**Bio-inspired optimization: Algorithm, analysis and scope of application**

In last few years, bio-inspired optimization techniques have been widely adopted in fields such as computer science, mathematics, and biology in order to optimize solutions. Bio-inspired algorithms are designed and developed with principles and motivations on evolution of biological components in nature for assumed robust competing techniques. Recently, combined efforts of bio-inspired optimization and machine learning techniques adopted to address optimal solutions of complex problems in science and engineering. 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 work comprises state-of-art of ten recent bio-inspired algorithms, gap analysis, and its applications namely; Particle swarm optimization(PSO), 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), cuckoo Search 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:** particle swarm optimization, Genetic bee colony algorithms; Fish swarm algorithm; artificial algae algorithm; Chicken swarm optimization; Grey wolf algorithm; Cat swarm optimization

**I Introduction**

Bio-inspired algorithms nowadays resolve application problems decision-making, information handling, and optimization purposes from different domains of science and engineering. Many techniques developed fields expected to next few year intelligent optimization algorithms more effective in solving different problems for anomaly and failure detection areas[1]. Optimization plays major role in more single or multi- objective problems deterministic or stochastic algorithms [2]. The focus of NP-hard problem based deterministic or stochastic algorithms to intensification and diversification for meta-heuristic optimization algorithm. Compared to conventional methods, bio-inspired algorithms are intelligent, improved, easy to test, and flexible[3].

In computer networks, security, mechanical problems, electronics image processing, electrical, robotics, production engineering, management, planetary and others are applying bio-inspired algorithms in new era to solve problems easily[4, 5]. Hence it is an emerging field, authors aim to review discussion and future scope on bio-inspired algorithms. Bio-inspired algorithms concern definitions, principles models, processing steps, merits and demerits reviewed for most frequently applied bio-inspired algorithms in this chapter. The study discuss on bio-inspired algorithms which are purely inspired from identifiable or special behaviour of biological organisms. This chapter covers both emerging and well-known techniques. Ten bio-inspired algorithms: Particle swarm optimization(PSO), 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), cuckoo Search Optimization Algorithm (CSOA), Moth flame optimization (MFO), and Grey Wolf Optimization (GWO) algorithm are analysed deeply in this work along with their future scope. Authors have restricted to ten potential algorithms few more potential bio-inspired algorithms is dealt in detail for authors other publications [6,7].The work carried on in two phases, in initial phase aims in recognizing algorithms and second phase in depth study of identified algorithms is performed. The chapter noticeably aid in identification of significant bio-inspired solutions for various problems. In section 1, overview of optimization technique and types are presented. Section 2 covers core part of authors work which gives in-depth information on ten bio-inspired algorithms. Section 3 focus on current observation of algorithms and in next section further scope and conclusion are briefed.

**II Overview of Optimization:**

Optimization methods execute and compare iteratively to find solutions for optimum solution to be searched. Optimization is part of all problems in all fields. Common types of optimization methods adopted to find solutions are briefed.

* 1. **Stochastic optimization**

Stochastic optimization (SO) computation involves more vagueness and impreciseness because of randomness in function of minimization or maximization to lend for real life scenarios. The involved unpredictability exists in form of noise in process of search by Monte Carlo randomness [8]. Stochastic annealing, approximation, programming, swarm based algorithms are common involved techniques of SO. They include high non linearity system noise and dimensional models. These models are present to analyze, solve, derive, numerical extraction of information in resolving decision making problems. Major investment of SO is in specific application oriented towards long and short programs. Aircrafts, missile, drug design, and network traffic control applications are getting advantage of SO. Stochastic application tool can be applied as a powerful modeling tool in few applications but estimation of real-life problems is another major uncertainly where solving through SO involves practical limitations. Another problem of SO is complete dependency on data available and modeling of it [3, 9].

**1.2 Robust optimization:**

The optimization model is robust based to deal upon data to regulate uncertainty. Key features are deterministic, easy computational tractability and set based. Model includes global or local or non- probabilistic or probabilistic models. Any a given problem will get involve all the features of robust optimization in order to search for a solution. Technique is also known as min-max or worst-case approach. Provide guarantee for solutions to problem application which involves more uncertainty in data. The parameters involved in process of estimation are to resolve estimation errors. One improved model for definition and interpretation is setting more robust constraints [10]. Engineering optimization design results mainly on reliability optimization and feasible input possible values to robust solution structure. Robust optimization gives same weight and values for parametric values in collection of uncertain data. Problems will be resolved with formulation of cost savings and stability, qualitative and quantitative. Complex problem considered for optimization may extent complexity to more significant level [6, 7].

**1.3 Dynamic optimization**

Dynamic programming is another name of dynamic optimization which process optimal profile of more than one parameter of a system. Do used to find possible solutions for a problem given. Variations of dynamic optimization with optimization discrete time, calculus variation and extend static optimization. The implementation includes a system controller to perform criterion with algorithm to execute control. Dynamic optimization involves system controller performs optimal substructure and overlapping sub-problems [8]. Dynamic optimization characterize structure, recursively define value, compute value and construct optimal solution for computation. Dynamic programming optimize problem recursively divide problem into sub-problems which can solve either bottom-up or top-down approach. Logic used is general and supple. It solves computation time and storage space [9]. Classification optimization based on different factors is summarized in table 1.

**Table 1**. Classification of Optimization

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Optimization** | **Factor** | **Taxonomy** |
| 1 | Stochastic | Constraints | Unconstrained  Constrained |
|  |  | Nature of equation | Non Linear  Polynomial  Linear  Quadratic |
| 2 | Robust | Physical structure | Optimal control  Non optimal control |
|  |  | Decision variable permissible value | Integer programming  Real-valued programming |
| 3 | Dynamic | Variable type | Deterministic  Non-deterministic |
|  |  | Function splitting | Separable  Non separable |
|  |  | Objective function | Single objective  Multi objective |

II **Bio inspired optimization algorithms**

This section brief on bio-inspired algorithms detailed. Concept advantage algorithm, flowchart and applications are briefed.

* 1. **Particle swarm optimization(PSO)**

In - proposed particle swarm optimization(PSO) algorithm inspired from intelligent behaviour of birds [11], Craig Reynolds simulated flock social birds behaviour for first time and later studied by Frank Heppner[12]. PSO search for optimal solution similar to flyting birds with specific velocities determined from previous results and neighbors in identified search areas[13]. Given a problem identified in search space represent solution in different n-dimension as result in PSO as n particles. The particle moves in n dimension solution space with different velocities. Particles moves and store previous behaviours of it and share experiences to store search space. Key merit od POS is its experience to share particle communicate to part or complete swarm to lead motion to detect search space[17]. Each particle will compare current fitness value with previous optimized result and neighbors in every iterations. Entire particles global and local algorithm is considered. Each particle best global value stored as local value. The entire search space particles best result is stored as global best optimal solution. In further iterations value will be adjusted to best optimal if current is best when compared to previous results.

