neighborhood source of food of the obtained solution among the children and grandchildren food sources.

Therefore, the performance of the basic ABC algorithm can be improved in binary optimization problems.

2.2. Fish swarm algorithm (FSA)

The FSA, which has advantages of deep and efficient search, quick convergence speed, is one of the important, intelligent optimization algorithms [15,16]. FSA imitate the behavior of fish, where each fish can search for its source of food based on different ways [17,18]. Also, each fish can allow information communications with others fish until to get a global optimization. This optimization algorithm is presented in Ref. [19.20].

Considering that the proposed problem that under discussion and investigation has D-dimensions and suppose that there is a swarm with N artificial fish. Suppose that the positions of the artificial fish are represented by the variable X, where $X = (x_1, x_2, \ldots, x_n)$. Let $Y = f(X_i)$, describes the fitness function (food source) of the artificial fish. In addition, there are four parameters in FSA which are $d_{ij} = \| X_j - X_i \|$, to represent the distance between X_i *and* X_j. *Visual* to represent the distance of the artificial fish individual, *Step* is used to express the size of the movement of the artificial fish, and δ which represent the crowd factor of the artificial fish. As mentioned, the behavior of the FSA includes different behaviors such as swarming, foraging, following and random behavior.

2.2.1. Preying behavior phase

In this phase, X_i is used to represent the current position of the artificial fish and the fish selects randomly $X_j$from its *Visual* range. There are two cases. The first one, if $f(X_j) < f(X_i)$, which is considered as a problem of minimization, then the artificial fish can move in the direction of $(X_j - X_i)$ or from X_i to X_j. The second one, otherwise the artificial fish can select randomly again another state X_j again. The mathematical equation that can be used to represent the preying step is described as follows:

$$\overrightarrow{X}_i = \begin{cases} X_i + step\, x \dfrac{X_j - X_i}{d_{ij}} x\, rand, & if\ \left(Y_j\right) < (X_i) \\ random\ behavior, & Otherwise \end{cases} \tag{5}$$

where $\overrightarrow{X}_i$ represent the new state of the fish, and *rand* is a value in the interval of [0,1].

2.2.2. The swarm behavior phase

In this phase, each fish, say X_i should explore it's the central position, say X_{cp} of in its current neighborhood fish Neb_{fish}. In this case, the fish will move forward to X_{cp}, if $Y_{cp}/Neb_{fish} > \delta Y_i$. The mathematical equations of the swarming phase can be represented by the following form:

$$\vec{X}_i = \begin{cases} X_i + step\, x \dfrac{X_{cp} - X_i}{d_{icp}} x\, rand, & if\left(Y_{cp}/Neb_{fish} < \delta x Y_i\right) \\ \text{preying}\ behavior, & Otherwise \end{cases} \tag{6}$$

where $\delta \in (0, 1)$ and it defines the concentration of food source.

2.2.3. Following behavior phase

If $X_{Ibestsol}$ is the best local current neighborhood of X_i in the search process and $(Y_{Ibestsol}/Neb_{fish} > \delta Y_i)$, after that the artificial fish X_i will move a step forward to $X_{Ibestsol} - X_i$. The mathematical equation of the following behavior phase is given by:

$$\vec{X}_i = \begin{cases} X_i + step\, x \dfrac{X_{Ibestsol} - X_i}{d_{i,Ibestsol}} x\, rand, & if\left(Y_{Ibestsol}/Neb_{fish} < \delta x Y_i\right) \\ \text{preying}\ behavior, & Otherwise \end{cases} \tag{7}$$

2.2.4. Random behavior phase

In this phase, the artificial fish can choose a position in its visual range randomly, and thus can move towards this position.

2.2.5. Best behavior phase

After completion of the previously mentioned phases, the best behavior can be selected for updating the current state of the artificial fish.

2.3. Cat swarm optimization (CSO)

CSO algorithm is a recent algorithm of optimization that can imitate the cats' behavior [21]. In the last years, CSO has been applied to find the optimal solution for some applications [22]. The mode seeking is applied during the resting period for cats, but they are alert; while the tracing mode is corresponding to the local search method to obtain the optimal solution of the given problem.

2.3.1. Seeking mode

The seeking behavior is mainly contained four main factors; seeking memory pool (SMP), which defines the pool size of seeking memory; seeking range of the selected dimension (SRD), which defines the minima and maxima values of the seeking range; counts of dimension to change (CDC), which represents the dimensions number that can be changed in the seeking mode; self-position consideration (SPC), which is a Boolean-valued variable. Then, we can use a term called mixture ratio (MR) as a fraction of the population that has a small value [23] to ensure that cats usually spend most of their time in the case of observing and resting). The process of seeking is briefly described as follows:

1. The MR can be selected randomly as a fraction of population n_p for seeking cats.
2. Make *SMP* copies for the *ith* cat.
3. Update the position of each copy as plus or minus SRD fraction of the current position value randomly and then replace them.
4. The values of fitness of all copies can be evaluated.
5. The probability of each candidate from all copies can be calculated and then choose the best one of them to place it at the position of *ith* seeking cat.
6. Repeat step number 2 to involve all seeking cats.

2.3.2. The tracing mode

The tracing mode is considered as an exploration method in the optimization process. In this phase, the cat can trace the intended target with high energy. The quick chase of the cat can be modeled in a mathematical form by changing its position. Therefore, we can define the position and velocity of *ith* cat in the D-dimensional space by $P_i = (P_{i1}, P_{i2}, \ldots, P_{iD})$, *and* $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})$, *and* $1 \le d \le D$. The best position of cat swarm can be described as $X_{gbp} = (X_{gbp1}, .X_{gbp2}, \ldots, X_{gbpD})$.

Therefore, the proposed steps that are involved in the tracing mode are presented in the next:

(i) Use the following mathematical form to calculate the new velocity of the i*th* cat:

$$V_{id} = iw.V_{id} + ac.rn.\left(X_{gbpd} - X_{id}\right) \tag{8}$$

where *iw* represents the inertia weight, ac is the acceleration constant, and *rn* is a number that can randomly selected in the interval [0, 1]. Then, the global best X_{gbp} can be randomly selected from the external archive.

(ii) Evaluate the updated position of an *ith* cat by using the following equation:

$$X_{id} = X_{id} + V_{id} \tag{9}$$

(iii) The corresponding boundary value is selected to be a new dimension.
(iv) Evaluate the fitness of each cat.
(v) Finally, we can update the contents of the archive with the position of the cats.

2.4. Whale optimization algorithm (WOA)

Whales are the biggest mammals among all animals and they are extravagant animals. There are some important main parts of this animal such as humpback, killer, blue, and finback. Whales never sleep because as they need to breathe most of the time from the seas and oceans. Moreover, half of the brains can only sleep. Wales live alone or in groups. Some of their parts such as the killer whales can live in a family most of their life. The humpback whales are considered as the biggest whales, and their favorite prey is small fish and krill species.

