

Introductory Review of Swarm Intelligence Techniques

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Abstract. With the rapid upliftment of technology, there has emerged a dire need to ‘fine-tune’ or ‘optimize’ certain processes, software, models or structures, with utmost accuracy and efficiency. Optimization algorithms are preferred over other methods of optimization through experimentation or simulation, for their generic problem-solving abilities and promising efficacy with the least human intervention. In recent times, the induction of natural phenomena into algorithm design has immensely triggered the efficiency of optimization process for even complex multi-dimensional, non-continuous, non-differentiable and noisy problem search spaces. This chapter deals with the Swarm intelligence (SI) based algorithms or Swarm Optimization Algorithms, which are a subset of the greater Nature Inspired Optimization Algorithms (NIOAs). Swarm intelligence involves the collective study of individuals and their mutual interactions leading to intelligent behavior of the swarm. The chapter presents various population-based SI algorithms, their fundamental structures along with their mathematical models.

Keywords: Optimization problems, Optimization Algorithms, Nature Inspired Optimization Algorithm, Swarm Intelligence.

1 Introduction

Optimization is the simple action to make the best utilization of resources. Mathematically, it is finding the most useful solutions out of all possible solutions for a particular problem. There are two types of optimization problems leaning on whether the variables are *continuous* or *discrete*. Comparatively, continuous optimization problems tend to be easier to solve than discrete optimization. A problem with continuous variables is known as continuous optimization. It aims at achieving maximum efficiency to reduce the cost or increase the overall performance. Variables in continuous optimization are permitted to take on any value within a range of values. In discrete optimization, some or all the variables in a problem are required to belong to a discrete set. Improvements in algorithms coupled with advancements in computing technology have dramatically

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increased the size and complexity of discrete optimization problems that can be solved efficiently. With the introduction of Swarm Intelligence (SI), conventional methods are less frequently utilized. Still, we need better SI techniques. Optimizing solutions comes with some challenges, for instance, it is time consuming, needs to be updated continuously and can consider only a small range of problems and the solutions obtained may be far from being optimal.

Let us take a small example to visualize the importance of SI over conventional techniques. Suppose, there are four explorers searching for a treasure which is located in a mountain region with several ridges and the treasure is located under one such ridge. The other ridges have small treasures which are not worth the effort. The treasure can be visualized as the optimal solution and the other small regions as the local solutions to the problem. Clearly, the four explorers do not want the small treasures and are definitely going to search for the bigger treasure. They start off with a conventional search for the treasure with a conventional technique known as the gradient descent. They randomly land on a place in the region and go downwards on the nearest slope to get to the nearest ridge and dig it up. What are the chances that they will find the treasure on their first try? It's obviously quite low. In fact, in the real world, finding optimal solutions with this approach is really time consuming if the data to search reaches a sufficiently large value. Next, they try a SI approach. One explorer each lands in different locations of the region, and they start exploring locally. But this time, they have phones to converse with each other. They communicate with each other and search areas which are optimally closer to the treasure. Finally, after some 'exploration' they find the actual treasure they are searching for. It is to be noted that since they could converse with each other, they can easily skip areas that have been searched by the others. Also, the area of search increases if we consider the whole unit, and also they are searching locally individually. Simply put, the unit *explores* the regions, and individually, they *exploit* a region to find the treasure. It is a lot quicker and less time consuming than the conventional mechanisms to reach the same solution. Mathematically speaking, optimal solutions refer to the minimums of the curve represented by the problem. There can be problems which have only one global minimum, i.e., there is only one slope and any point on the curve can reach that point if we follow the downward slope of the curve. However, most problems in the real world have multiple minimums, which means, there are local minimums effective to only a particular area in the curve and global minimums which are the optimal solution to the problem (or curve).

Swarm intelligence can solve complex and challenging problems due to its dynamic properties, wireless communications, device mobility and information exchange. Some examples of swarm are that of bees, ants, birds, etc. They are smarter together than alone and this can be seen in nature too, that creatures when working together as unified system can outperform the majority of individual members when they have to make a decision and solve problems. Swarm Intelligence is based on clustering individually or adding to existing clustering techniques. Besides the applications to the already present conventional opti-

mization problems, SI is useful in various other problems like communication, medical data-set classification, tracking moving objects, and prediction. To put it simply, SI can be applied to a variety of fields in fundamental research, engineering and sciences. However, to think that an algorithm developed matches the criteria for solving every problem out there in the real world is quite naive. Techniques developed using SI are more problem based, and several changes are made already in present algorithms to reach the solutions of the specific problems. Thus, developing an algorithm without a clear objective (, or problem) is not possible. SI techniques are especially useful to find solutions of non-deterministic polynomial-time problems, which would take exponential time to solve if we take a direct approach to solve the problem. Thus, swarm-based techniques are used to find approximate solutions which are relatively good for the problem.