**2.1.1 PSO Concept**

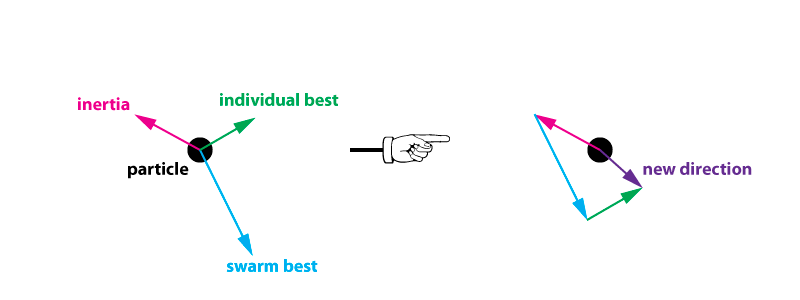
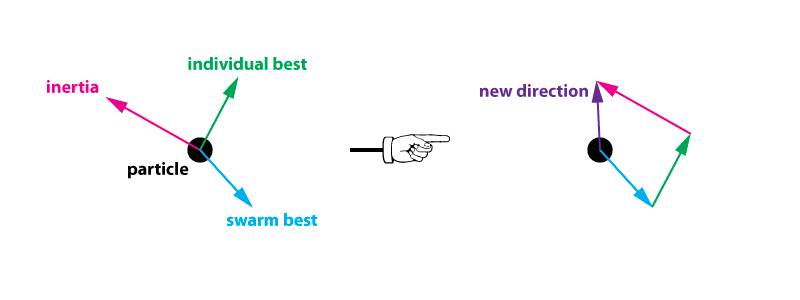
Each particle is running in PSO to identify feasible solution to the optimization problem in a given search space. The behavior of flight of particles is considered as search of individual particle. Velocity of particles is dynamically updated based on position of particle and optimal swarm population. The swarm population is composed of M particles in D dimensional space and historical optimal position of the ith particle is represented by pi, iϵ {1,2,3…M} and optimal position of swarm population is denoted by pg. In every step velocity and position of each particle are updated dynamically tracking its corresponding previous positions and optimal position of swarm population. The detailed equations are expressed as follows,

(2.1.1)

(2.1.2)

In eq 2.1.1 and 2.1.2 t indicates iteration number , d ϵ {1, 2, 3, ….. D} indicates dimension, *xi*,*d*(*t*) is the *dth* dimension variable of the *ith* particle in the *tth* iteration, and variables *vi*,*d*(*t*), *pg*,*d*(*t*), and *pi*,*d*(*t*) have the similar meanings in turn. 𝜔 is inertial weight, and *c1* and *c2* denote acceleration coefficients, *r1* and *r2* are random numbers uniformly distributed in interval [0, 1]. The objective function to be set, and resultant objective values of each particle correspond to fitness values. These fitness values are used to measure position of particles, historical optimal position of particles and the optimal position of swarm population.

The main concept of PSO is clear from the particle velocity equation that a constant balance between three distinct forces hauling on each particle: (i) particles previous velocity (inertia), (ii) Distance from the individual particles’ best known position (cognitive force) and (iii) Distance from the swarms best known position (social force). These forces are dependent on c1 and c2 weight constants and randomly concerned by r1 and r2 constants. Three forces are shown in vector form as in figure 1(a) where weight values are specified in vector magnitude. The particles will continue to explore as in search space similar to bird as shown in figure 1(b) to converge to best position.



**(a)**

**(b)**

**Figure 1**: (a) Exploration of PSO (b) Search of new position (4)

PSO shows sufficient better performance on optimization related problems of small scale. The original POS later on improved versions of PSO have been proposed by many researchers. Few incremental works of PSO is been discussed in this sub section which support for large scale and multiple optima [17].

Opposition based PSO discussed by Jabeen et al[4]. Particle has been classified into two class bad and good. Population of two class generated with fitness computation then original PSO applied. The opposite particle computed using equation

2.1.3

Where in Eq. 2.1.3 D is the dimension and R is real number. Quasi-oppositional comprehensive learning particle swarm optimizers (QCLPSO) proposed Chang et al [7]. Swarm initialization applied by qausi opposite number. The constriction factor balance incremental approach to proposed by Clerc [8]. The equation with constriction factor velocity updated equation is summarized in Eq. 2.1.4 -2.1.6,

2.1.4

2.1.5

2.1.6

A random value is distributed between [0, 1] for particles by Zhang et al [13]. The dependency inertia weight to maximize number of iterations to another one is applied to avoid problems in original PSO to search local ability to end. Speed and accumulation based inertia weight computation is proposed in Wei et al [14]. A Cauchy mutation an improved PSO proposed by Wang et al [17]. The original fitness of particle is selected to mutate the particle to distribute with increase in parameter scale t=1. It is defined between test function to choose randomly to assign velocity and pop size for particles in swarm. A variation in computation of power distribution among particles applies global best value with power mutation function. The fitness calculation for both particles select appropriate one in Wu et al [13]. Power mutation function based another opposition based power mutation function applied for PSO by Imran et al [14]. Two times mutation being applied on opposite swarms and global best particle power mutation. Global selection for best mutation avoids stagnation. Still improved PSO presented by Imran et al [15] with student T mutation. Global best particle T student particle identified to work over adaptive and Cauchy mutation.

Initialize the population randomly

While (Population Size)

{

Calculate fitness If fitness value is better from the best fitness value (pbest) in history then

Update pbest with the new pbest

Select the particle with the best fitness value from all particles as gbest

While maximum iterations or minimum error criteria is not attained

{

For each particle Calculate particle velocity by equation (1)

Update particle position according to equation (2)

}

}

Randomly initialize oopulation

Compute fitness

Select best solution

Update particle velocity

Terminating condition met?

Store best solution & stop

**Figure 2:** PSO Algorithm & Flowchart

**2.1.2 Merits of PSO:**

* Communication capability: particles can communicate efficiently each other as positions of best particle of all previous iterations are stored.
* Faster Convergence: accelerates more towards optimal solution in optimization
* Simplicity: Updation of velocity and position equations are simple to calculate
* Adaptable to environment: have ability to choose best optimal solutions in changing environment.

**2.1.3 Demerits of PSO:**

* PSO fails to resolve problem which lack in storage and not able to may clear distinction between previous and next particle positions.
* Assume all particles are same hence inertial and velocity also remain same
* PSO donot identify multiple optima.
* Convergence is harder with varied inertia weight

**2.1.4 Applications**

PSO is been applied in most of domains to optimize solutions from agriculture to industry. PSO has been extensively applied in different geotechnical engineering aspects such as slope stability analysis, pile and foundation engineering, rock and soil mechanics, and tunneling and underground space design [16]. PSO has been widely used in various kinds of planning problems, especially in the area of substation locating and sizing [17]. But in area of heating supply, PSO is mainly applied in heating load forecasting [18-20], but rarely used in Heat System Planning. PSO can be applied for various optimization problems, for example, Energy-Storage Optimization. PSO can simulate the movement of a particle swarm and can be applied in visual effects like those special effects in the Hollywood film.

* 1. **Genetic Bee Colony (GBC) Algorithm**

Bee food identification and collection intelligent swarm technique is defined in artificial bee colony. The best bee for required problem selected through parameters communication link, task allocation, reproduction, dance, placement mating and movement. GBC is optimizes towards solution iteratively in attempt to increase efficiency for any critical problem. Bee swarm is categorized as employee, onlooker and scouts. The employee bee identifies fresh source of food. Scout bees job is to assign fitness quotient to entrust job of random search for employee bee identified spots. The assigned is random based. If freshly identified food is better than earlier findings then, bees will collect from fresh location. Constantly employee bees look for best site for food collection. The onlooker bee is responsible to identify best food source considering quantitative factor of food availability [21,22].

**2.2.1 Concept**

The ABC algorithm consists of four main steps: initialization, employed bee phase, onlooker bee phase, and scout bee phase. After the initialization step, the other three main steps of the algorithm are carried out repeatedly in a loop until the termination condition is met. The main steps of the ABC algorithm are as follows.