As indicated by Ref. [24], whales have basics cells in specific regions of their brains. These cells are in charge of judgment, feelings and emotions, and the behavior of humans. But whales are different than human by their twice number of these cells which represent the main advantage of their smartness. Whales behave smart like a human but with low level; can learn, think, communicate, and have emotions as a human does, Whales can develop their dialect as well. The special hunting way of humpback whales is considered as the main interesting point of these whales which can be defined as bubble-net feeding method.

The mathematical model of WOA involves the following phases:

2.4.1. Encircle the prey

The WOA supposes that the optimal candidate solution is the objective prey. The following equation describes how the wales encircle the prey:

$$D = \left| C\overrightarrow{X^*}(t) - X(t) \right| \tag{10}$$

$$X(t+1) = \overrightarrow{X^*}(t) - \overrightarrow{A}.\overrightarrow{D} \tag{11}$$

where t refers to the current position iteration, $\overrightarrow{A}$ and C are considered as coefficient vectors. $\overrightarrow{X^*}$ represents the position vector of the current optimal solution, $\overrightarrow{X}$ is defined as the position vector, $|\quad|$ can be defined as the absolute value, and **.** is defined as element-by-element multiplication. The vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ can be evaluated by using the following mathematical forms:

$$\overrightarrow{A} = 2 \quad \overrightarrow{a}.\overrightarrow{r} - \overrightarrow{a} \tag{12}$$

$$\overrightarrow{C} = 2.\overrightarrow{r} \tag{13}$$

where $\overrightarrow{a}$ can be selected from 2 to 0 during the iterations, and $\overrightarrow{r}$ is defined as a random vector in the interval of [0, 1]. In this case, the humpback whales are attacking the prey by using the bubble-net method.

2.4.2. Bubble-net attacking phase

In this algorithm, there are two methods that are used to describe the mathematical model of the bubble-net phase of the humpback whales according to the following scenario:

(i) The shrinking encircling method: in this method, we can decrease the value of $\overrightarrow{a}$ in Eq. (3) and $\overrightarrow{A}$ is then considered as a value which is selected randomly in the interval $[-a, a]$ such that a can be decreased from 2 to 0 during the iterations. Suppose that $\overrightarrow{A}$ has random values in the interval [−1, 1].
(ii) The spiral updating position method: in this method, a spiral equation can be evaluated for the position of whale and prey by the following equation:

$$\overrightarrow{X}(t+1) = \overrightarrow{D'} \ . \ e^{bi}\cos(2\pi l) + \overrightarrow{X^*}(t) \tag{14}$$

where $\overrightarrow{D'} = \left| \overrightarrow{X^*}(t) - \overrightarrow{X}(t) \right|$ defines the distance of the ith whale to the prey, b is a constant, and l is a random number in the interval of [−1, 1], and **.** is defined as element-by-element multiplication.

During the optimization phase, humpback whales are swimming around its prey in a shrinking circle with the probability of 0.5 percent to choose between spiral model to update the position of whales or the shrinking encircling mechanism. Therefore, the mathematical model of this behavior can be expressed by the following equation:

$$\overrightarrow{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \overrightarrow{A} \ . \ \overrightarrow{D} & \text{if } p < 0.5 \\ \overrightarrow{D'} \ . \ e^{bi} \ . \ \cos(2\pi l) + \overrightarrow{X^*}(t) & \text{if } p \geq 0.5 \end{cases} \tag{15}$$

where p is defined as a random value in the interval of [0,1].

2.4.3. Search for prey phase

In this phase, we define $\overrightarrow{A}$ as the random values which are between 1 and − 1. Suppose that $|\overrightarrow{A}| > 1$ to enable this algorithm of performing the global search. This mechanism can be represented by the following mathematical equations:

$$\overrightarrow{D} = |\overrightarrow{C}.X_{rand} - \overrightarrow{X}| \tag{16}$$

$$\overrightarrow{X}(t+1)X_{\overrightarrow{rand}} - \overrightarrow{A}.\overrightarrow{D} \tag{17}$$

where $\overrightarrow{X}_{rand}$ is defined as a random position vector. The WOA algorithm starts the searching process based on using some solutions that have been selected randomly. The search agents with each iteration update their positions randomly by choosing search agent that obtained yet. The parameter ranges from 2 to 0. The random search agent is selected when $|\overrightarrow{A}| > 1$.

2.5. Artificial algae algorithm (AAA)

AAA is a recent bio-inspired algorithm, and it is mimic the living lifestyles and behavior of microalgae [25]. This algorithm has been based simulated based on microalgae lifestyles such as the algal tendency, reproduction, and adaptation to the surrounding environment to change the dominant species. Therefore algae have three main basic processes called, evolutionary process, helical movement, and adaptation. The population in this algorithm is composed of algal colonies. The algal cells in algal colonies will grow if it receives enough light and then the algal colony will grow to a bigger size. However, in the growing process, the algal colony may not grow enough due to they suffer from insufficient light. In helical movement, each algal colony will be able to move towards the best algal colony.

To describe the main processes of AAA, let $x_i = (x_{i1}, x_{i2}, \ldots, x_{ia})$ where $i = 1, 2, \ldots, n$, and x_i describes the solution in the search space of solution. Consider the population of algae is represented by the following matrix (18):

$$PAC = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1a} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{na} \end{bmatrix} \tag{18}$$

Let the algal colony size of *ith* algal colony is S_i, where $i = 1, 2, \ldots, n$ and the objective function is $f(x_i)$ and S_i will be updated according to the following mathematical equations:

$$S_i = size(x_i) \tag{19}$$

$$\mu_i = \frac{S_i + 4f(x_i)}{S_i + 2f(x_i)} \tag{20}$$

$$S_i^{t+1} = \mu_i S_i^t, i = 1, 2, \ldots, n \tag{21}$$

where μ_i represents the update coefficient of S_i and t describes the current generation.

2.5.1. Helical movement phase

As mentioned algal colony moves in 3D. Therefore, the movement of the algal colony in 3D can be represented the following equations:

$$X_{ih}^{t+1} = X_{ih}^t + \left(X_{jh}^t - X_{ih}^t\right)(sf - \sigma_i)p \tag{22}$$

$$X_{ik}^{t+1} = X_{ik}^t + \left(X_{jk}^t - X_{ik}^t\right)(sf - \sigma_i)\cos\alpha \tag{23}$$

$$X_{il}^{t+1} = X_{il}^t + \left(X_{jl}^t - X_{il}^t\right)(sf - \sigma_i)\sin\beta \tag{24}$$

where equation (22) describes the movement in the 1D, say x, and equations (23) and (24) represent the movement in the two other dimensions, say y, z, k, h, and l represent random integers uniformly generated between 1 and d, X_{ih}, X_{ik}, X_{il} simulate x, y, z, coordinates of the *ith* algal colony, j indicates the index of a neighbor algal colony, p is an independent random number in $(-1, 1)$, α and β are random degrees between 0 and 2π, *sf* is the shear force, and finally σ_i represents the friction surface area of *ith* algal colony and is calculated by the following equation:

$$\sigma_i = 2 \ni \pi r_i^2 \tag{25}$$

$$r_i = \left(\sqrt[3]{\frac{3S_i}{4\pi}}\right) \tag{26}$$

where r_i describes the radius of the hemisphere of the i*th* algal colony, and S_i represents its size.

