IJCSN - International Journal of Computer Science and Network, Volume 7, Issue 6, December 2018
ISSN (Online): 2277-5420
www.IJCSN.org
Impact Factor: 1.5

Survey on Recent Bio-Inspired Optimization Algorithms

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Abstract - Bio inspired algorithms are meta-heuristic optimization algorithm that mimics the intelligence features from biologic behavior in animal , bird, fish and so on. Bio inspired algorithms considered as a major subset of nature inspired algorithm. They become very important in computing a wide range of applications in different domains .The main goal of this paper is to make a literature survey of some recent bio inspired algorithms to investigate the reasonable performance of the current algorithms and predicting suitable algorithms for solving optimization problems. In this paper, some recent research papers of bio inspired algorithms are summarized such as bat algorithm (BA), cuckoo optimization algorithm (COA) , krill herd algorithm (KHA), dolphin echolocation algorithm (DEA), grey wolf algorithm (GWA) and crow search algorithm (CSA).The paper focuses on algorithms concepts, behavior ,principles , mathematical models and algorithms steps. In addition to experiments evaluation and the advantages of each algorithm. Implementation of bio inspired algorithms is more efficient compared to conventional algorithms in terms of optimization problems solutions.

Keywords - *Optimization algorithms, Bio-inspired Algorithms, Meta-heuristic, Optimization problems.*

1. Introduction

In the last several years, optimization played an important role in several aspects of various optimization problems such as engineering problems, whether they are single objective problems or multi-objective problems and so on [1]. Optimization is the process of selecting the best solution among available solutions for optimization problems [2].The optimization problems solved by using optimization algorithms. In general terms, the optimization algorithms categorized into two broad categories deterministic algorithms and stochastic algorithm. In fact, some optimization problems cannot be solved using deterministic algorithms such as NP-hard problems. Therefore, stochastic algorithm developments as new algorithms for solving them in an optimal way. Such algorithms are built on the trial and error techniques. usually, they focus on finding intensification (local) and diversification (global) solutions also called meta-heuristic algorithms. The most of these algorithms inspired by the biological behavior called bio-inspired stochastic optimization algorithms. Bio-inspired algorithms proved to be excellent methods to process these complex optimization problems and employed to solve many such problems belong to different domains[3- 4]. The main objective of this paper is to make a literature survey of some recent bio-inspired algorithms to investigate the reasonable performance of the current algorithms and predicting suitable algorithms for solving optimization problems. This literature review provides a brief description of those algorithms concerning definitions, behavior, principles, proposed model, steps (algorithm), experimental evaluation and advantages. Bio-inspired algorithms become a new era in computing a wide range of applications in different domains such as computer networks, security, mechatronics (Mechanical + Electronics), robotics, biomedical engineering, control systems, parallel processing, data mining, big data, power systems, production engineering and many more [5]. Bio-inspired algorithms have some advantages: flexibility in terms of size, No saturation limit in terms of performance and improvement scope innovation. These algorithms have few parameters to adjust with easy implementation.
Unfortunately, Bio-inspired algorithms have few disadvantages: component design, poor in data biological system are hard to study and poor of data on the system may affect the design of the algorithm, poor incomplete adaptability, and low performance because they aim to behave well in different situations compared to obtain the objective quickly [6] . The rest of this paper is organized as follows. Section 2, provides a survey of some bio-inspired algorithms that briefly explains the definition, principles, proposed model, steps, experimental evaluation, and advantages. In Section 3, observation from the literature review. Finally, Section explained conclusion.

2. Literature Review

This section of the paper focuses on some recent bio-Inspired algorithms such as Bat algorithm (BA), Cuckoo Optimization Algorithm (COA), Krill Herd Optimization Algorithm(KHA), Dolphin Echolocation Algorithm(DEA), Grey Wolf Optimization (GWA) and Crow Search Algorithm (CSA).

2.1 Bat Algorithm(BA)

Developed by Xin-She Yang et al in 2010. Bat algorithm is a population-based meta-heuristic optimization algorithm. The BA is inspired by the echolocation behavior of bats, based on the idea of hunting process (searching for prey). In fact, bats have sonar called echolocation to detect prey, avoid obstacles, and locate their home gaps in the dark [7]. The sonar system is a method by which bats detect prey. The bats use their sonar system at short ranges of up to approximately 3–4m [8]. Those bats emit a very high sound pulse and listen for the echo that returns back from surrounding objects within the environment. Bats pulses change in terms of their features, but they correlate with hunting methods based on types. Most bats use short frequency signals while others use constant frequency signals to sweep through about an octave [7]. Their signal depends on the types, though some types can emit higher frequencies and often increase the bandwidth of the signal by using more harmonics. When the bats get close to their prey, the pulse rate increase, in turn, the frequency signal increases, which lead to the fast detection of the prey [7]. The bat behavior include a set of principles such as (a) Bats use echolocation to recognize the distance and differentiate between the prey and obstacles. (b) Bats can adjust the frequency of their emitted pulses and the rate of pulse emission, depending on the closeness of their goals. (c) The values of loudness change from range maximum A0 to minimum constant value Amin [9] . The mathematical model of the bat algorithm, assumes that the number of bats is ' x_i (i = 1, 2, ..., n) ', every bat connected with the velocity represented by 'v_i', positions represent by 'x_i', frequency represents by 'f ' , iteration represents by 't' , best solution represent by 'x_*', in a d-dimensional search. Therefore, based on principals mentioned above to compute the frequency, velocity, and position represented by the following equations[10].