*Step 1 (initialization).*In the initialization step, the ABC generates a randomly distributed population of*SN* solutions (food sources), where*SN* also denotes the number of employed or onlooker bees. Let  represent the ith food source, where  is the problem size. Each food source is generated within the limited range of ith index by where ,    is a uniformly distributed random real number in , xmin and xmax and  are the lower and upper bounds for the dimension , respectively. Moreover, a trial counter for each food source is initialized as in Eq. 2.2.1.

2.2.1

*Step 2 (employed bee phase).*In the employed bee phase, each employed bee visits a food source and generates a neighboring food source in the vicinity of the selected food source. Employed bees search a new solution, by performing a local search around each food source as follows: where  is a randomly selected index  and is a randomly chosen food source that is not equal to ; that is, .  is a random number within the range  generated specifically for each  and  combination. A greedy selection is applied between and by selecting the better one as in Eq. 2.2.2.

2.2.2

*Step 3 (onlooker bee phase).*Unlike the employed bees, onlooker bees select a food source depending on the probability value , which is determined by nectar amount associated with that food source. The value of  is calculated for the food source as follows considering Eq. 2.2.3 and 2.2.4:where  is the fitness value of solution  and calculated as in (4) for minimization problems. Different fitness functions are employed for maximization problems. By using this type of roulette wheel based probabilistic selection, better food sources will more likely be visited by onlooker bees. Therefore, onlooker bees try to find new candidate food sources around good solutions. Once the onlooker bee chooses the food source, it generates a new solution using (2). Similar to the employed bee phase, a greedy selection is carried out between.

2.2.3

2.2.4

*Step 4 (scout bee phase).*A trial counter is associated with each food source, which depicts the number of tries that the food source cannot be improved. If a food source cannot be improved for a predetermined number of tries (limit) during the onlooker and employed bee phases, then the employed bee associated with that food source becomes a scout bee. Then, the scout bee finds a new food source using ([1](https://www.hindawi.com/journals/cin/2016/8085953/#EEq1)). By implementing the scout bee phase, the ABC algorithm easily escapes from minimums and improves its diversification performance.

It should be noted that, in the employed bee phase, a local search is applied to each food source, whereas in the onlooker bee phase better food sources will more likely be updated. Therefore, in ABC algorithm, the employed bee phase is responsible for diversification whereas the onlooker bee phase is responsible of intensification. The flow chart of the ABC is given in Figure 3.

**Figure 3:** GBC flowchart

Initialization & Evaluation of Population

**Employee Bee phase**

Select a new food source and produce a new food source

Calculate probability values

Evaluate new food source &update food source position if necessary

Onlooker Bee Phase

Select a new food source according to probability values

Produce new food source & evaluate

Update food source position if necessary

If Termination condition met?

Best solution & food position and Stop

Set Control Parameters & Initialize food source Place

**2.2.2 Merits of GBC**

 The ABC algorithm is a population-based algorithm with the advantages of finding global optimization solution, being simple and flexible, and using very few control parameters. The ABC algorithm has been applied to many real-world applications, for example, function optimization, real-parameter optimization, digital filter design, clustering, and neural network training. ABC algorithm based applications are easy to build, robust, converge fast, flexible and time efficient. Compared to PSO ACO parameters considered in ABC is less.

**2.2.3 Demerits of GBC**

Inspite of mentioned advantage GBC has few problems also. GBC are slow convergent speed in large computations and accuracy is less. GBC may face premature convergence problem for more duration application. The population size is fixed and size is variations or non-autonomous. individuals can extend the searching space and increase the probability of finding global optimization solution; however, it costs much time in each generation; oppositely, it may obtain a local minimum.

**2.2.4 Applications of Artificial Bee Colony (ABC) Algorithm**

GBC are more affine towards single-objective numerical optimization problems but not limited can be extended to multi-parametric. Decision making, Time schedule, assignment, search, inception, boundary setting, and network issued are other more applied fields of GBC [21]. GBC is capable to handle constrained and unconstrained, continuous and discrete, differential and non-differential oriented problems [22]. GBC is not specific in domain, applicable from agriculture to industry, and rural area to military field.

* 1. **Fish Swarm Algorithm (FSA)**

Fish swarm algorithm inspired by the behaviour of movement of aquatic fish in liquid medium. The target picked randomly and moves toward in iterative manner. Visually shorter distance considered in initial step, it influences on final step. Initial values remain constant and consider along parameters. Suitable initial value selection leads towards best optimum solution. Fishes are capable of venturing into bigger steps in search of larger environment where they exist. So, fish is capable of escaping from unfavorable circumstances at any stage. But some deficiencies in large values may cause low steadiness. Global search is potential factor of generating local search with larger visual position of FSA. The better fitness can be found for better fitness to search for parameters to make algorithm steady and accurate. Fish are capable of moving quickly towards target and can get pass from local best search results. FSA algorithm design has undergone many changes in design in order to fulfill needs of different types of problems. The variation in algorithm can be grouped into solution of FSA for continuous and discrete, combinatorial and binary, multi-parametric and hybrid FSA. Fei et al. [24] selected nine search positions to initialize the AFs for motion estimation. Zhu et al. [23] and Gao et al. [25]used the chaotic transformation [26] method to generate a more stable and uniform population. Kang et al. [28] used a uniform initialization method to initialize the population, while Liu et al. [27] initialized the

AFs based on the optimization problem in hand. The MSAFSA [29] model introduced both the leaping and swallow behaviors to escape from the local optima and reduce, Yazdani et al. [30] introduced mNAFSA for optimization in dynamic environments.

**2.3.1 Concept**

Fish Swarm algorithm and background is discussed. Notations used are X, V, S, Xv indicate current position of fish, distance, step, position respectively. N visual fishes are indicated as X1, X2, X3…….. Xn. Y = f(X) denotes the food concentration of the AF at the current position, di;j =||Xi - Xj ||. The FSM involves four key operations: preying behaviour, swarming behaviour, following behaviour and random behaviour. Preying is fish behaviour to move itself towards high concentration of food. It is represented mathematically as in Eq. 2.3.1 considering with in visual distance ith fish. The fish preying will continue Trynumber of times if not satisfied within, then randomly computed using Eq. 2.3.2. Fishes group among themselves to from any danger situations against them. Mathematically, central position in fish swarm is computed as in Eq.2.3.3. Fish when a locates good concentration of food. The preying movement for fish in step movement is represented in Eq. 2.3.4. Few fishes randomly moves freely if lie in sparely concentrated food. This behaviour is modeled as in Eq. 2.3.5.

Xn1

Xn1

Xn

Xnext

Visual

Figure 4: FSA Visual

2.3.1

2.3.2

2.3.3

2.3.3

**2.3.2 Algorithm & Flowchart**

FSA perform record one if new. This search continues until end is not met following four operational steps as mentioned in previous section. The algorithm FSA is shown in briefed in Figure 5.

**Algorithm: FSA**

**Input:** Initialize necessary parameters

**Output:** Optimal fish state as solution

Generate n random fishes within the given search space

while not m steps then

for n fishes do

Compute fitness value

Evaluate behaviour

end for

update best solution

end while

Initialize number of fish and other parameters

Generate fish with initial fish swarm value

Preying behaviour

Swarming behaviour

Following behaviour

Move towards high concentration of food

Move to form group Move to located food region

Move to better food region than identified

Behaviour selecting & state updating

Confirm state behaviour of fish and access

Select optimization state

If Termination condition met?