2.5.2. Evolutionary process phase

In AAA, algal colony X_i becomes bigger when it moves toward an ideal position to obtain the feasible solutions. The following equations describe the simulation of this process:

$$Biggest = \operatorname{argmax}\{size(X_i)\},\ i = 1, 2, \ldots, n \tag{27}$$

$$Smallest = \operatorname{argmin}\{size(X_i)\}, i = 1, 2, \ldots, n \tag{28}$$

$$Smallest_j = Biggest_j.j = 1, 2, \ldots, d \tag{29}$$

where *Biggest* and *Smalles*t describe the biggest and smallest algal colony, j is a random value which represent the index of a selected algal cell randomly.

2.5.3. Adaptation phase

The algal colony which is not growing sufficiently can adapt itself to the surrounding environment. The value of the objective function is considered as inferior or superior to the value after movement. After algal colony completion movement, then the algal colony that has the highest starvation value as described by equation (30) adapts itself to the biggest algal colony with adaptation probability A_p.

$$X_S = \operatorname{argmax}\{starvation(X_i)\}, i = 1, 2, \ldots, n \tag{30}$$

The adaptation phase of AAA of the algal colony process can be described by the following equations:

$$X_{sj}^{t+1} = \begin{cases} X_{sj}^t + \left(Biggest_j - X_{sj}^t\right).Rand1, & if\ Rand\,2 < A_p.j = 1, 2, \ldots, d \\ X_{sj}^t. & otherwise \end{cases} \tag{31}$$

where s is the index of the algal colony with the highest starvation value, and starvation (X_i) is used to measure the starvation level of algal colony X_i, j is the index of algal cell, *Rand1* and *Rand2* generate random value between 0 and 1, and A_p is the adaptation probability and proposed to take values between 0.3 and 0.7.

2.6. Elephant Search Algorithm (ESA)

ESA belongs to the group of contemporary met heuristic search optimization algorithms. This algorithm mimics the behavior and characteristics of an elephant, and its strategy is based on dual search mechanism, or the search agents can be divided into two groups [26] Elephants live in groups, and an elephant group is divided into several subgroups or clans under the leadership of the oldest one in the main group. The ESA mimics the main characteristics and features of herds of elephants. The social structures of elephants are different, where male elephants prefer to live in isolation and females prefer to live in family groups, The spatial enhancement is considered by the female of elephants while male elephants are responsible for the targets of exploration. In this scenario, ESA has three main characteristics as effective search optimization algorithm; (i) the search process iteratively refines the solution to get the optimal solution; (ii) chief female elephants lead intensive local searches at places, where higher probability of finding the best solution is expected' (iii) The male elephants have duties of explorations out of the local optima. Elephants have several features and characteristics that make the inspiration process from elephant's biological behavior is important [27,28]. The ESA is described as follows.

Since elephants live together under the leadership of the oldest one, suppose that each elephant in a clan *cli*. The elephant j in the clan *cli* can be described according to the following mathematical equation:

$$X_{new,cli,j} = X_{cli,j} + c.\left(X_{Best,cli} - X_{cli,j}\right).r \tag{32}$$

where $X_{new,cli,j}$, $X_{cli,j}$, are newly updated and old position for elephant j in clan *cli*, respectively, and $c \in [0,1]$ is a factor that determines the influence of clan *cli* on $X_{cli,j}$, $X_{Best,cli}$ represents the clan *cli*, and $r \in [0,1]$. When $X_{cli,j} = X_{Best,cli}$, equation (1) cannot be used and the fittest elephant can be describes according to the following mathematical equation:

$$X_{new,cli,j} = \alpha.X_{center,cli} \tag{33}$$

where $\alpha \in [0,1$ represents the influence of the $X_{center,cli}$ on $X_{new,cli,j}$. Then the d-th dimension of new individual $X_{new,cli,j}$ is updated based on following mathematical form:

$$X_{center,cli,d} = \frac{1}{n_{cli}}. \sum_{j=1}^{n_{cli}} X_{cli,j,d} \tag{34}$$

where $1 \le d \le D$indicates the d-th dimension, and D is its total dimension, n_{cli} is the number of elephants in the clan *cli*, and $X_{cli,j,d}$ is the d-th of the elephant individual $X_{cli,j}$.

As mentioned adult male elephants leave their families and live alone in the isolated area. This situation can be simulated by separating operator to solve complex optimization problems. To improve the search ability of ESA, let us consider that the elephant individuals with the worst fitness case will implement the separating operator according to the following equation:

$$X_{Worst,cli} = X_{Min} + (X_{Max} - X_{Min} + 1).Rand \tag{35}$$

where X_{Max} and X_{Min} are represent the upper and lower bound of the position of elephant individual, $X_{Worst,cli}$ represent the worst elephant individual in clan *cli*, and $Rand \in [0,1]$ is stochastic distribution. Finally, ESA is developed with the description of clan updating and separating operator.

2.7. Chicken Swarm Optimization Algorithm (CSOA)

CSOA is a recent optimization algorithm that mimics the behaviors of the chicken swarm and their hierarchal order [29,30]. The swarm of chicken can be described by different groups; each group consists of only one rooster and many chicks and hens. There is a competition in this warm between different chickens with a specific hierarchal order. The hierarchal order in this swarm is important in the social lives of chickens such as flock structure, the hens, the chicks and the mother hens. The behavior of the chicken swarm varies with male or female. The head rooster will positively search for the food, and fight with chickens who are around the search area of the group. The chicken that forages for food will be consistent with the head roosters, and the submissive chicken will be standing in the same location of the group to search for their food. Generally speaking in this swarm, there is a competition between chickens; however, chicks search for the food around their mother.