Rest of the chapter is organized as follows. Section 2 presents a generic framework for SI techniques and briefed primary components of SI techniques. Section 3 shows how different SI techniques evolved with time. Section 4 briefly explains working principles of prominent SI techniques. Section 5 highlights various application domains of SI techniques. Lastly, section 6 concludes highlighting different nuances, shortcomings, and applicability of SI techniques.

2 Generic Framework of Swarm Intelligence Techniques

When we need to find a solution to an optimization problem, we first observe the attributes, constraints, whether it will have a single objective or multiple objectives etc. With traditional optimization, we try to find the solution by traditional methods such as brute force, simulation or apply conventional optimization techniques which is time consuming, requires huge computation cost and requires frequent human intervention. To understand how we approach an optimization problem conventionally, a flow chart is shown in Fig. 1.

As conventional techniques work best for finding solutions to simple continuous, linear optimization problems, real world optimization are often non-linear and discontinuous in nature. When solving a real world optimization problem complication such as a large number of local solution and constraints, discrete variables, multiple objectives, deceptive search space etc. needs to be addressed. When we plug in these conventional techniques in the real world problem it leads to problems such as non-optimal solutions, being stuck on a local solution, low convergence rate etc. A need to develop an intelligent system to efficiently solve these real world problems have become a necessity. To develop these intelligent systems over the years, researchers and scholars have taken inspiration from various phenomena of nature as these phenomena always tend to self-organize even in the most complex environments of nature. Swarm Intelligence techniques are a subset of these Nature Based algorithms which is based on the swarming behavior of insects, birds, fishes, animals etc. to develop a collective intelligence, self-organized way of solving complex, discontinuous, nonlinear systems efficiently with higher convergence and less time consumption as compared

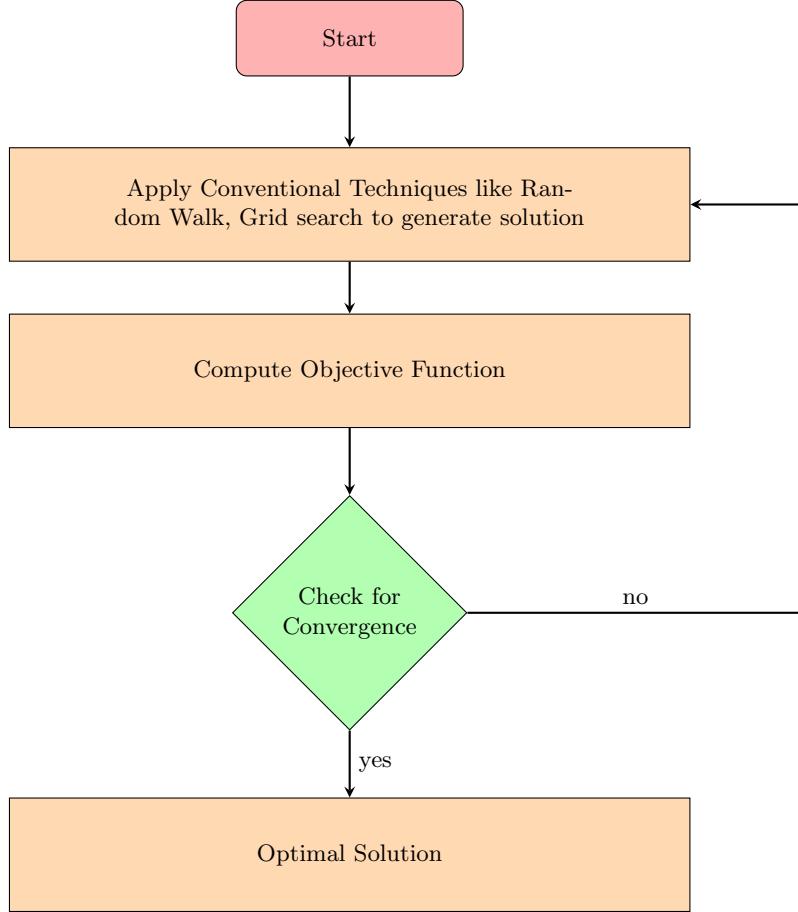


Fig. 1. Generic Flowchart of optimization using Traditional Techniques

to conventional techniques. In Swarm Based algorithms members of the swarm interact with each other and the environment to develop a collective intelligence.