$$f_i = f_{min} + (f_{max} - f_{min})\beta \quad (1)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*)f_i \quad (2)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (3)$$

Where $\beta \in [0, 1]$ represents the random vector drawn from a uniform distribution, (f_{max} and f_{min}) represents the maximum and minimum frequency, x_i^t represents the new solutions and x_* represents the current global best location (solution).

The algorithm of the bat starts with population initialization, specifically, initializing a velocity , loudness, pulse rate, and pulse frequency. Then it starts iterating through generating new solutions by adjusting the frequency, updating velocities, locating and selecting a solution among the best solutions. The algorithm also checks pulse rate, selecting the best solution and producing the local solution, otherwise creates a new solution by flying randomly. Also, the algorithm checks loudness and pulse frequency to accept the new solutions then increases r_i and decreases A_i. Finally, Rank the bats and find the current best solution as shown in figure (1).

Begin
Initialization population of bats xi (i = 1, 2, ..., N), pulse frequency Qi, pulse rates ri, loudness Ai and velocities Vi (i = 1, 2, . . . , N).

While ($t < MaxGeneration$) do
Generate new solutions by adjusting frequency, and updating velocities and location.
If (rand > ri) then
Select best solution from among of solution .
Generate a location solution around the selected best solution.
End if
Generate a new solution by flying randomly
If (rand< Ai && $f(xi) < f(x*)$)
Accept the new solution.
Increase ri and decrease Ai .
End if
Rank the bats and the find the current best solution $x*$.
End while
Post-processing the results and visualization.
End

figure (1)

The bat algorithm performance is measured and compared with genetic algorithms (GA) and particle swarm optimization (PSO). The experiment result shows that the bat algorithm is able to solve different optimization problems with high efficiency, flexibility, and robustness, such as continuous non-linear problems [12]. The bat algorithm has some advantage: successfully formulated for continuous constrained optimization problems, it's a good adjustment of the parameters, therefore, it's very easy to implement. quick convergence rate by switching from intensification to diversification to get optimal solutions, it also processes the complex problems [13]. This algorithm is considered a very promising algorithm [7][13].

2.2 Cuckoo Optimization Algorithm(COA)

Developed by Ramin Rajabioun in 2011. Cuckoo Optimization Algorithm is population-based meta-heuristic optimization algorithm. The COA is inspired from the special lifestyle of cuckoo birds and their features such as egg laying and breeding [15]. The cuckoo lives as a parasitic bird on the other hosting birds in terms of egg laying and breeding . They do not construct their nests, but, it puts eggs in other birds' nests. The female of the cuckoo is able to mimic eggs colors and patterns in the selected nests of other host birds to reduce the probability of discovering its eggs by that host bird [16]. As mentioned above, the cuckoos put their eggs in the host bird nest, if the host bird detects those eggs that do not belong to their own eggs, then they drop them out of the nest. Otherwise, the host birds do not detect those eggs, then cuckoos eggs would have an opportunity to grow and become chicks. The cuckoo chick is capable of imitating the call of host chicks to acquire access to more feeding opportunity [17]. The cuckoo behavior includes the following principles: (a) Each cuckoo lays one egg at a time and puts its egg in a randomly chosen nest. (b) The best nests with high quality eggs will be carried over to the next generations. (c) The number of available host nests is fixed and the egg put by cuckoo is discovered by the host bird with a probability pa $\in$ [0, 1] [18]. The mathematical model of the cuckoo algorithm starts with to search for the best place or environment to maximize their eggs' life lengths. After turning Cuckoos eggs into mature chicks then, they form communities. Each one has its habitat to survive and it could be represented in the form of an array as(Habitat = $[x_1 , x_2 , x_3,.,.., x_{Nvar}]$). To evaluate the suitability of habitat is to compute the profit function f as (profit= f b(habitat)=f $b(x_1 ,x_2 ,...,x_N)$). The best habitat of different societies will be the next destination for cuckoos in other groups. All groups move to the best currently existing zone. Each group will be the resident in a zone near the best currently existing zone[1]. Each cuckoo lays from 5 to 20 eggs. These values are considered the maximum and minimum limits of eggs dedicated to each cuckoo at different iterations[15]. cuckoos begin laying eggs randomly in the nests within their egg laying radii. An egg laying radius (ELR) will be computed regards to the number of eggs each cuckoo lays and its distance from the current optimized zone. This process continues until an achieving the best place for egg laying (a zone with the most profit). This optimized zone is the place in which the maximum number of cuckoos gathers together [1] .an egg laying radius presented in this equation:

$$ELR = \alpha \times \frac{\text{Number of current cuckoos eggs}}{\text{total number of eggs}} \times (var_{hi} - var_{low}) \quad (4)$$

where represent the upper and lower limit for variables, represents an integer, supposed to handle the maximum value of ELR.