In the next, we describe the mathematical model of the CSOA. This swarm is based on several groups, and each group consists of a rooster, a couple of hens, and chicks. In this case, the chickens with best several fitness values will be considered as roosters, while the chickens with worst several fitness values can be assigned to chicks and the others can be the hens which can choose the group to live in. This hierarchal order and relationship between hens and chicks will be updated every several time steps, say S. Therefore, chickens will follow their group-mate rooster to search the food, while chicks search the food around their hens. Suppose that *NR*, *NH*, *NC*, *NM* represent the number of the roosters, hens, chicks and the mother hens, respectively. The best *NR* chickens are considered to be roosters, and the worst *NC* ones will be represented as chicks. Let $(X^t_{i,j},\ i \in [1,2,\dots,N], j \in [1,2,\dots,D])$ represents all N virtual chickens at time step t. The roosters that have best fitness values will be able to access the food than other those who have worst fitness values. This case can be modeled by the following equations:

$$X^{t+1}_{i,j} = X^t_{i,j} \cdot \left(1 + rand\left(0, \alpha^2\right)\right) \tag{36}$$

$$\alpha^2 = \begin{cases} 1, \ if\, f_i \le f_k \\ \exp\left(\frac{(f_k - f_i)}{|f_i| + \varepsilon}\right), \ k \in [1, N], \ k \ne i \end{cases} \tag{37}$$

where *and* $(0, \alpha^2)$ is a Gaussian distribution where 0 describes the mean and α^2 describes the standard deviation, ε is a small value in order to not to divide by zero, k is the index of the rooster which is selected randomly from the roosters group, and f represents the fitness value for each corresponding x. As mentioned, in chicken swarm, the group-mate roosters lead hens to search their food. This situation can be modeled by the following equations:

$$X_{i,j}^{t+1} = X_{i,j}^t + S1\ .\ rand\ .\ \left(X_{r1,j}^t - X_{i,j}^t\right) + S2.rand\ .\ \left(X_{r2,j}^t - X_{i,j}^t\right) \tag{38}$$

$$S1 = \exp\frac{(f_1 - f_{r1})}{abs(f_i)} + \varepsilon \tag{39}$$

$$S2 = \exp(f_{r2} - f_i) \tag{40}$$

where *rand* is a random value in the interval [0, 1], $r1$ *and* $r2 \in [1, 2, \ldots, N]$ are an index of the rooster and an index of the chicken respectively, $r1 \ne r2$. Therefore $S2 < 1 < S1$ only if $f_i > f_{r1}, f_i > f_{r2}$. Suppose that $S1 = 0$, then the *ith* hen will not move around her head rooster, and it will search for food by herself. If $S2 = 0$, then the *ith* hen searches for the food in their own surrounding area. The values of *S1* and *S2* will be different because of competitions in the group. The chicks then will move around their mother in order to search their food which can be simulated by the following equation:

$$X_{i,j}^{t+1} = X_{i,j}^t + UV\ .\ \left(X_{m,j}^t - X_{i,j}^t\right) \tag{41}$$

where $X_{m,j}^t$ represents the position of the *ith* chick's mother and $m \in [1,\ N]$, *UV* is a parameter and *UV* belongs to *(0,2)* which represent the chick that will follow its mother to search its food.

In the described CSA above, there are two key parameters in this algorithm; the total number of iterations, say *I*, and the interval of relationship update, say *L*. I and J should be set to select values based on the problem. If *I* is too large, it is not conducive to convergence to the global optimum quickly for the CSOA; if *I* is small enough, then the algorithm may find a local optimum.

2.8. Moth flame optimization (MFO) algorithm

Moths in their behaviors are similar to the butterflies, and the main features of moths are their way of navigation by night to fly in the direction of moonlight. Moths usually use a method which is called transverse orientation to navigate in the night.

In the mathematical model of MFO algorithm, we will consider that the candidate solutions can be represented by moths and the position of moths in the space represent the problem's variables. The moths then will be able to fly one or two or three dimension or hyperdimensional space. In this algorithm, the set of moths is described by the following matrix form:

$$M = \begin{bmatrix} m_{1,1} & m_{12} & \cdots & \cdots & m_{1,4} \\ m_{2,1} & m_{22} & \cdots & \cdots & m_{2,4} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n2} & \cdots & \cdots & m_{n,4} \end{bmatrix} \tag{42}$$

where n represents the total number of moths and d represents the number of variables. Now, we can consider that for all the moths; there is an array can be used for storing the values of the corresponding fitness as described in the following array:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \tag{43}$$

The first row of the matrix M in Eq. (42) of each moth is passed to the fitness function and then the output of the each fitness function will be assigned to the corresponding moth as its fitness value. There is another important element in this algorithm which is called flame. Consider the following matrix which is similar to the matrix in Eq. (42) as the following:

$$F = \begin{bmatrix} F_{1,1} & F_{12} & \cdots & \cdots & F_{1,4} \\ F_{2,1} & F_{22} & \cdots & \cdots & F_{2,4} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{n2} & \cdots & \cdots & F_{n,4} \end{bmatrix} \tag{44}$$

where d represents the number of variables.

For the flames, we consider the following array to store the corresponding fitness functions values as descried in the following array:

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \tag{45}$$

We can note then that flames and moths then represent solutions. But, the flames and moths have a different way of obtaining the solution that they are treated and updated them in each iteration.

The MFO algorithm can be described by three-tuple to approximate the global optimal of the given problems and can be described by the following mathematical form:

$$\mathrm{MFO} = (\mathrm{I}, \mathrm{P}, \mathrm{T}) \tag{46}$$

where I represent the function which generates randomly a population of moths and the fitness values and the mathematical form of this function is given by the following form:

$$I : \theta \to \{M, OM\} \tag{47}$$

and P represents the main function that moves the moths around the space of search and this function can be represented by the following form:

$$P : M \rightarrow M \quad (48)$$

and finally T function returns true or false based on the termination criterion and is defended by the following form:

$$T : M \rightarrow \{true, false\} \quad (49)$$

The functions I, P, and T, represent the general scheme of the MFO algorithm.

2.9. Grey Wolf Optimization (GWO) algorithm

2.9.1. Inspiration analysis

The GWO algorithm is one of the recent meta-heuristic algorithms which has been introduced by Ref. [31]. The main inspiration techniques in this algorithm are based on hunting and social leadership of grey wolves (Canis Lupus) which belong to the Canidae family. Gray wolves usually live in groups, and the leader of the group is called *alpha* and is responsible for some activities such as making decisions about sleeping place and hunting. Their second wolf is called *beta*, and he helps the wolf *alpha* in making decisions. The third gray wolf is called *omega* and is responsible for providing the information to all the other wolves. The all other remaining gray wolves are called *delta* and are responsible for dominating the *omega*.

The main phases of the GWO algorithm of gray wolves are based on the following steps:

(i) track, chase and approach the prey;
(ii) pursue, encircle and harass the prey;
(iii) attack toward the prey.

In the designing process of the GWO, the fittest solution is supposed to be the *alpha* (α) wolf. The second best solution is called *beta* (β) and third best solutions is called *delta* (δ) wolves. The other candidate solutions are considered to be *omega* (ω) wolves.

2.9.2. The mathematical model of GWO

The GWO swarm simulates the social behavior of wolves to find the optimal solution for an optimization problem.

(i) Encircling prey

To describe the mathematical model of encircling behavior of wolves, we propose the following two mathematical equations:

$$D = \left| C.X_p(t) - X(t) \right| \quad (50)$$

$$X(t+1) = X_p(t) - A.D \quad (51)$$

where t describes the current iteration; A and C are considered to be coefficient vectors; X_p represents the position vector of the prey, and X describes the position vector of a grey wolf.