Over the years as more and more Swarm Intelligence techniques are developed and used, let us look at some important aspects of these swarm based algorithms:

- **Exploration:** One of the most important aspects of every swarm intelligence techniques is its exploration also known as diversification. Exploration traverses the search landscape to search for new solutions which are different from the current solution. This helps us in finding solution which is better than the current solution and helps us in diversifying our solution. It also helps us to escape from a local solution to find new and better solutions. But we should be careful as too much exploration will lead to slow convergence, which is not desired at any swarm intelligence techniques.

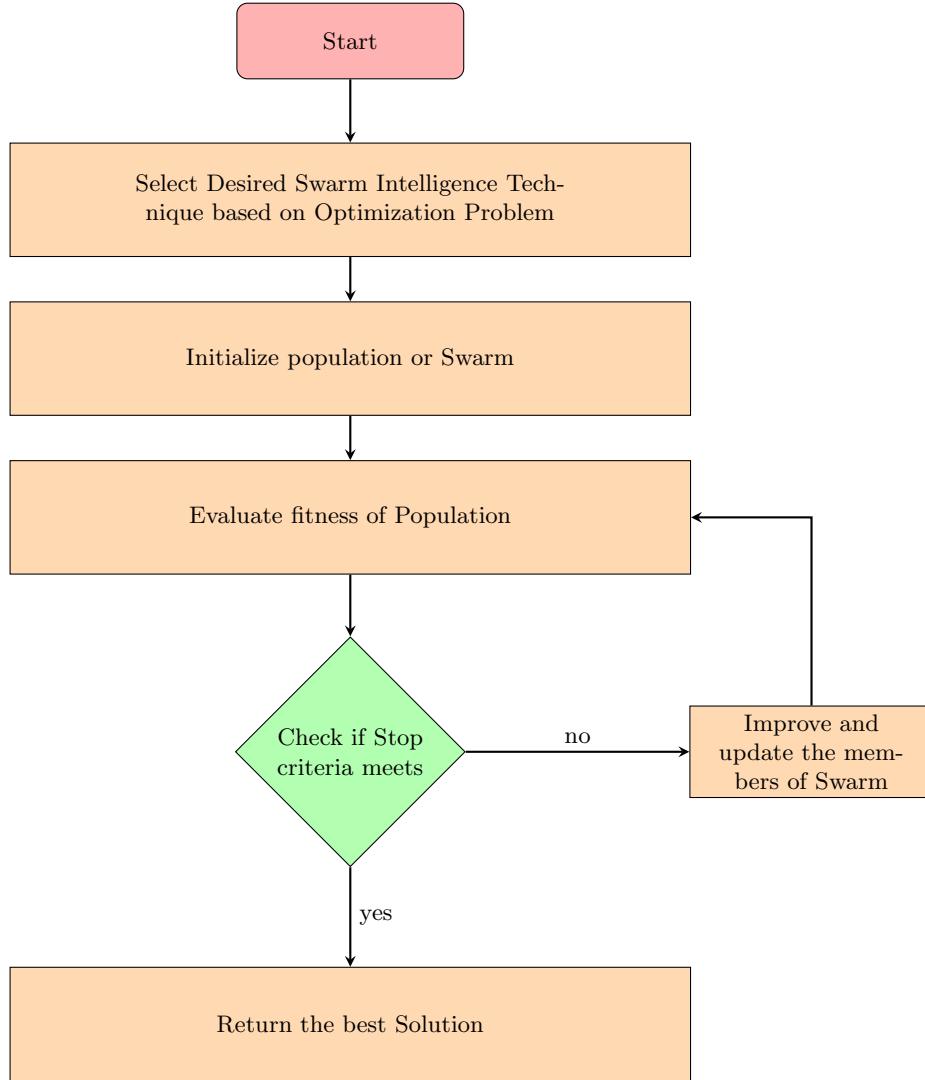


Fig. 2. Generic Flowchart of Swarm Optimization Techniques

– **Exploitation:** While exploration traverses the whole landscape, exploitation, also known as intensity, focuses on a local search area, which will lead to finding better solution in the local search space. This will lead to high convergence in our algorithms but too much exploitation will lead to being stuck in a local solution only. So, a fine balance is needed between the exploration and exploitation [1] of every swarm intelligence techniques and based on the

optimization problem we can fine tune the exploration and exploitation to our requirement.