Best solution print & Stop

N

Figure 5: FSA algorithm &flowchart

**2.3.3 Merits**

FSA similar to GBC has got increased convergence power and flexible. In addition it exhibits fault to tolerant and accuracy feature. Global search ability, tolerance of parameter setting and robustness are other merits of FSA. It solves nonlinear and multi modal problems.

**2.3.4 Demerits**

FSA exhibits high complexity, lack of balance among one is ineffective if lack balance between local search. Not suitable for global convergence problem. the information transfer if experience low search rate. as good robustness, global search ability, tolerance of parameter setting, and it is also proved to be insensitive to initial values

**2.3.5 Applications**

FSA has been applied for network related problems, control of resources, image processing related problems. In order to increase evolutionary capabilities of FSA, in few swarm solutions hybrid to FSA.

FSA incorporate to optimise solutions in wireless sensor networks[30,32,33], tracking [53],medical estimations [37,39], segmentation [32], clustering[33], regression[34],image processing [35, 36], calibration(37), localization[38], power systems[39,41].

* 1. **Cat Swarm Optimization (CSO)**

Chu et al. introduced cat swarm optimization technique to solve most of engineering problems inspired by the movement of cats. The process is carried on in two different modes seeking and tracing modes. Nodes virtually move in fixed areas as cats to determine optimal solution. Number of virtual cats are fixed in both modes and predefined in few cases ratio known as MR. the N virtual cats is placed randomly. Processed and unprocessed cats are identified for each dimension based on it value of MR set either to 0 or 1 for tracing or seeking in coming rounds. Every cat compute fitness function in evaluation then among the existing best will be chosen initially existing is compared if It best retained for fitness function otherwise coordinates will be changed to new best cat. The movement of cat adjusted towards solution space identified as identified in initially. Choose for unprocessed cats in tracing mode through permutation. Tracing mode ends if no more cats are left. Traced coordinate nodes will be selected as best solution at end. In seeking mode cats movement will be slow and conformist. Essential parameters of seeking mode are seeking memory pool, Ra range of identified dimension, counts of dimensions to change and self-position. Improved CSO algorithm proposed by Tsai et al supports parallel information exchange in tracing mode. The parallelizing of virtual agents is adopted in PCSO [42, 43]. PCSO finds application in parallel processing inspired by colonies of cats tracing for food.

**2.4.1 Concept**

CSO identification of optimized solution is described in this sub section step by step. The seeking feature of cats carried on in five processing steps. In first step, j copies of cat generated recognized applying equation 1. Addition or decrement of SRD value on selected search space defined by equation 2, 3 & 4 in step two. In next step fitness value for all candidates is selected. In step four, calculation of probability of cat performed by equation 5. Sort and select best solution by roulette wheel selection in last step. In tracking mode cats imitate movement of prey during tracing. This process can be discrete into three operational steps. In first step, velocity of each cat is updated as in equation 6 for given search space. The random value for cat adjusted in range 0-1. In step 2, the valued are rearranged based on velocities of cat. Velocities are set to maximum velocity value. Position of cat is updated selecting by equation 7 in last step.

2.4.1

2.4.2

2.4.3

2.4.4

2.4.5

2.4.6

2.4.7

**2.4.3Algorithm & flowchart**

The algorithms and flow of operations of CSO is summarized in Figure 6.

Initialize position, velocity of n cat

Evaluate fitness values of cats

Store position of the cat having best fitness value

Is in seeking mode?

Seeking machanism

Tracing Mechanismm

Distribute cats randomly distribute cats for each position seeking, tracing and update

Evaluate fitness value and pick best solution

Terminating Condition met?

Keep best solution & stop

Algorithm : CSO

**Input:** Number of cat,

**Output:** Best cat as solution

Begin

Determine best MR applying minimal rounds

Create cat population

While not termination condition do

For size n do

If cat is in seeking mode then

Apply seeking mode

Else

Tracing mode

End for

Evaluate best fit

End while

Store best solution

end

**Figure 6:** COA algorithm & Flowchart

**2.4.3 Merits**

COA is Simple to construct and have minimal parameters to adjust. COA has got ability to execute in parallel system. The design is robust. Can converge fast, find global solution, overlap and mutate. Have computational time less. Find accurate mathematical models. Discover good and rapid solutions. Adapt changes in new system and dependent on random decisions.

**2.4.4 Demerits**

Definition of initial parameters is time consuming. COA not works better for scattering problems and can converge at faster rate if trapped in complex problems. The time to converge and towards convergence for multi objective and larger sized problem is more.

**2.4.5 Applications**

CSO optimization is being incorporated in media for information hiding [43], aircraft scheduling recovery in limited processing time [44]. Voltage stability, economically dispatch in transmission system, hybrid generation systems, task allocation, data mining, project scheduling, optimal contract capacity, global numeric optimization problems. Applied for clustering technique in green expression classification, travelling sales man problem, data hiding, graph coloring, SVM, K means. CAO even find its application in stock market and supply chain in currency exchange rate analysis and stock prediction. COA is applied in image processing for machinery fault detection, plant modeling, image edge enhancement, water marking and single bit map. COA extended application in electronics for cognitive radio engine cooperative, spectrum sensing, linear antenna array synthesis, aircraft maintenance, routing for wireless sensor network.

**2.5 Whale Optimization Algorithm (WOA)**

Whale optimization algorithm proposed by Mirjalili at. El. WOA is also based on population of whale. It simulate bubble-net attacking method of humpback whales when hunting their preys. Whales are intelligent due to the spindle cells in their brain. They live in group and are able to develop their own dialect. Whale optimization algorithm consists of two modes of operation. The two mode of operation named as exploitation and exploration. In first prey encircling and position update in spiral manner carried on. Searching for prey randomly done in second phase[45-47]. WHO exploitation phase for prey encircling is mathematically equalized as bubble net attack system. Humpback characteristics of whales considered for phase one behaviour. Whales encircle prey with identification of them in an undefined search space. Initial solution of nearby prey or ideal assumed as best further best solution will be updated once exploration begins. Distance between prey and whales calculated initially then, updates for spiral positioned distance to it. WOA has modified and incorporated improvements by many researchers[48-52]. Few notable changes included in AWOA, IWOA, chaotic WOA, ILWOA, and MWOA research work. WOA hybridized with other meta-heuristic algorithms PSO, BA, and others in order to improve local search[53-56]

**Concept**

Whale has a special hunting mechanism which is called bubble-net feeding method. This foraging behaviour is done by creating a special bubbles in a spiral shape or 9 shape path. Humpback whales know the location of prey and encircle them. They consider the current best candidate solution is best obtained solution and near the optimal solution. After assigning the best candidate, the other agents try to update their positions towards the best search agent as computed by Eq. 2.5.1. In Eq. 2.5.1 and 2.5.2, t is the current iteration, A and C are coefficients vectors, X\* is the position vector of the best solution. The vector A and C are calculated using Eq. 2.5.3 and 2.5.4. In Eq. 2.5.3 and 2.5.4 a are linearly decreased from 2 to 0 over the course of iterations and r is random vector in [0, 1].the humpback whales attack the prey with the bubble-net mechanism in exploitation phase. in shrinking encircling mechanism, the value of A is a random value in interval [-a, a] and the value of a is decreased from 2 to 0 over the course of iterations. Spiral updating position mechanism calculate the distance between the whale location and the prey location is calculated then the helix-shaped movement of humpback is created using Eq. 2.5.6. D’ = |X\*(t) – X(t)| is distance between the prey and the ith whale, be is a constant, l is random number in [-1, 1]. Whale selectively apply swim around prey techniques suitably. The mathematical model of these two mechanisms assumes to choose between these two mechanisms to update the position of whale as in Eq. 2.5.7. In steady exploitation phase the humpback whales search for prey and change their position of whale. The force the search away from reference whale the mathematical model of exploration is computed as in Eq. 2.5.7 and 2.5.8.