(ii) Exploration phase: searching for the prey

The mechanism of GWO depends on identifying the position of the *alpha*, *beta*, and *delta wolves*. To mathematically model the divergence mathematically, we suppose that A is utilized randomly with values which are greater than 1 or less than -1. There is another important component of GWO is called C vector which has random values in the interval [0,2]. The vector C is very useful in the case of obtaining the local optima in the final iterations.

(iii) Attacking prey

To mathematically model the behavior of wolves in hunting the prey, the value of a should linearly decrease. Therefore, A has a random value in $[-a,a]$ and S has a random value in $[-1,1]$ provided that $(|A| < 1)$, then GWO enables the wolves to attack their prey.

(iv) Hunting

To describe the hunting behavior of grey wolves mathematically, the first three best solutions obtained yet are stored and can be updated their positions based on the position of the best search agents. To describe this situation mathematically, we propose the following mathematical forms:

$$D_a = |C_1.X_a - X|, \ D_\beta = |C_2.X_\beta - X| \ D_\delta = |C_3.X_\delta - X| \quad (52)$$

$$X_1 = X_a - A_1 \ D_a, X_2 = X_\beta - A_2 \ D_\beta, X_3 = X_\delta - A_3 \ D_\delta \quad (53)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (54)$$

To summarize, the search procedures in GWO starts by creating the grey wolves population randomly. With the iteration process, *alpha*, *beta*, *and delta* wolves can estimate the position of the prey and then each candidate solution can update its distance from the prey. The candidate solutions, in this case, tend to diverge from the prey if $|A| \geq 1$ and can converge to the prey if$|A| < 1$. Finally, the GWO swarm algorithm can be terminated by finding the optimal solution.

2.9.3. Overview of literature

The first challenge for our study was to identify the database which may help us to identify relevant literature. Therefore Scopus was used as one of the largest databases that includes different academic journal articles. In addition, Scopus provides various areas of research on which the user can search for related papers. Foe searching the related works, we focused on the algorithm name in the "Article Title" or "Article Title, Abstract, Keywords". We recorded the counts of published studies year wise, document-wise, continent-wise and subject wise for each algorithm in the spreadsheet. For year wise evolution of the bio-inspired algorithm, last ten years counts were recorded from 2007 to 2016. In document wise counts five categories were recorded. The categories are an article, conference paper, review, book and miscellaneous. To understand the popularity of the bio-inspired over different location the counts of all the countries over the world was recorded. For plotting the graphs, the count was sum continent-wise. To have the overview of implementation subject wise, the counts were sum subject wise. The counts were group into following subjects applied science, basic science, business studies, engineering, medical science, multidisciplinary and social science. For all these counts the graphs were plotted. The graphs will help in analyzing the evolution of the bio-inspired algorithm. Fig. 1 presents the overall evolution of the bio-inspired algorithm over the last ten years. From Fig. 1, it can be concluded that genetic bee algorithm is the most popular among all the currently reviewed bio-inspired algorithms. After that FSA is second, regarding popularity. There are very few publications on AAA, CSOA, GWO, CSO, ESA, WOA, and MFO algorithm over the last ten years, probably due to they are recent algorithms.

From Fig. 2 it can be concluded most of the publications using genetic bee colony algorithm has published the research paper as an article. Among conference papers, FSA has highest numbers of the publication. The conference paper using FSA is twice the number of conference paper using the genetic bee colony algorithm. As compared to others the CSO, ESA, WOA, and MFO has very fewer publications. From this it can be concluded these algorithms are still evolving and they are very less popular.

From Fig. 3 it can be concluded across the various domains, engineering domain used the bio-inspired algorithm the most followed by applied science, basic science, medical science, business studies and social sciences. Applied science area researchers are mostly using the genetic bee algorithm. Basic science and business studies area researchers are equally using the genetic bee algorithm and fish swarm algorithm. In engineering, researchers are using FSA mostly.

From Fig. 4 it can conclude that Asia is leading in the usage of bio-inspired algorithm. The number of the publication published by Asia using bio-inspired algorithm is more than the sum of the publication published by rest of the continent using bio-inspired algorithm. FSA is popular in Asia among all the other algorithms whereas in rest of the continents genetic bee algorithm is popular.

The search process of these algorithms in Scopus database describes the dominant contributors, promising subject areas, and applications, dominant journal and publication volume till the end of 2016, for these algorithms are presented in Table 1.

3. Domains of Applications

Scopus return 1545 documents for genetic bee colony algorithm, 1031 documents for fish swarm algorithm, 83 documents for artificial algae algorithm, 15 documents for chicken swarm optimization, 126 documents for grey wolf algorithm, 160 documents for cat swarm optimization, 21 documents for ESA, 12 documents for both WOA and MFO algorithm. These 3004 documents were screened. Some of the applications in these documents where using a bio-inspired algorithm for solving the real-life problems, so some of the most interesting applications are listed below.

For doing text summarization, the genetic bee colony algorithm has been used for extracting the data among the sentences and to optimize the similarity [32]. The genetic bee colony algorithm in the past has been used for optimizing the multi-objective layout for robot cellular manufacturing systems [33]. Shortest path in the network can be computed using genetic bee algorithm [34], authors have showcased the computation of shortest path within a wireless sensor network. This algorithm used for evaluating and updating the optimal speed references as in Ref. [35].

The FSA used by Ref. [36] to formulate the clusters and to choose the optimal cluster head among them. In literature, there are references researchers had generated the test data for software testing using FSA [37]. According to them the method was fast, had higher success rate and more stable related to other similar algorithms. It has been purposed, FSA can be used to detect the weak features under strong background noise [38]. In wireless sensor networks for energy efficiency, FSA was used for identifying the stable path for routing purposes [39].

The AAA can be used for solving many NP-hard problems. The multidimensional knapsack problem is considered as one of the important NP-hard optimization problem [24] has demonstrated how AAA can be used to solve multidimensional knapsack problem. The performance of the AAA was compared to other algorithms as in Ref. [40] it was found that AAA performance was better than the others, but the algorithm takes a higher number of the parameters as compared to the other algorithms. The authors in Ref. [41] has shown AAA with multi-light source movement has increased the performance of the AAA.

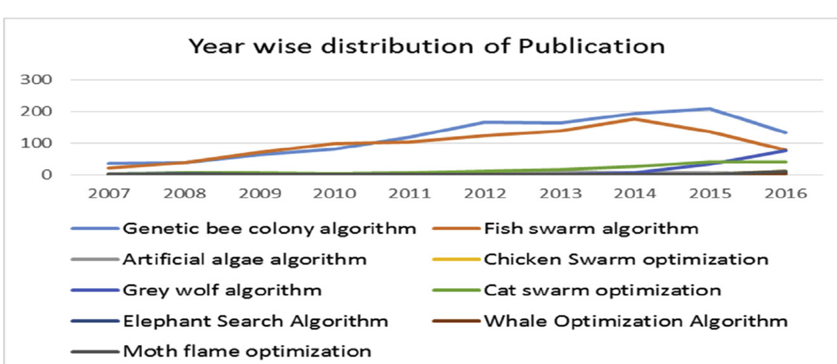


Fig. 1. Evolution of the algorithms over ten years.