The algorithm of the cuckoo starts by initializing of habitats, specifying maximum and minimum of eggs (E_{max}, E_{min}) and the maximum number of iterations ($iter_{max}$), the maximum number of cuckoos(N_{max}) and determine the upper and lower limits of the parameters of the optimization problem (va_{rhi}, var_{low}). Then it starts iterating some processes such as specifying some eggs for each cuckoo, calculating the radius of laying eggs for each cuckoo(ELR) and position of egg ($X_{i\ new}$) for each cuckoo in (ELR). The algorithm also checks the position of egg, evaluating the fitness function of each egg (F_x), otherwise, it destroys cuckoos in unsuitable areas. These processes repeated until the goal is obtained as shown in figure (2).

Begin
Initialize habitats of cuckoos by generating xi (i = 1, 2, ..., N) , maximum number of cuckoo N_{max} , maximum and minimum number of eggs (E_{max}, E_{min}) , maximum number of iteration ($Iter_{max}$) an d the upper and lower limits of the parameters of the optimization problem (var_{hi}, var_{low}) .

While (Iteration $\leq Iter_{max}$) do
Specify some eggs to each cuckoo .
Calculate (ELR) for each cuckoo.
Consider egg position (Xi new) for each cuckoo in (ELR).

If ($Xi_{new} < N_{max}$)
Evaluate the fitness function of each egg (F_x)
Else
Destroy cuckoos in unsuitable areas.
End if
End while
End

figure (2)

The cuckoo optimization algorithm performance is measured and compared with genetic algorithms (GA) and particle swarm optimization (PSO). The experiment result shows that the cuckoo algorithm has superiority on another in terms of convergence speed and obtaining global optima. The COA test by five benchmark functions, the results show that the COA has very good and acceptable estimation of the global minimum in less iteration. The cuckoo optimization algorithm has advantages: It's successful in mimic of nature, it's suitable for continuous nonlinear optimization problems, it has the convergence speed of the other algorithms and has higher performance in reaching to the better results [15] [19].

2.3 Krill Herd Algorithm (KHA)

Developed by population-based Amir Hossein Gandomi and Amir Alavi in 2012. Krill Herd Algorithm (KHA) is population based meta-heuristic optimization algorithm. The KHA is inspired from the behavior of the krill swarms in response to specific biological and ecological procedures, or it is inspired from the lifecycle of krill in the oceans [21] . The herding of the krill individuals has a multi-objective process, including two main goals .The first goal increases krill density that means the density dependent attraction of krill, the second goal reaches the food that means finding food in areas of high food concentration [1][22] these goals consider as a constrained optimization process . In this process, an individual krill search for the highest density and food to reach to the best solution .The krill behavior includes the following principles: (a) movement induced by other krill individuals . (b) foraging activity . (c) physical diffusion [23]. The mathematical model to the krill herd algorithm . KHA used the lagrangian model to extend the search space to an n-dimensional decision space as represented in the equation:

$$\frac{dx_i}{dt} = N_i + f_i + fD_i \quad (5)$$

N_i presents the first process motion product, F_i presents the second process foraging motion, and D_i presents the three processes physical diffusion of the ith krill individuals [24]. In the process movement induced, αi , the direction of movement of a krill individual is evaluated by approximately by the target swarm density, a local swarm density, and a repulsive swarm density, this movement can be as represented in this equation :

$$N_i^{new} = N^{max} \propto_i + \omega_n N_1^{old} \quad (6)$$

Where $\alpha_i = \propto_i^{local} + \propto_i^{target}$.

N_i^{new} represent the motion of the ith krill individual at the current iteration, N^{max} represent the maximum induced speed, ω_n represent the inertia weight of the motion induced in the range [0,1], N_1^{old} represent the motion of the ith krill individual in the previous iteration, $\propto_i^{local}$ represent the local effect provided by the neighbor $\propto_i^{target}$ represent the effective coefficient of the krill individuals with the best fitness to the ith krill individual.

The foraging motion of the krill herd is influenced by the two main effective factors: firstly, food location and secondly, the previous experience about the food location. This motion represented as in this equation:

$$F_i = V_i \beta_i + \omega_f F_i^{old} \quad (7)$$

Where $\beta_i = \beta_i^{food} + \delta_i^{best}$.