2.5.1

2.5.2

2.5.3

2.5.4

2.5.5

2.5.6

2.5.7

2.5.8

**2.5.2 Algorithm & flowchart**

The detailed workflow and algorithms is presented in Figure 7

**Algorithm :**Whale Swarm Algorithm

**Input:** Number of whale, position,variable v=0,u =infinity

**Output:**  Optimal solution

Begin:

Initialize parameters

Initialize whale positions

Compute fitness value of all whale

while not final criterion do,

for n whales do,

Find the better and nearest whale among all n

For i in m objective values do

If u not equal to m then

If f(mi) < 0.5 then

If dist(mi, mv) < u then

v= i & u dist(mi, mv)

end if

end if

end if

end for

if Solution exist then

N moves under guidance of best near whale

Evaluate fitness value

end if

end for

end while

store better optimal solution

end

Initialize number of whale and position in search space

Evaluate fitness function of all whales in position

Select best whale near to all

If p < 0.5?

Spiral update

Encircle mechanism

Update position and fitness value

Terminating criteria met?

Store best solution & stop

Figure 7: WOA Algorithm & Flowchart

**2.5.3 Merits**

Whale optimization avoid problem of local optima have got ability to compute local and global optima for any constrained or unconstrained optimization applications. During the process it even doesn’t require any structural are parametric rearrangement or alteration in value. The exploration for best solution computed simply and easily at faster rate. Improve quality of generated population and converge at faster rate.

**2.5.4 Demerits**

WOA is not suitable for larger spaced problem incurs more time to explore and converge. The accuracy of solution is questionable. The optimal solution cannot be recognized for optimization of problems to solve high dimensional problem. Randomization technique of core WOA solution is complex. Balance among process of exploration and exploitation is lacking. The encircle mechanism slows WOA to jump from one local optima to another yielding low performance. Application problems of classification and dimensional reduction problem

**2.5.5 Applications**

WOA has ability to incorporate in dynamic applications. Most of researchers applied WOA for electrical, mechanical and management problems. WOA is been used to solve problem in engineering, multi objective, binary, identification classification and scheduling. WOA has found problems Power plants and systems scheduling [57] has confirmed to standard radial systems. Verify test system in execution of IEEE 30-bus [58, 59]. Size of pillars and optimization to increase efficiency of building is analysed [60]. Energy rise of solar energy to get importance in design of photovoltaic cells. WOA benefit solar cell and photovoltaic cells[61] by calculating internal parameters automatically. The partially cloudy atmosphere traced to get highest power region by a modified artificial killer whale optimization algorithm (MAKWO [62]. Medical image analysis for classification and diagnose liver and cluster based abdominal to avoid intensity values to overlap [63]. WOA incorporated in economic and emission dispatch [64], vehicle fuel consumption [65], mobile robot path planning [66], optimal allocation of an ameliorative of water resource [67], design problem [68], heat and power economic dispatch [69].

**2.6 Artificial Algae Algorithm (AAA)**

Artificial Algae Algorithm initially proposed in 2015 by Uymaz et al. is also a meta-heuristic bio inspired algorithm. Microalgae growth and reproduction in presence of sunlight behaviour are considered in algorithm AAA. Algae swim towards presence of sunlight for food production following process as photosynthesis. The movement of algae towards sunlight will be in helical manner. They live in groups as algae colonies. The algae identify best sunlight presence to carry on photosynthesis itself considering largest size and reproduce algae’s with highest energy. In case sunlight presence is less, then size of algal colony and energy level is less and starts for high starvation level. If sunlight is less algae colony tries to adopt itself in environment for its survival otherwise algae cells die because of starvation. The adaptation of algae cells in unsupportive environment is known as evolution [70]. Uymaz et. al. developed AAA then they modified to perform better [71]. From then many researchers contributed for AAA by incorporating AAA in different fields. Multi-objective optimization for AAA designed by Babalık et.al.[72]. Binary version presented by Zhang et al[73]. AAA applied in various fields from processing to manufacturing and in applications ranging from agriculture to home[74]. Few researcher improved AAA through hybridization [75]

**2.6.1 Concept**

AAA proposed for first by Uymaz et al deals with considering advantages of research area of the properties found in algae. Algae moves from helically towards lighter sources. Algae adopt in nature to adapt and reproduce forming colonies which represent a solution. Colony of algae consist set of cells which dwell together. The colony exposed to external forces. The algae is divided into group and each become new colony as can move jointly, under in appropriate circumstance to from new colony. AAA process incorporated by three parts: Evolutionary, adaptation and helical movement. In evolutionary process, algae colony grows and flourish to get sufficient light, and benefit conditions. The algae undergo mitosis to result in two new algae. If not algae will perish under less nutrition and lighter conditions. In few scenarios if algae cannot grow in an environment due to lack of supporting factors. In such environments algae adapt by itself to environment in order to survive as other species. Finally algae if it could not adapt then moves toward large grouped algae. If starvation occurs algae stop to adopt. Algaes move in helical movement by swim. In order to live they try to remain close to surface of water to get light. The search capacity will not remain same. Algae growth is more in region where frictional surface is more. The chance of algae movement is more in fluid. Helical motion supports to move algae at higher rate. The energy in different surfaces is not constant and is directly proportional to quantity of food and type of nutrient available in the environment. Capability and survival of algae existence depend on its adaptation and movement. The algae survival process mathematically applied in functional parts. Initially fix size of algae by Eq. 2.6.1. Evaluate fitness value of algae and size of colony by Eq. 2.6.2. Adaptation of algae is through growth of algae and use of nutrients by Eq.2.6.3. The energy of algae computation inclusion of frictional force is computed applying Eq.2.6.3 and 2.6.4. During adaptation process algae build itself under non favorable or movement to nearby stronger and larger algae colony part. The optimization for given problem can be computed by Eq.2.6.5 - 2.6.8. The three sub group of algae considered for adaptation. Identification of starvation be Eq.2.6.9 and 2.6.10. Section of best solution is selected by Eq.2.6.11.

2.6.1

2.6.2

i=1,2,3,…….N 2.6.3

2.6.4

2.6.5

2.6.6

2.6.7

2.6.8

2.6.9

2.6.10

2.6.11

**2.6.2 Algorithm & flowchart**

The algorithm and flow of operation of AAA is shown in Figure 8.

Initialize parameters of AAA

Evaluate fitness of n algae in search space

Evolutionary phase

Adaptation phase

Helical movement phase

Keep best colony, optimal solution & stop

Terminating

Condition?

Algorithm : Artificial Algae Algorithm

Input: number of algae and colony

Output: Best solution and colony

Begin

Generate an initial population of *n* algal colonies with random solution

evaluate *f(xi), i = 1, 2, …, D*

while stopping condition not reached do

for n algae do

while energy of *i*th colony not finished do

modify the colony with helical movement

end while

end for

apply evolutionary

apply adaptation

apply helical movement

end while

keep best solution

end

Figure 8: AAA Algorithm & Flowchart

**2.7.3 Merits**

AAA exhibits accuracy for identified colonies. Converge faster towards local and global solution compared to ACO or PSO. Algorithm is convenient and efficient. The method helps find efficient and high accurate result. Produce robust algorithm for real-time optimization problems. Main benefit for gradient based problems provide by an efficient optimize in few steps and simple to generate.