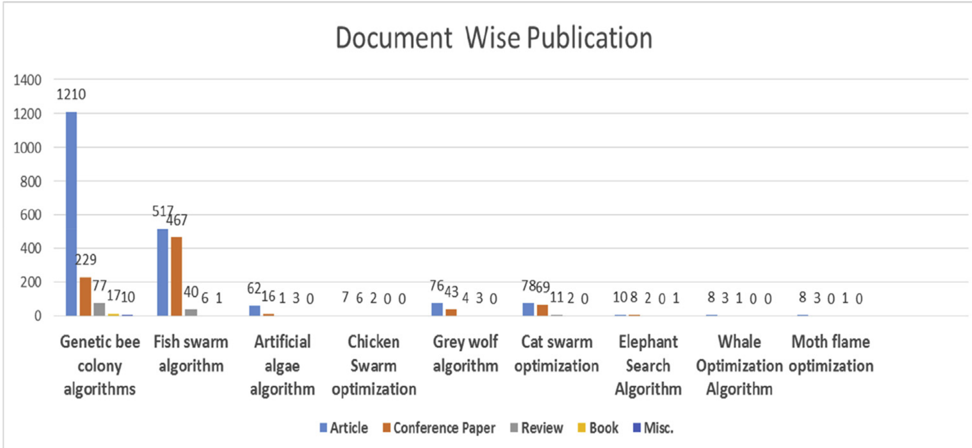
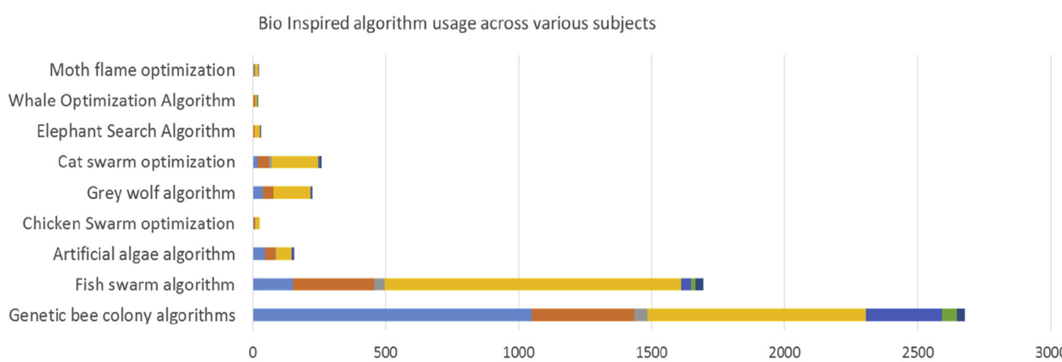


Fig. 2. X-axis contains the algorithms and Y-axis contains the number of the publications.



	Genetic bee colony algorithms	Fish swarm algorithm	Artificial algae algorithm	Chicken Swarm optimization	Grey wolf algorithm	Cat swarm optimization	Elephant Search Algorithm	Whale Optimization Algorithm	Moth flame optimization
Applied Science	1049	152	48	4	39	19	1	3	4
Basic Science	386	304	37	5	38	42	6	6	2
Business Studies	50	42	2	0	1	10	1	0	4
Engineering	821	1114	59	17	139	176	20	7	11
Medical Science	286	36	8	0	6	4	2	2	1
Multidisciplinary	55	17	0	0	0	3	1	1	0
Social Science	30	31	1	0	3	7	1	0	0

Applied Science ■ Basic Science ■ Business Studies ■ Engineering ■ Medical Science ■ Multidisciplinary ■ Social Science

Fig. 3. Usage of the bio-inspired algorithm across various subjects domain.

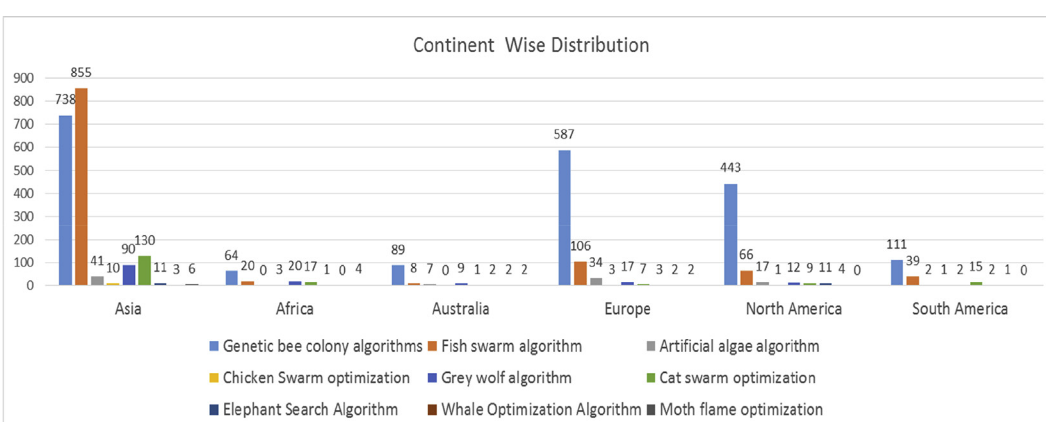


Fig. 4. Bio-inspired algorithm usage across continents.

Table 1
Scopus Database of the proposed algorithms.