V_f represents the foraging speed, w_f represents the inertia for the foraging motion in the range of [0,1], β_i^{food} represents the food attraction parameter, and β_i^{best} represents the effect value of the best fitness of the ith krill.

The physical diffusion of the krill herd is a random process. This motion can be expressed in terms of a maximum diffusion speed and the random direction vector, as represented in this equation [25-26].

$$D_i = D_{max}\ \delta \quad (8)$$

Where D_{max} represents the maximum diffusion speed, δ represents the random directional vector and its arrays are random values between[–1- 1].

The algorithm of the krill starts Initializing the population X_i, defining the set of parameter, population size (N) and maximum iteration number (I_{max}).Then it set the inertia weight of the motion induced (n), foraging motion (f) and evaluate each krill individual according to its position. After initialization and configuration setting, it starts iterating through two loops. The inner one employed to perform motion calculation for each krill based on three sub-processes: induced motion, foraging motion, and random diffusion, in addition, it updates the krill individual position and evaluates each krill individual according to its position. While the outer loop repeats the inner loop process, in addition, to sort the population krill from best to worst and find the current best. [25] as shown in figure(3).

Begin

Initialize generate of the population Xi for i = 1, 2,3…, N ,define set of parameter population size (N) and maximum iteration number (I_{max}) .

Set the iteration counter I =1

Set the inertia weight of the motion induced (n) and foraging motion (f)

Define Δt

Evaluate each krill individual according to its Position

While (I < Imax) do

For i = 1: N

Perform the following motion calculation:

Movement induced by other krill

individuals
Foraging activity
Physical diffusion
Update the krill individual position in the search space
Evaluate each krill individual according to its position
End for i
Sort the population krill from best to worst and find the current best
End while
Post-processing the results and visualization.
End

figure (3)

The krill herd algorithm performance is measured and compared with genetic algorithms (GA), particle swarm optimization (PSO), dolphin echolocation (DE), Evolutionary Strategy (ES),biogeography based optimization (BBO), and ant colony optimization algorithm (ACO). The experiment result shows that the krill herd has faster convergence, it has found a very good estimation of the real global minimum , and it has the best performance which confirms robustness compared them. The krill herd algorithm has advantage its algorithm has able to solve the optimization problems and begin on the exciting algorithm in permeation , It's used operator of the crossover in effective , it's each agent can contribute to the moving process according to its fitness and it's each neighbor has an attractive effect on the movement of the krill individual. Therefore, these effects can act as a local search for each krill individual [21-22][1].

2.4 Dolphin Echolocation Algorithm (DEA)

Developed by A.Kaveh, N.Farhoudi in 2013. dolphin echolocation algorithm is population-based meta-heuristic optimization algorithm. The DEA is inspired from the dolphin echolocation feature [27]. This algorithm based on the mechanism that used by dolphins during the process of hunting. In fact, dolphins generate a voice called sonar to locate the goal, this action changes sonar to modify the target and its location [28]. Dolphin able to generate two high frequency clicks. The dolphins first click is used to search for the goal, while the second click used to estimate the distance to that goal. Dolphins can detect goal at ranges varying from a few tens of meters to over a hundred meters [29]. The dolphin behavior includes the following principles: (a) Search space order. (b) number of loops [27]. The mathematical model to the dolphin echolocation algorithm has mimicked a method that used in searching for the prey and hunting. DEA initial search around all the search space to find the prey . When the dolphin gets close to the goal, it incrementally increases its clicks to focus on the location [30]. The algorithm starts by using the first principle that is searching space ordering : For each variable to be optimized during the process, sort alternatives of the search space in an ascending or descending order. If available options contain more than one features, conduct ordering based on the most important option. Using this method, for variable j, vector Aj of length LAj is created which includes all different options for the jth variable locating these vectors next to each other, as the columns of a array, the array alternatives MA*NV is created, in which MA is max(LAj) j=1:NV; with NV being the number of variables. Furthermore, during the optimization presented in this equation:

$$pp(Loopi) = pp1 + (1 - pp1)\frac{Loop^{power}-1}{(loops\ Number)^{power}-1} \quad (9)$$

Where 'PP' represent the Predefined probability, 'PP1' represent the Convergence factor of the first loop in which the answers are selected randomly, '$Loop_i$' represents the Number of the current loop, and ' Power' represent the degree of the curve. The algorithm also implements the second principle: loops number the algorithm should reach to the convergence point through the number of loops, and this number should be chosen by the user according to the computational effort that can be afforded for the algorithm [31]. The algorithm of the dolphin starts initializing the number of locations, computing the probability (PP) of loopi based on (9), then it computes the fitness of each location to maximize the fitness. Next, it computes the accumulative fitness based on the three nested loops allocated for locations, variables, accumulative fitness based on (10). Then it computes the probability of choosing alternative i (i =1toALj). Moreover, the algorithm assigns the probability PP to all alternatives selected for all variables of the best location and devotes rest of such probability to the other alternatives used two for loops, first associates with the number of variables, while the second associated with the number of alternatives for computing pi, j. Finally, Calculate the next step locations according to the probabilities assigned to each alternative as shown in figure(4).