**2.7.4 Demerits**

Major problem of AAA is its expensive apparatus, consumption of time and specialized operator. If data and input size increases accuracy will be minimized. They tend to stick to local optima, increased dependency. AAA apply randomness by this methodology is simple but result accuracy is questionable. Hence applications involved in AAA are complex and provide unstable result.

**2.7.5 Applications**

 In optimal placement distributed power flow controller (DPFC) with MCFC, optimal coverage, routing and selection of cluster head in wireless sensor network.

* 1. **Elephant Search Algorithm (ESA)**

Elephant search algorithm developed by Adams et al inspired by elephant search for water. Normally elephants search for water in drought with in swarm. Elephant swarm together search water source. Each elephant swarm consists of leader responsible to make decision regarding movement of whole group. Elephant is identified by its particular position and velocity in each group very similar to other swarm techniques. Leader elephant informs rest of elephants in group in case best water source is identified. the communication is through chemical, tactile, acoustic or visual means. The fitness function is computed considering water source quality and quantity. The elephants group can move from one water source to another and visits previous also if necessary as they got good memory. Group visit previous water source in case older identified is best solution in compassion to new water source. Elephants search for best solution locally and globally then best solution will be identified in given solution space following long and short distance communication. Switching probability is key controller in considering water search either local or global.

**2.8.1 Concept**

EHO is meta-heuristic simulated behaviour in herds of elephants []23] introduced by Wang. Optimize solution for global optimization tasks [5]. Each solution I in each clan ciis updated considering current information such as position and matriarch. The generations are updated by algorithm execution through separating operators. Each individual in heard represent vectors in 2D. The dimensions in unknown population are included. The population is divided into n clans. Updating operator is modeled by increment or decrement each solution i in the clan by ci by influence of ci to identify best fitness value in generation. Fitness update solution in each clan ci represented in Eq.2.8.1. New and old position in clan, incremental factor based on influence of matriarch are parameters included of Eq.2.8.2. In 2D the central clan is computed through Eq.2.8.3. It updates individual value of elephants in heard. The total search space indicates number of solution in clan. The separating search space and nci indicates number of solutions in clan in ci. The separate operator is applied at each generation for execution on worst individual in population. Choose random population [0-1] be uniform distribution range within lower and upper limits of the position of the individual by Eq.2.8.4.

2.8.1

2.8.2

2.8.3

2.5.4

**2.8.2 Algorithm & flowchart**

The detailed algorithms and flow of operation of EHOA is presented in Figure 9.

Algorithm 1 Pseudo-code of EHO algorithm

Input: n elephant and max. generation

Output: Best solution

Begin

Generate population and calculate fitness

Divide population into m clans

Calculate fitness of each individual

For n individuals

While not termination condition do

Sort all solution according to their fitness

For all clans do

Update generation and find fitness

End for

Update best

End while

End for

Select best if existing is best retain

end

Initialize parameters of elephant heard

Generation collection

Clan update

Separation of population

Evaluation of fitness

Store best solution & stop

Termination condition met?

**Figure 9**: EHOA Algorithm & Flowchart

**2.8.3 Merits**

EHOA is more performance stable than other meta-heuristic algorithms such as PSO. Convergence is faster because they are in herd. Have ability to search a population in parallel. Rapidly discover good solutions similarly adapt to changes such as distance. The computation is simple. EHOA is efficient in solving problem which are difficult to find accurate mathematical models. Computational time is less and overlap is avoided.

**2.8.4 Demerits**

Probability can change for each iteration, theoretical analysis is difficult, and sequence of random decisions are major hindering factors of EHOA. Time requirement for convergence is uncertain.

**2.8.5 Applications**

EHO applied to optimize training artificial neural network [126], selection structure and weight for neural networks[127], training neural netwosk[128], optimizing underwater sensor networks[129], unmanned aerial vehicle path planning[130], clustering[132], support vector machine[133,135], control problem[137].

* 1. **Cuckoo search Optimization Algorithm (CSOA)**

Yang and Deb introduced cuckoo optimization in 2009 a meta-heuristic algorithm. Later Gandomi, Yang, & Alavi, 2013; Yang & Deb, 2013 extended to solve single or multi-objective problems involved in any constraints or complexity. The solution is capable to resolve potential solutions of any randomly selected population in habitants of cuckoo. The function of CSOA is global optimality, real-world problems are NP-hard for problem used in any problem. Construct workable solution required to be globally optimal solution replicating behaviour of cuckoos. They lay eggs in nest of other birds and obliterate eggs of birds to guarantee hatching of its breed. Cuckoos brood parasitism is simulated in three different ways: Intra-specific brood parasitism, nest take over and co-operative breed. The basic cuckoo search algorithm has undergone changes convergence speed of cuckoo search algorithm is increased in modified cuckoo search [74] by avoiding cross overs. Binary version of cuckoo search algorithm is presented in [75] to increase accuracy by reducing problem to binary coordinated feature. In [76] improves cuckoo search by resetting position and random vector value of eggs rather considering as static parameter value.

**2.9.1 Concept**

CS algorithm is based on the obligate brood parasitic behaviour of some cuckoo species in combination with the

Levy flight behaviour of some birds and fruit flies. Some species of Cuckoo birds lay their eggs in communal nests. If a

host bird discovers the eggs are not their own, they will either throw these alien eggs away or simply abandon its nest

and build a new nest elsewhere. CS, can be described using following three idealized rules:

a) Each cuckoo lays one egg at a time, and dump its egg in randomly chosen nest;

b) The best nests with high quality of eggs will carry over to the next generations;

c) The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host birth a

probability pa Є [0, 1].

**2.9.2 Algorithm & flowchart**

The algorithm and flow of operations of CSOA is presented in Figure 10-.

**Algorithm : Cuckoo search algorithm**

**Input:** n nests with eggs

**Out**put: best egg as solution

Begin

Objective function f(X), X = (x1, ..., xd)T

Generate initial population of n host nests Xi (i = 1, 2, ..., n)

while (t <MaxGeneration) or (stop criterion)

Get a cuckoo randomly by L´evy flights

evaluate its quality/fitness Fi

Choose a nest among n (say, j) randomly

if (Fi > Fj ),

replace j by the new solution;

end if

A fraction (pa) of worse nests are abandoned and new ones are built;

Keep the best solutions

Rank the solutions and find the current best

end while

Postprocess results and visualization

end

Initialize random population of n host nests

Choose cuckoo by random levy flights

Evaluate fitness and select nest among n random

Old fitness(fj) <fitness new(fi)?

Identify i solution

Replace j by new solution

Worst nest are abandoned, build new location via levy flights

Find best by objective function

Termination condition met?

Record best solution and stop

**Figure 10:** CSO Algorithm & Flowchart

Initialize random population of n host nests

**2.9.3 Merits**

A meta-heuristic method exhibits several advantages as easier for applications to change parameters to meet requirement of applications. It is very easy fall for optima of local solution to slow convergence rate. In addition cuckoo search is simple and easy to follow with real-world engineering applications. Cuckoo search algorithm easy to implement in comparison to other population algorithms.

**2.9.4 Demerit:**

CSA is about easy to fall in to local optima solution due to its simplicity. Slow the convergence rate randomness is still a problem. Self-adaptability may be limitation under certain problems. Low efficiency, less accuracy can be experienced while dealing with multi-peak function.