Bio-Inspired Algorithm	Dominant Contributors	Dominant Subject Areas	Popular Journals
Genetic bee colony algorithm	• Moritz, R.F.A. • Page, R.E. • Robinson, G.E. • Rinderer, T.E.	• Agricultural and Biological Sciences • Computer Science • Engineering • Biochemistry, Genetics and Molecular Biology • Medicine • Energy (new and renewable energy)	• Apidologie • Journal of Apicultural Research • Behavioral Ecology and Sociobiology • Insectes Sociaux • Applied Soft Computing Journal
Fish swarm algorithm	• Fernandes, E.M.G.P. • Jiang, M. • Rocha, A.M.A.C. • Zhou, Y. • Yazdani, D.	• Engineering • Computer Science • Mathematics • Physics and Astronomy • Energy (new and renewable energy)	• Applied Mechanics and Materials • Advanced Materials Research • Communications in Computer and Information Science • International Journal of Control and Automation • Mathematical Problems in Engineering
Cat swarm optimization algorithm	• Pan, J.S. • Tsai, P.W. • Crawford, B. • Soto, R. • Panda, G.	• Computer Science • Engineering • Mathematics • Energy • Physics and Astronomy	• Advances in Intelligent Systems and Computing • Expert Systems with Applications • International Journal of Applied Engineering Research • Communications in Computer and Information Science • Mathematical Problems in Engineering
Whale Optimization Algorithm	• Breckenridge, C. • Cárdenas, A.E. • Dametto, M. • Ebrahimi, A. • Ghazaan, M.I.	• Engineering • Computer Science • Mathematics • Physics and Astronomy • Medicine • Energy (new and renewable energy)	• Advances in Engineering Software • Journal of Applied Sciences Research • Journal of Biomechanics • Journal of Natural Gas Science and Engineering • Journal of the Acoustical Society of America
Artificial algae algorithm	• Ector, L. • Gevrey, M. • Jeong, K.S. • Joo, G.J. • Lek, S.	• Computer Science • Environmental Science • Engineering • Agricultural and Biological Sciences • Biochemistry, Genetics and Molecular Biology	• BMC Bioinformatics • Ecological Modelling • Applied Mechanics and Materials • Applied Soft Computing Journal • Biosystems
Elephant search algorithm	• Deb, S. • Fong, S. • Dienno, D. • Rahn, C.D. • Tian, Z.	• Computer Science • Mathematics • Engineering • Medicine • Energy	• ACM Transactions on Computer Systems • American Journal of Roentgenology • Dongbei Daxue Xuebao Journal Of Northeastern University • Energy Conversion and Management • IEEE Transactions on Computational Social Systems
Chicken Swarm optimization algorithm	• Emary, E. • Hafez, A.I. • Hassanien, A.E. • Kong, F. • Wu, D.	• Computer Science • Engineering • Energy • Mathematics • Environmental Science	• Advanced Materials Research • Advances In Intelligent Systems and Computing • Advances In Science and Technology of Water Resources • Applied Thermal Engineering • Dianli Xitong Baohu Yu Kongzhi Power System Protection and Control
Moth flame optimization algorithm	• Hassanien, A.E. • Allam, D. • Bhesdadiya, R.H. • Emary, E. • Eteiba, M.B.	• Computer Science • Engineering • Business, Management, and Accounting • Decision Sciences • Mathematics • Physics and • Astronomy	• Knowledge-Based Systems • Applied Intelligence • Applied Sciences Switzerland • Energy Conversion and Management • Journal of Industrial And Production Engineering

Table 1 (*continued*)

Bio-Inspired Algorithm	Dominant Contributors	Dominant Subject Areas	Popular Journals
Grey wolf optimization algorithm	• Hassanien, A.E. • Sulaiman, M.H. • Mustaffa, Z. • Emary, E. • Mohamed, M.R.	• Computer Science • Engineering • Energy • Mathematics • Environmental Science • Physics and Astronomy • Energy (new and renewable energy)	• Advances in Intelligent Systems and Computing • Neural Computing and Applications • Advances In Engineering Software • Arpn Journal of Engineering and Applied Sciences • International Journal of Electrical Power and Energy Systems

CSOA can be used for feature selection based on maximizing the performance of classification process while minimizing the selected features number. It has been done by Ref. [42] they had applied the CSOA on 18 datasets for feature selection. The flood disaster assessment method based on the CSOA was purposed by Ref. [43]. The assessment model was applied on dataset and results were discussed. Using CSOA, an optimized serially concatenated convolution turbo code (SCCTC) was suggested by Ref. [44] to improve bit error rate. Using this at higher values of signal noise ratio also the bit error rate can be improved. To compare the performance of CSOA with other algorithms experiments were conducted by Ref. [45] on twelve benchmark complex problems with a speed reducer design.

The GWO was used by Ref. [46] for optimizing the wide-area power system stabilizer (WAPSS) parameters. According to [47] grey, the wolf does not need operators like crossover and mutation, and it needs very less memory and time to run. Through the interactions of the individuals in the population, grey wolf algorithm can find out the optimal areas of the complex search space. To plan the underwater route terrain aided positioning the method based on GWO algorithm was purposed by Ref. [48]. They have beautifully showcased the implementation method in their research paper. Because of the low computational cost of the GWO algorithm, it has been used by Ref. [49] for reducing the parametric sensitivity in fuzzy control systems.

Using CSO algorithm authors [50] had proposed the solution to solve a NP-hard flow shop problem. The flow shop problem has applications in various fields. According to them, CSO algorithm solves the problem with 50 jobs or lesser without any error. According to [51], cat swarm algorithm is an effective tool to evaluate and identify the parameters of single and double diode solar cell model. The technique purposed by them can find the global optimal solution and consistency solution. The problem of channel cross-section optimization was solved by (Shang et al., 2016) using the CSO algorithm. According to them, the method has the high efficiency and high precision for solving the problem. Using cat swarm algorithm, the problem of wind power system design optimization was solved by them [52]. This is done by optimizing the reliability with the help of the cat swarm algorithm.

According to [53] ESA perform well and stable on some benchmarking optimization functions such as Ackley's, Easom's, Griewank's, Michalewicz's, Rastrigin's, Rosenbrock's, Schwefel's, Sphere's, and Zakharov's with comparing to other metaheuristic algorithms. The ESA is ranked after Firefly algorithm for the fitness values optimization. To solve the NP-hard traveling salesman problem, ESA is used by Ref. [54] in their research paper. In solving the traveling salesman problem different ratio of the female and male elephants are put under testing to compute the least cost paths.

The WOA was proposed by Ref. [23] and they have conducted experiments mathematically based on 29 different mathematical functions for analyzing the exploration, exploitation, convergence, and local optima avoidance behavior of the whale optimization algorithm. The authors using the WOA solved the six structural engineering problem. There are well known six engineering structural problems in the literature that can be solved by WOA which are considered as the design of a welded beam, design of a pressure vessel, design of a tension or compression spring, design of a 15-bar truss, design of a 25-bar truss, and design of a 52-bar truss design [55]. For production optimization, the authors [56] had used the whale based algorithm. The authors had pointed out the algorithm had reduced the time by half for finding the optimum answer of production optimization.

Using the MFO algorithm, the parameters of the least squares support vector machine were optimally determined and then the model was used for annual power load prediction [57], and they showed that the MFO algorithm is promising and attractive. Using the algorithm for optimizing parameters had improved the accuracy of the forecasting. For parameter extraction of the diode of a solar cell, MFO algorithm was used by Ref. [58]. The performance of the used algorithm in this work was compared with other algorithms and the results showed that this algorithm is reaching to the best solution with lower time of execution. The multi-layer perceptron trained by MFO algorithm in Ref. [59] research paper. Their method had experimented with five standard classification and three function-approximation datasets. The results of the experiment show moth flame algorithm solves the local optima problem and achieves the high accuracy. With the help of the MFO, an optimal shape of a marine propeller was designed [60].

We reviewed the applications of the proposed algorithms in this paper, and we summarized the scope of these applications with the objective that can be fulfilled by these recent bio-inspired algorithms as presented in Table 2.

Table 2
Application areas of the proposed algorithms.