Begin
Initiate number of locations for a dolphin randomly.
Calculate the probability of the loop.
Calculate the fitness of each location, the purpose optimization to reach maximize the fitness.
Calculate the accumulative fitness according to dolphin rules.
for i=1 to the number of locations
for j=1 to the number of variables
find the position of L(i, j) in jth column of the alternatives matrix.
for k=-Re to Re

$$AF_{(A+K)j} = \frac{1}{R_e} * (R_e - |k|) Fitness(i) + AF_{(A+K)j} \quad (10)$$

end
end
end

Calculate the probability of choosing alternative i (i =1toALj).

$$P_{ij} = \frac{AF_{ij}}{\sum_{i=1}^{LA_j} AF_{ij}} \quad (11)$$

Assign a probability equal to PP to all alternatives chosen for all variables of the best location and devote rest of the probability to the other alternatives.

for j=1: number of variables
for i=1: number of alternatives
if i= the best location (j)

$$P_{ij} = PP$$

Else

$$p_{ij} = (1 - pp) p_{ij}$$

end
end
end

Calculate the next step locations according to the probabilities assigned to each alternative.

End

figure (4)

The dolphin echolocation algorithm performance is measured and compared with genetic algorithms (GA) and particle swarm optimization (PSO), ant colony optimization (ACO), harmony search (HS), and others algorithms. The experiment result shows that the dolphin echolocation algorithm has better results achieves and convergence rates very fast compared to other algorithms and its very few loops are needed to reach the final answer compared them. Additionally, the quality of the results obtained is very good in each run. for this reasons, the low speed of the algorithm in each loop is compensated. The dolphin echolocation algorithm has advantage the main advantage it doesn't need empirical parameter [32], it's can control in order to perform a suitable optimization reasonable convergence rate, it has the capability of adopting itself by the type of the problem in hand, and it's leading to an acceptable optimum answer in a number of loops specified by the user [27][31].

2.5 Grey Wolf Optimization(GWO)

Developed by Seyedali Mirjalilia in 2014. Grey Wolf Optimization is population-based meta-heuristic optimization algorithm. The GWO is inspired from the social leadership hierarchy and intelligent hunting process of grey wolves in nature [1]. The grey wolves favorite live in a pack. The average size of the pack is 5-12. The process of hunting is performed by four level of grey wolves that is alpha, beta, delta, and omega. The first level in the hierarchy of grey wolves is alpha (α), the alpha includes leaders consist of male and female. alpha is responsible for making decisions like where to go for hunting, where to go for sleeping, time to wake, and so on. The alpha is best in managing the pack but not necessarily the strongest member. These manes that the organization and discipline of a pack is much more important than its strength. The second level in the hierarchy of grey wolves is Beta (β). The beta also includes male or female. Beta (β) is subordinate wolves that help the alpha to make decisions and other activities of the pack. Beta play important role in giving advisor to the alpha and discipline for the pack, in addition, the beta reinforces the alpha’s commands throughout the pack and gives feedback to the alpha. The third level in the hierarchy of grey wolves is delta(δ) the delta submit to alpha and beta.But they dominate the omega, delta plays important roles in hunter, caretaker, elder, sentinels, scouts. Firstly, hunters able to help the alphas and betas when hunting prey and providing food for the pack. Secondly, caretakers able to be responsible for caring for the weak, ill, and wounded wolves in the pack. Thirdly, elders able to provide services as experienced wolves who make support for alpha or beta. Fourthly, sentinels able to protect and guarantee the Security of the pack. Finally, Scouts able to be responsible for watching the boundaries of the territory and warning the pack in case of any danger expected. The fourth level in the hierarchy of grey wolves is omega (ω). The omega plays the role of scapegoat. Omega has to submit to all the other dominant wolves. The Omega does not have an important role in that pack, but it will observe all internal fighting and problems to protect their pack. It is last wolves to eat their prey. Omega assists in satisfying the entire pack and maintaining the dominance structure , the omega are also babysitters in the pack. The grey wolf behavior includes the following principles : (a) searching for prey (b) encircling prey. (c) attacking prey [33]. The mathematical models of the grey wolf algorithm include social hierarchy, encircling, hunting and attacking the prey. social hierarchy: The social hierarchy includes α which represents the fittest solution, while the second and the third solutions are represented by 'β', and ' δ' respectively and 'ω' represents the rest candidate solutions. encircling prey: In order to make a mathematical behavioral model for encircling prey during the process of hunting, the following equations are expressed [34-35]:

$$\vec{D} = |\vec{c}\,\vec{x}p(t) - \vec{x}\,(t)| \quad (12)$$

$$\vec{x}(t+1) = \vec{x_p}(t) - \vec{A}.\vec{D} \quad (13)$$

where 't' represents the current iteration, $\vec{A}$ and $\vec{c}$ represent the coefficient vectors, $\vec{x_p}$ represent the position vector of the prey, and $\vec{x}$ represent the position vector of a grey wolf. Calculate A and C vectors based on