**2.9.5 Applications**

Cuckoo search optimization algorithm applied for different problems in various domains. Power generations to minimize the cost of flues , n power with probability to generate in different values, Cloud computing security frameworks are-Gathering information, Network mapping, vulnerabilities exploration, audits and penetration tests, vulnerabilities enumeration and categorization, technology selection for vulnerability remediation, security solutions implementation. The security technology is used to decrease the vulnerability and costs are called Set covering problem [75] that is the Distribution systems will have more power loss and poor voltage regulation and voltage stability. VANET protocols design [76], electromagnetic and antenna arrays[77], classification of IDS [78]. Self-adaptive algorithm for search accuracy of the CSA [79], Compression factor to build[80], dynamic appropriate step-size[81]. CSA have been applied in many researchers in different application problems such as multilevel image thresholding, flood forecasting, wireless sensor networks, data fusion, cluster in wireless networks, clustering, ground water expedition, supplier selection, load forecasting, surface roughness identification, DG allocation in network, BPNN neural network, web service composition, speaker recognition, face recognition, training neural networks[82-85].

* 1. **Moth flame optimization (MFO)**

Mirjalili proposed moth flame optimization algorithm a swarm algorithm inspired by movement of moths in spiral path around light source. Moth flames randomly start searching in solution space. The fitness value estimated based on position by each moth in group. Falling category to best position flame by all is optimal solution. The function category updates following spiral movement function to achieve better division towards light source. The best position can be individual positions and repeats updating moths distance and position generate new position to terminate criteria to be met. The variations in moth flame design inoder to improvement are for multi-objective, binary and hybridization

**2.10.1 Concept**

Mirjalili proposed meta-heuristic algorithm based on population. MFO moths randomly with in space recognize fitness value and identify position suitable without flame. The movement is continuous and repeated to recognize better position. Update position suitably until termination criteria is met. The process MFO is carried on in three main steps. In first step initialization of population and parameters are assumed in hyper dimensional space. The difference in way updates and treats in iterations. The position of each moth is stored. The selection of best moth is also performed so that results are stored longer time. In second step, three main functions converge to global result in Eq. 2.10.1. The identification to optimization is implemented randomly. Movement is spiral in moths applying logarithmic spiral function by Eq.2.10.2. Moth and flame fixed position and indicate [-1, 1] ranges. It balances between exploitation and exploration to guarantee moths circulation in search space guarantee in spiral motion. The fly of moth is traps of the local optima. Moth positioned near flame represented in matrix. In step 3, number of flames is updated; Moths locations search the exploitation in search space. Decrease and solve issue based on Eq.2.10.3.

2.10.1

2.10.3

**2.10.2 Algorithm & flowchart**

The algorithm and flow of operations of MFOA is presented in figure 11.

Algorithm : Moth-flame optimization Algorithm

Input: Number of moth-flame

Output: Best optimized solution

Begin

Parameter math-flam initialization

Moth position Pi randomly

For n moths do

Calculate fitness of all moths

end for

While not termination condition do

update position of Pi

calculate flames number

evaluate fitness function

if initial round then

sort all moths & store best and second best

else

sort excluding previous best moth end if

For n moths do

For d flames do

Update parameters of moth flame

compute number of flame near to each moth and update respectively

end for

end for

end while

store best solution

end

Initialize parameters of moth-flame & generate moths randomly

Calculate fitness of all moths

Update flame number t and r

Calculate D of all moths

Compute D & update corresponding moths

Terminating condition met?

Report best position among moths &stop

Figure 11: MFO Algorithms & Flowchart

**2.10.3 Merits**

MFO similar to most population based algorithm flexible and robust. The local opitma for individuals is avoided. Construction is easy and flexible in design. Moth has been incorporated to solve many engineering problems.

**2.10.4 Demerits**

Convergence is major issue in MFO.

**2.10.5 Applications**

MFO advantages have been incorporated in many domains. Navigation approach to solve the inequality and equality constrained optimization are real problem, to optimize real function for constrained selected variables. Chemical identification to improve single level production which can be extended to incorporate as include in determination of optimal production portfolio in other industries, applied in agriculture based to recognize problems of tomato[51]. Applied for medical field to improve time consuming Alhemeris disease[109], detection and diagnosis of breast cancer[125], to train networks RBFN[41], deployment of Wifi [114], determination of optimal solution in placement, location problem solution [118].

**2.11 Grey Wolf Optimization (GWO) algorithm**

Grey wolf optimization a meta-heuristic swarm technique introduced for first time by Simon Fong [86]. Hunting behaviour in pack of wolf inspired in design of grey wolf optimization. Wolves in pack will not communicate physically during hunting, each wolf identify and attack prey individually silently. They follow levy flights model in search of food during hunting. Wolves unify to another pack of wolves or to new location if they find new food location better and suitable compared to their current dwelling place. A random hunter will be selected among pack to hunt for prey. The hunter identifies potential position itself to catch prey from current line of sight[87].

**2.11.1 Concept**

The social hierarchy consists of four levels in GWO. The level one called Alpha. They are the leaders of the pack and they are male and female. They are responsible for making decisions about hunting time to walk, sleeping place and soon. The pack members have to dictate the alpha decisions and they acknowledge the alpha by holding their tails down. The alpha wolf is considered the dominant wolf in the pack and all his/her orders should be followed by the pack members. Next level group is labeled as Beta. The betas are subordinate wolves, which help the alpha in decision making. They can be either male or females. If consider the best candidate to both alpha when the alpha passes away or becomes very old. The beta reinforces the alpha’s commands throughput the pack and gives the feedback to alpha. The third group of wolves is called Delta. They are subordinates. They need to submit their work report to alpha and beta. Scouts are responsible for watching boundaries of the territory and warning the pack in case of any danger. Sentinels are responsible for protecting the pack. Hunters are response got helping the alphas and beta involves beta in hunting and provide food for the pack. They are not important individuals in the pack and they are allowed wolves were outwards. They are fighting i the case of loss.

Wolf search has been used to select two relay nodes: inter and intra relay nodes. Within a cluster, cluster members sense and transmit sensed data directly to the CH irrespective of their distance from CH. Hence, the nodes far away from CH dissipate more energy resulting in reduced network lifespan. To overcome this problem, the Wolf search is used in order to identify intra relay nodes for every cluster. The cluster member will send the sensed data to intra relay node and it in turm to CH. Similarly, all CHs communicate directly to BS irrespective of distance between CHs and BS. Hence, the CHs far away from BS dissipate more energy which leads to selection of new CHs resulting in next iteration, resulting very low network lifespan. To overcome this PEGASIS protocol introduced inter relay node as final node to communicate with BS. In proposed work, Wolf search is used to identify the inter relay nodes. The working principles of Wolf search for identification of inter and intra relay nodes are described in this section. The pseudo code of Wolf search is described in Algorithm 2.11.2.

are the coordinates of unknown node/target node and are the coordinates of the anchor node in the neighborhood. The computations of WS) for encircling, and hunting process are shown below.

Eq. 2.11.1 – 2.11.6 used in WSO are as follows.

2.11.1

2.11.2

2.11.3

2.11.4

2.11.5

2.11.6

where represents the current iteration, and are coefficient vectors, position vector of the prey is represented , X the position vector, is the absolute value, and is an element-by-element multiplication, is linearly decreased from 2 to 0 in each iteration and is a random vector in .

**2.11.2 Flowchart & Algorithm**

The algorithm and flow of operation of GWO is presented in Figure 12.