The Proposed Algorithm	Problem domain description	Potential solution objectives (Keywords)
Genetic bee colony algorithm	• To overcome local optima problem; • Multi-objective layout optimization; • Network optimization;	• Clustering (Abbasi-ghalehtaki et al., 2016) Group scheduling (Yue et al., 2016) • layout design (Lim et al., 2016) • Shortest path (Ebrahimnejad et al., 2016) • Optimal speed (Abbes and Allagui, 2016) Classification (Moosa et al., 2016)
Fish swarm algorithm	• Software testing • Synchronous optimization • Packet routing • Fault identification	• Selection of Optimal Cluster head (El-said et al., 2016); • Path coverage test cases (Liao, 2016); • Fault feature information (Xie et al., 2016); • Energy efficiency in wireless sensor networks (Chakravarthy and Palaniswami, 2016);
Cat swarm optimization algorithm	• Minimal total time execution • Parameters estimate of single diode and double diode • Channel cross-section optimization • Reliability optimization	• Flow shop problem (BOUZIDI and RIFFI, 2015) • Solar cell models (Guo et al., 2016) • Irrigation channel section (Shang et al., 2016) • Wind power system design optimization (Amara et al., 2015)
Whale Optimization Algorithm	• Parameters optimization • Exploration of unknown search spaces	• Structural design problems (Mirjalili et al., 2016) • Designing layout problems (Mirjalili et al., 2016) • Production optimization problem (Ebrahimi and Khamehchi, 2016)
Artificial algae algorithm	• Continuous optimization problems • Numerical optimization • Search Space	• Multidimensional knapsack problem (Zhang et al., 2016); • Balance between local and global searching ability (Uymaz et al., 2015)
Elephant search algorithm	• Searching nearby and afar simultaneously • Travelling salesman problem	• Average variation scores (Deb et al., 2015) • NP-hard problems (Deb et al., 2016)
Chicken Swarm optimization algorithm	• Feature selection • High global optimization • To improve bit error rate performance	• Maximizing classification performance of Dataset (Hafez et al., 2015) • Evaluation of flood and drought disasters (Cui,2016) • Error control coding (Banerjee and Chattopadhyay,2015)
Moth flame optimization algorithm	• Parameter estimation • Parameter extraction • Training multi-layer perceptron • Optimal shape	• Annual power load forecasting (Li et al., 2016) • Three diode model (Allam et al., 2016) • Neural networks (Yamany et al., 2015) • Marine propeller design (Mirjalili, 2015)
Grey wolf optimization algorithm	• Damping the inter-area oscillations • Attribute reduction strategy • Route planning • Reduced parametric sensitivity	• Designing wide-area power system stabilizer (WAPSS) (Shakarami and Davoudkhani, 2016) • Rough set-based attribute reduction (Yamany, 2016) • Underwater terrain aided positioning (Shen et al., 2016) • Fuzzy control systems (Precup et al., 2016)

4. Concluding discussion and future remarks

In conclusion, nine bio-inspired optimization algorithms are presented and analyzed in this paper: Genetic Bee Colony (GBC) Algorithm, Fish Swarm Algorithm (FSA), Cat Swarm Optimization (CSO), Whale Optimization Algorithm (WOA), Artificial Algae Algorithm (AAA), Elephant Search Algorithm (ESA), Chicken Swarm Optimization Algorithm (CSOA), Moth flame optimization (MFO), and Grey Wolf Optimization (GWO) algorithm which have been inspired by the social behavior of animals. There are several simulation stages are involved in the developing process of these algorithms which are (i) observation of the behavior and reaction of the animals in the nature, (ii) designing a model that represent the behavior of these animals (iii) converting into mathematical module with some assumptions and setting up of the initial parameters, (iv) developing the pseudo code to simulate the social behavior of these animals (v) testing the proposed algorithm theoretically and experimentally, and redefine the parameter settings to achieve better performance of the proposed algorithm.

To sum up, FSA mimics three behaviors of fish which are defined by (i) food searching, (ii) swarming according to the threat, (iii) trying to increase the opportunity to achieve an accepted solution. Therefore, there are three main parameters are involved in FSA which is defined by visual distance, the step of maximum length, and a crowd factor. From the discussion and analysis of FSA, it is clear that the effectiveness of this algorithm seems to be influenced by the former first two parameters.

WOA was presented in the last years to be competitive enough with other optimization algorithms. In this algorithm, there are three operators are used to model different phases of this algorithm such as searching and encircling for prey, and bubble-net foraging behavior of whales. In this algorithm, there is 29 mathematical benchmark functions are used with the aim of analyzing exploration, exploitation, avoiding convergence behavior and local optima of WOA.

CSO algorithm can be generalized into two different modes which are seeking and tracing modes. Also, CSO tries to maintain a population of a swarm of cats to find the optimal solution of optimization problems. In CSO, cats look for the position of the prey randomly and then move toward the search space. Finally, the optimal solution can be considered as the best position of one of the cats.

AAA has three control parameters which are represented by energy loss, adaptation parameter, and shear force. Energy loss is responsible for determining the number of the new candidate solutions of algal colonies that are produced at each iteration. Loss of energy can be determined based on the energy loss parameter. As a result, the local search capability of the algorithm is based on the smaller the energy loss parameter.

The main idea of ESA is based on utilizing a ratio of females and males elephants to represent the search agents to perform dual tasks of both exploration and exploitation which are an essential criterion in the process of searching in metaheuristic algorithms to find the optimal solution.

The CSOA is one of the promising optimization algorithms because it inherits important characteristics of other main algorithms. In CSOA, the movements of the chickens can be conducive for this algorithm to provide a balance between the randomness and determinacy to determine the best solution. The chicken swarm in this algorithm consists of several multi-swarm because of chickens of the different groups can collaborate to look for their food. As a result, this algorithm can behave intelligently to find the best solution of the optimization problems.

In MFO, moths use an effective method to travel in a straight line to fly in nigh with maintaining a fixed angle with the moonlight. On the other hand, this may cause deadly spiral path around the artificial lights. Therefore, there is a need for research and studies in the future to work on the effect of different spirals to improve the accuracy of the MFO which can be based on using new binary versions of MFO swarm algorithm.

Finally, the GWO algorithm simulates the social behavior of grey wolves during their life style. In this algorithm, there are four main types of grey wolves namely; *alpha*, *beta*, *delta*, and *omega* are used in this algorithm to mimic the leadership hierarchy.

Currently, the bio-inspired optimization algorithm could hybridize together. Due to the problem of convergence speed which can be encountered in solving real challenging applications and in the future these bio-inspired algorithms could be hybridized with other approaches and methods such as quantum computing and chaotic theory to enhance the performance of bio-inspired optimization algorithms. Recently, the quantum computing features and capabilities are integrated with some bio-inspired algorithms to improve the convergence rate and the overall performance of the used system to avoid premature convergence. One of the promising mathematical methods that recently has been applied to improve the search process is chaos theory. Chaos theory is applied by the integration with the bio-inspired algorithms to increase the level of the performance of the proposed system to find the optimal solution of the optimization complex problems.

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