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \quad \text{and} \quad \vec{C} = 2.\vec{r_2}.$$

where components of '$\vec{a}$' are linearly decreased from 2 to 0 over the course of iterations, and r_1, r_2 are random vectors in [0, 1]. Hunting: In order to make a mathematical model for the grey wolves hunting behavior, it is assumed that 'α' the best candidate solution while 'β', and ' δ' have better knowledge about the possible position of prey. Therefore, the first three best solutions are saved and obtainable solutions so far, then the other search agents are imposed the other search agents (including the 'ω') to update their positions according to the position of the best search agents. The following formulas are expressed in this regard [36]:

$$\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}| \tag{14}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{15}$$

$$\vec{x}(t+1) = \frac{\vec{x_1}+\vec{x_2}+\vec{x_3}}{3} \tag{16}$$

attacking prey: In order to make a mathematical model for the grey wolves for attacking prey behavior, it is prey stop moving the grey wolves attack. Therefore, the behavior of grey wolfs approaching is represented by equation [37]:

$$\alpha = 2 - 2\left(\frac{t}{max}\right) \tag{17}$$

The grey wolf algorithm firstly: initializes of population size X_i (i = 1, 2,..., n) and parameters: α, A, C, secondly: it computes the fitness values of search agents and grades them. Thirdly: it starts iterating through using loop each search agent to update the position of the current search agent by Equation (16). Fourthly: it updates parameters α, A, and C. Fifthly: it computes the fitness values of all search agents, grades them. Finally: update the positions of Xα, Xβ, and Xδ. as shown in figure (5).

```
Begin
        Initialize the population of grey wolves Xi (i = 1,
                2, ... , n)
          Initialize a, A, and C
          Calculate the fitness values of search agents and
                grade them.
        (Xα = the best solution in the search agent,
              Xβ = the second best solution in
          the search agent, and Xδ = the third best
                solution in the search agent)
    While (t < Max number of iterations)
          For each search agent
                Update the position of the current search
                    agent by equation (16)
          End for
        Update a, A, and C
        Calculate the fitness values of all search agents
            and grade them
        Update the positions of Xα, Xβ, and Xδ
    End while
End
```

figure (5)

The grey wolf optimization algorithm performance is measured and compared with swarm intelligence (SA), evolutionary computation(EC), harmony search algorithm(HSA), gravity search algorithm(GSA), invasive weed optimization (IWO), and modified imperialist competitive algorithm(MICA). The experiment result shows that the grey wolf optimization algorithm has a better performance in finding the optimal design of nonlinear double layer grids over other[1], it has the more desirable optimal solution and has the ability to provide very competitive results compared to others. The grey wolf optimization has advantages: it has the ability to avoid local optima, it provides higher performance in conversion rate and exploration and it provides high performance on constrained problems not only on unconstrained problems [34].

2.6 Crow search algorithm(CSA)

Developed by Alireza Askarzadeh in 2016.Crow search algorithm is a population-based meta-heuristic optimization algorithm. The CSA is inspired from the intelligent behavior of crows, based on the idea of stealing the food of another crow and retrieving it. In fact, a crow store, it's excess food in hiding places and retrieving it when the food is required, unfortunately, during this process, other crows follow that crow to find the hidden place to steal such food. Crows are intelligent and have big brains compared to their body size [38], the crow has the ability to use bread crumbs to bait fish, construct and use tools effectively, choose a tool of the correct length, width, size [39], they have the ability to remember faces of people [40] .In addition, they have the ability to understand causal in water displacement[41-42] . In addition to some other intelligence features. The crow behavior includes following principles : (a) Crows live in the form of a flock.

IJCSN - International Journal of Computer Science and Network, Volume 7, Issue 6, December 2018
ISSN (Online): 2277-5420
www.IJCSN.org
Impact Factor: 1.5

(b) Crows memorize the position of their hiding places. (c) Crows follow each other to make stealing business. (d) Crows are protected, their caches from being pilfered by a probability [43]. The mathematical model of CSA , assume that number of crows are 'N' and the position of the crow is 'i' at an iteration iter is presented by $X^{i.iter}$ and $iter_{max}$ is the maximum number of iterations. The position hiding place of crow i is presented in $m^{i;iter}$. Crows searches for the best food locations in the environment. When the crow j wants to visit it's food in the hiding location, $m^{i;iter}$. At an iteration, crow i decide to follow the crow j to approach the jth crow food hiding place. In this situation, two cases may happen: State 1: Crow j does not know that crow i is following it. As a result, crow i will approach to the hiding place of crow j. In this case, the new position. Present in equation :

$$X^{i,iter+1} = X^{i,iter} + ri\ x\ fl^{i,iter} X\left(M^{i,iter} - X^{i,iter}\right) \tag{18}$$

where r_i is represented the random number with a uniform distribution between [0 – 1] and $fl^{i;iter}$ represents the flight length of crow i at iteration iter .