- **Convergence:** Another important aspect of swarm based algorithms is its high convergence rate. Convergence rate can be defined as the speed in which our algorithm converges to a solution over some iterations beyond which a repeating sequence is generated. While some algorithms use defined global best to converge faster [2] to a solution while other algorithms use their own exploration and exploitation [3] to converge to a solution.
- **Randomization:** In most swarm intelligence techniques, randomization parameters are used for better exploration in the search landscape to find alternate solutions which might be better than the current solutions.

As we try to understand these swarm based algorithms and how they work collectively as a member of a swarm to achieve collective intelligence, we look at a generic framework of how these swarm based techniques operates in Fig. 2.

3 Evolution of Swarm Intelligence Techniques

As swarm based optimization techniques provide self-organized, collective, intelligent and faster convergence in solving complex, discontinuous, nonlinear systems, researchers and scholar are looking to develop novel swarm based optimization techniques that are inspired by biological [4], physical [5] and chemical phenomena [6] to solve various optimization problems efficiently and effectively compared to traditional techniques. As of now there are more than 140 optimization techniques based on natural phenomenon to solve various optimization problems in field of Science, Medicine, Artificial Intelligence, Engineering etc. Some of the popular swarm intelligence algorithms that have been developed over the years are listed in Table 1.

Table 1: Some of the popular bio-inspired meta heuristic algorithm inspired by swarm intelligence

Year	Algorithm proposed	Inspiration
2021	Flamingo Search Algorithm [7]	It is based on migratory and foraging behaviour of flamingos
2021	Horse herd Optimization Algorithm [8]	It implements what horses do at different ages using six important features: grazing, hierarchy, sociability, imitation, defense mechanism and roam.
2020	Chimp Optimization Algorithm [9]	It is inspired from the individual intelligence and sexual behaviours of chimps, when they find a group to be in.

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Year	Algorithm Proposed	Inspiration
2020	Black Widow Optimization Algorithm [10]	It is based especially on the interesting sibling cannibalism behaviour offered by Black Widow spiders.
2020	Sparrow Search Algorithm [11]	This algorithm is based on intelligent techniques used by sparrows to search for food depending on the situation they are in.
2020	Rat Swarm Optimizer [12]	It is inspired by the chasing and attacking behaviour of rats
2019	The Sailfish Optimizer [13]	This algorithm uses sailfish population while searching, and sardines population for diversifying the search space, based on a group of hunting sailfish.
2018	Meerkat Clan Algorithm [14]	It is based on Meerkat with their exceptional intelligence, tactical organizational skills, and remarkable directional cleverness in its traversal of the desert when searching for food
2018	Grasshopper Optimization Algorithm [15]	It is inspired by the foraging and swarming behaviour of grasshoppers.
2017	Salp Swarm Algorithm [16]	It is inspired by the swarming behaviour of salps in oceans.
2017	Camel Herds Algorithm [17]	This algorithm is based on camels, and how they have a leader for each herd and how they search for food and water depending on humidity of neighbouring places.
2017	Duck Pack Algorithm [18]	It is based on the foraging behaviours of ducks depending on imprinting behaviour and food orientation.
2016	Dragonfly Algorithm [19]	It is based on the static and dynamic behaviour of dragon flies.
2016	Sperm Whale Algorithm [20]	It is based on the sperm whale's lifestyle.
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Year	Algorithm Proposed	Inspiration
2016	Dolphin Swarm algorithm [21]	It is based on the biological characteristics and living habits such as echolocation, information exchanges, cooperation, and division of labor of Dolphins.
2016	Crow Search Algorithm [22]	It is based on how crows search for food, and hide their food from other crows and remember their hiding places.
2015	Ant Lion Optimizer [23]	This algorithm mimics the hunting nature of ant-lions in nature.
2015	Elephant Herding Optimization [24]	It is based on the herding behaviour of elephants, different group elephants living under a matriarch.
2015	Moth-flame Optimization algorithm [25]	It is based on the navigation method of moths in nature called transverse orientation.
2014	Grey Wolf Optimizer [26]	It mimics the living hierarchy and hunting behaviour of grey wolves in nature.
2014	Pigeon Optimization algorithm [27]	It is based on the swarming behaviour of passenger pigeons.
2014	Spider Monkey Optimization Algorithm [28]	It is inspired by the Fission-Fusion social structure of spider monkeys during foraging.
2013	Spider Optimization [29]	It is based on the cooperative characteristics of social spiders.
2012	Bacterial Colony Optimization [30]	It is based on the life cycle of a bacteria named, E. Coli.
2012	Zombie Survival Optimization [31]	It is based on the foraging behaviour of zombies, when they find a hypothetical airborne antidote which cures their ailments.
2010	Bat Algorithm [32]	It is based on the echolocation of micro-bats in nature, with varying pulse rates of emission and loudness.
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Year	Algorithm Proposed	Inspiration
2010	Termite Colony Optimization	It is based on the intelligent behaviour of termites.
2010	Fireworks Algorithm [33]	In this method, two types of explosion processes are performed, and the diversity of them are kept based on fireworks.
2009	Cuckoo Search [34]	It is inspired by the behaviour of cuckoos to lay eggs in the nests of birds of other species.
2009	Gravitational Search Algorithm [35]	It is based on Newton's laws and laws of gravity to search for solutions.
2009	Glowworm Swarm Optimization [36]	It simulates the behavior of lighting worms or glow worms.
2008	Fast Bacterial Swarming Algorithm [37]	This algorithm combines the foraging behaviour of E. Coli from Bacteria Colony Algorithm and flocking mechanism of birds from Particle Swarm Algorithm.
2007	Firefly Algorithm [3]	It is inspired from the fireflies in nature.
2006	Cat Swarm Optimization [38]	It is based on the behaviour of cats, and includes two subprocesses – tracing mode and seeking mode.
2005	Artificial Bee Colony [39]	This algorithm simulates how honey bee colonies work, including the employed, workers and scouts.
2004	Honey Bee Algorithm [40]	It is based on how honey bees forage for food in nature.
1995	Particle Swarm Optimization [2]	It is based on how flocks of birds move in the world and search for food, both individually and considering the entire group.
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Year	Algorithm Proposed	Inspiration
1992	Ant Colony Optimization [41]	This algorithm is based on the pheromone based searching done by ants in nature and how they keep track of the food found using their pheromones as location trackers.