Figure 12: GWO Algorithm & Flowchart

Algorithm : Grey wolf optimization Algorithm

**Input:**

**Output:**

Begin

Initialize population of n candidate solutions Xi(I = 1, 2, 3……n)

Initialize α->best agent, β-> second best agent, δ->third best agent

While termination condition not met do

For each candidate wolf do

Update value of current candidate solution

End for

Update α β δ

Calculate fitness value

End while

end

Initialize search agents(wolves)

Initialize α β δ

Calculate fitness value

Find distance parameters Xα, Xβ, Xδ

Update position

Calculate fitness value of parameters α β δ

Termination condition met? met

Store best solution & stop

**2.11.3 Merits**

GWO experience alpha and beta experience is good for complex problems. More heads identification and building are experienced wolves is built. The goodness is identified better through GWO. It is not easy to apply local optima compared to meta-heuristic has lesser parameters. It searches in local search space. The convergence is faster. GWO is easy to implement in any platform. In more iteration avoids local optima and provide higher performance in search problems.

**2.11.4 Demerits**

In short problem slow convergence and easy premature can be expected. Piece-wise linear cost approximation and update of equation to build local exploration ability are problem in GWO. The accuracy solving can be considered a research challenge. Bad local search ability and slow velocity and falling optimum behaviour and position update are required. Easy falling of velocity and fall into local optimum.

**2.11.5 Applications of Wolf-Based Algorithm**

GWO algorithm finds application adaption in different domains. Fault system estimation [114] and prediction, hydro-power optimal operation station, Optimization in multi-layer perception [116]. Electronics based domain to find optimal allocation to determine system power loss[120], link functional net construction by q-Gaussian radial basis [117], Control operation of DC motors [122]. Fault detection in power systems [125]. Prioritization of problem [123], selection problem, solve combined economic emission dispatch problem to find optimum allocation [119]. Multi-input and multi-output contingency management problem [124]. Multi-input multi-output contingency management problems [124] and for detection of faulty sections in power systems [125], to name a few.

**III Comparison of algorithms**

Literature Survey reveals complex problems can be resolved in simple steps by applying bio-inspired principles and rules effectively by giving importance to each relationship. The discussed social and population based ten algorithms are involved in processing stages they include,

* 1. Identification of natural behaviour and responses of biological organism
  2. Replica model to simulate behaviour of biological organism
  3. Translating developed model to mathematical model with certain required assumptions
  4. Pseudocode generation for behaviours of biological organism
  5. Experimenting practically and theoretically both models of biological organism for guaranteed performance improvements in real-world problem.

**IV Issues, challenges and future direction**

This section briefs on bio-inspired algorithm current challenges, issues and further direction for next works to be carried in this direction.

1. **Literary issues**

The database identification was first challenge to identify supporting literature. Scopus a largest database of academic articles was primary focus in collection of articles from journals. The published articles on specific bio-inspired algorithm searched for publication number from 2008 – 2020. During search process name was considered as keyword. Obtained results were analysed for algorithm, document-wise and subject wise. Documents are categories are article, conference paper, review, book and others. More research publication in different categories can be found based on bio-inspired algorithms PSO and GBA compared to other emerging algorithms which is plotted in Figure 13. To have clear view of published article year wise plot was plotted as shown in Figure 14. The evolution of algorithms is clearly shown in fig 14. More publications is on established algorithm PSO and GBA and on other remaining algorithms publications are comparatively low hence more research can be carried on to identify suitable optimization position for this algorithms.

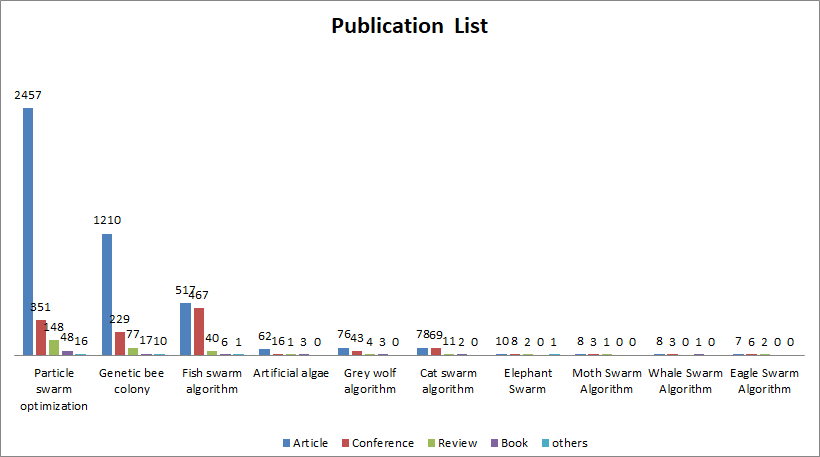
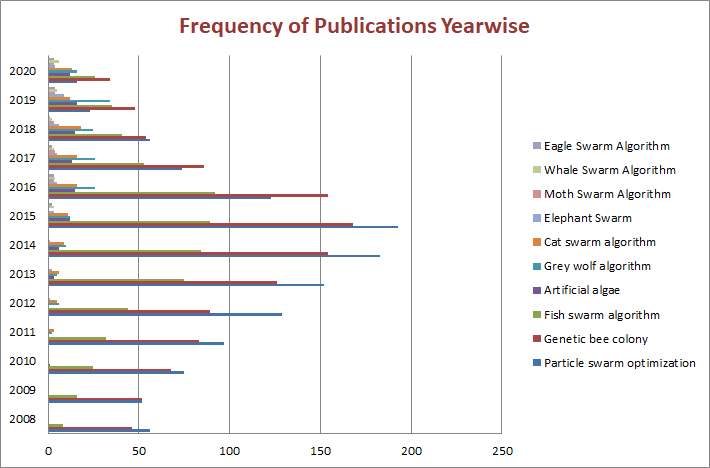
 

Figure 13. List of publications on different Bio-optimization Figure 14. Frequency of research articles published on various

based algorithms till 2021 bio-inspired algorithms year wise.

**B Challenges**

Bio –inspired algorithms face challenges in design of competitive and interactive component design. Biological systems are find lack in information exchange so algorithm has to be developed in absence of data. Improve or develop bio-inspired algorithms to design solution to adapt for any real-world problem. Performance of bio-inspired algorithm is another issue which need to be sorted in working environment.

**C Future scope**

Bio-inspired algorithms brought revolutionary changes in different domains as well got power to impact further generation computing. The application coverage area is vast compared conventional methods includes modeling, algorithm, engineering and computing. Generally optimization techniques based on swarm search procedures incorporate random changes and identification and still has capacity grow which is attracting many young researchers. Bio-inspired algorithms still require addressing new technologies along with it by exploring new ways to adopt algorithms. In order to achieve they need to be collaborated with research communities like computer science, biology, artificial intelligence, ecology, quantum and others. Currently, many bio-inspired algorithms exist and application field is also extensive and obviously work require further exploration,

-solution for specific application suitability of selection of parameters

- optimization in range and value of parameters.

- theoretical analysis of convergence of algorithm

- new application of bio-inspired algorithms needs to be explored

- identify suitable hybridization of algorithms with function or algorithms either convention or bio-inspired based.

**V Conclusion**

Bio-inspired algorithms have got roots in both pure science and engineering domains. Methods and related theories are mature got huge practical potential benefits to provide in different domain problems. To conclude ten bio-inspired algorithms, FSA imitates food search behaviour of fish considering three parameters distance, length, crowd factor among them first two influence function much. WOA whale inspired algorithm has three operators applied to model search, encircle and foraging behaviour of whales. CSO includes two key operations seeking and tracing in computation of optimum solution. In AAA control parameters influence whole functionality. MFO accuracy is based on spiral movement towards artificial light. ESA is based on exploration and exploitation in searching. GWO algorithm simulates wolves by dividing into four group; alpha, beta, delta, and omega.

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