State 2: Crow j knows that crow i is following it. As a result, in order to protect its cache from being stolen, crow j will fool crow i by going to another position of the search space [44-45]. Totally, states 1 and 2 can be presented as follows:

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + ri\ x\ fl^{i,iter} X\left(M^{i,iter} - X^{i,iter}\right) & rj \geq AP^{i,iter} \\ a\ random\ position & otherwise \end{cases} \tag{19}$$

$AP^{i,iter}$ represents the awareness probability of crow j at iteration iter.

The algorithm of the crow starts by initializing locations and memory of crows , evaluate the position of the crows. Then it starts iterating through loops to choose one crow randomly to follow another crow which based on and specific awareness probability. The algorithm also checks awareness probability ($AP^{j.iter}$) of the new positions then obtain the position of crow by equation(18) when the condition is satisfied, otherwise, a random position of search space for the crow $X^{i,iter+1}$ is created. Finally, check the feasibility of new positions, evaluate the new position of the crows, update the memory of crows[46] as shown in figure (7).

```
Begin
    Randomly initialize the positions and the memory
    of a flock of size N crows in the search space
    Evaluate the position of the crows
    while ( iter < iter_max) do
        for i = 1 : N (all N crows of the flock)
            Randomly choose one of the crows to
            follow (for example j)
            Define an awareness probability
        If ( r_j ≥ AP^(j,iter) ) then
            X^(i,iter+1) = x^(i,iter) + r_j × fl^(i,iter) , × ( m^(i,iter) - x^(i,iter))
        else
            x^(i,iter+1) = a random position of search space
        end if
        end for
        Check the feasibility of new positions
        Evaluate the new position of the crows
        Update the memory of crows
    end while.
End
```

figure (6)

The crow search algorithm performance is measured and compared with genetic algorithms (GA), particle swarm optimization (PSO) and harmony search (HS) . The experiment result shows that the crow search algorithm has better improve efficiency in both time and accuracy compared them [1], and it has higher performance in case finding optimization because it has fewer parameters to adjust compared to others. The crow search algorithm has some advantages such as a minimal number of parameters, memory for storing solutions, as long as it's not a greedy algorithm, it increases the diversity (global solutions) based on the parameter of awareness probability that controls the diversity of the algorithm. CSA has promising performance[38]

3. Algorithms comparison

The main objective of this paper is to make a brief literature review on bio-inspired algorithms to investigate the reasonable performance of the current algorithms and predicting suitable algorithms for solving optimization problems. The following tables show the bio-inspired optimization algorithm summarization focusing on source inspiration, merits, parameters, application, and invention year.

IJCSN - International Journal of Computer Science and Network, Volume 7, Issue 6, December 2018
ISSN (Online): 2277-5420
www.IJCSN.org
Impact Factor: 1.5

Table 1: shows comparison of algorithms

Name algorithm	*Source of Inspiration*	*Algorithm Advantages*	*Algorithm parameters*	*Algorithm Application*	*Year publish*
1-Bat algorithm	Inspired from echolocation features for hunting process.	1- It is easy to successfully formulate for continuous optimization problems. 2- It is easy to implement because it has a good capability of parameters adjustment. 3- it has quick convergence rate by switching from intensification to diversification to obtain optimal solutions. 4- it is considered a promising algorithm.	bat algorithm has two parameters : 1- Loudness 2- pulse rate	bat algorithms used to solve problems in many filed such as engineering, computer science, mathematics, energy, materials science and optimization, classifications (image processing, feature selection, scheduling, data mining) and so on.	2010
2-Cuckoo optimization algorithm	Inspired from the feature in terms of egg laying and breeding.	1- It has a higher performance to reach better results. 2- It is suitable for continuous nonlinear optimization problems. 3- It gets better solutions because of using intensification and diversification technique. 4- It has a success in mimic of nature.	cuckoo optimization algorithm has two parameters: 1- λ 2- ϕ	Cuckoo optimization algorithms used to solve the problem in many filed such as Computer science, mathematics, energy, engineering and so on.	2011
3-Krill herd algorithm	Inspired from features of the herding of the krill in response to specific biological and environmental activities.	1- each agent can contribute to the moving process according to its fitness. 2- each krill individual neighbor has an attractive effect on its movement. Therefore, these effects can work as a local search for every krill individual. 3- it has the ability to solve the optimization problems . 4- apply the crossover operator in manner effective. 5- the center of food determined according to the finesses of all of the krill individuals is considered as an approximation for the global best solution.	Krill herd algorithm have two parameters: 1- population size (N). 2- maximum iteration number (Imax).	Krill herd optimization algorithm used to solve the problem in many filed such as engineering optimization problems, clustering, numerical optimization problem and so on.	2012
4-Dolphin echolocation algorithm	Inspired from echolocation features for hunting process to search their prey.	1- it does not require to have a parameter in the experiment. 2- it performs a suitable reasonable optimization based on the controlled convergence rate. 3- it has the ability to adapt itself based on the type of the problem it processes. 4- it is leading to an acceptable optimum answer in a number of specified loops.	Dolphin algorithm has five parameters: 1- Loops number 2- Convergence curve formula 3- Effective radius (Re) 4- E 5- Number of locations (NL)	Dolphin echolocation algorithm used to solve the problem in many filed such as: manufacturing cell design, multi-objective reactive power dispatch problem, Continuous search space problem, truss structures and so on.	2013
5-Grey Wolf optimization	inspired from the social hierarchy and hunting mechanism of grey wolves in nature.	1- it has the ability to avoid local optima. 2- it provides higher performance in unknown and challenging search space. 3- it provides high performance on constrained problems not only on unconstrained problems.	Grey wolf optimization has only two parameters: 1- A 2- C	Grey wolf optimization algorithm used to solve the problem in many filed such as engineering, optimization problems, constrained optimization problems, Multi-objective problems and so on.	2014
6-crow search algorithm	Inspired from the intelligent behavior of crow, based on the concept of storing and retrieving food whenever it is required.	1- it has a minimal number of parameters. 2- it easy to implement. 3- it gets the better solutions because of using intensification and diversification technique.	Crow search algorithm has two parameter: 1-awareness probability 2-flight length	Crow search algorithm used to solve engineering optimization problems, complicated objective functions, numerous decision variables, a considerable number of constraints and so on.	2016

4. Observation

In observation, six bio-inspired algorithms are explained in this paper: Bat algorithm(BA), cuckoo optimization algorithm (COA), krill herd algorithm (KHA), dolphin echolocation algorithm(DEA), grey wolf algorithm (GWA) and crow search algorithm (CSA). On one hand, we observe that each algorithm mentioned above has inspired from special creature behavior such as bat, dolphin and grey algorithms. These algorithms able to carry out the hunting process but each one uses a special feature for hunting. Both bat and dolphin use the same feature which is the echolocation with different ranges of that echolocation. For example, bat echolocation has short ranges approximately varies between 3– 4m, whereas dolphin has longer echolocation compared to bat echolocation. It varies between tens of meters to over a hundred meters. The hunt of grey wolf able to recognize the location of prey and encircle them and it guides hunt process by alpha, beta, and delta. On another hand, the remaining algorithms are not similar to each other in terms of obtaining their prays. For examples: the cuckoo algorithm, inspired from lifestyle behavior of the cuckoo in terms of laying on eggs and breeding chicks and the krill inspired from herding behavior, while the crow algorithm based on storing and retrieving prays when it is required. In this survey paper, we observed the behavior of various bio-inspired algorithms which has advantages in terms of solving several optimization problems in different dominoes. crow search algorithm can increase the diversity of generated solutions and can solve engineering problems, solve multi-objective optimization problems in an optimal way. The cuckoo optimization algorithm solves the continuous nonlinear optimization problems with high performance compared to genetic optimization. The bat algorithm also solves continuous nonlinear optimization problems. The gray wolf optimization has better performance in finding the optimal design of nonlinear double-layer grids and helps to solve unknown and search space problems. The krill hard algorithm used to solve several optimizations problems. The dolphin echolocation algorithm can solve complex problems in an efficient manner. One of the obstacles which face optimization algorithms is Parameter setting. Therefore, algorithms which have few parameters to adjust are easy implementation. In this paper, we compare between algorithms mentioned above through easy implement depend on the parameter , we note that the crow, cuckoo, bat, krill herd, gray wolf algorithms have only two parameters, therefore , these algorithms easy to implement in an effective manner to solve several problems in different domain . On the other hand, the dolphin has more than two parameters, therefore , these algorithms not easy to implement because of the high number of parameters.

5. Conclusions

This paper explains some bio-inspired optimization algorithms such as BA, COA, KHA, DEA, GWA, and CSA. These bio-inspired algorithms can be applied to solve several optimization problems in an efficient and optimal or near optimal way. Therefore, the bio-inspired algorithm based on the intelligent behavior of animals could be used to overcome some problems that may occur with conventional algorithms, in terms of solving optimization problems.

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