As we can see from Table 1, there are various novel nature based optimization techniques to choose from. While some algorithms focus on exploration and exploitation, some focus on faster convergence and parameter tuning etc.. So, before choosing an optimization technique, we need to understand what type of optimization problem we are dealing with, the constraints associated with the optimization problem, the attributes and the mechanism of the algorithm.

As the nature of optimization problem is different with one another, it has become a necessity to either modify an existing SI algorithm, hybridize with another algorithm or to develop a novel SI based algorithm to obtain the best optimal solution of different optimization problem as it is impossible for a single algorithm to get the best solution for every optimization problem as the nature of the problems are complex in nature.

4 Prominent Swarm Intelligence Algorithms

Swarm intelligence techniques in comparison with traditional algorithms provide a novel way to address complex problems and processes efficiently and effectively. These algorithms are based on the swarming behaviours of various insects, birds, animals found in nature where they work collectively to achieve a collective intelligence. While some algorithms work towards achieving faster convergence, some focuses on the exploration and exploitation of optimization problem. In this section, we will briefly discuss some swarm intelligence algorithms and analyze them.

4.1 Particle Swarm Optimization

Particle Swarm Optimization was introduced by Kennedy and Eberhart in 1995 [2], by observing the social foraging behavior of animals such as flock of birds or school of fishes. In flocking of birds, whether it is flocking towards a destination or searching for food, the goal is achieved by cooperating with all the birds in the flock. Each bird learns from its current experience and updates it with the other birds to achieve its goal. The birds follow a leader which is closer to the best solution and any changes made by the leader is followed by all the birds in the flock hence achieving a collective, intelligent and a self-organized behavior as a swarm. Observing this, Kennedy and Eberhart summarized the

Particle Swarm Optimization into two equations, one for the position of every particle in the swarm and other equations for the velocity of the particles in the swarm.

In Particle Swarm Optimization we initialize a group of particle randomly and then search for the best optimal solution over many iterations. Each particle in a swarm maintains three things its personal best solution also known as pbest, its global best solution also known as gbest and its current direction. To search for the best optimal solution each particle in the swarm needs to update the velocity equation and the position equation over many iterations. The velocity and position of a particle, V_i and X_i , respectively can be updated over the iterations as follows:

$$V_i(t+1) = V_i(t) + C_1 R_1 [X_{pb}(t) - X_i(t)] + C_2 R_2 [X_{gb}(t) - X_i(t)] \quad (1)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (2)$$

where R_1, R_2 are two random vector in the range (0,1) and C_1, C_2 are cognitive acceleration coefficient and social acceleration coefficient respectively. In equation (1), $V_i(t)$ denotes the current direction of the particle, $X_{pb}(t) - X_i(t)$ describes the cognitive component of the particle where, $X_{pb}(t)$ denotes the position vector of a particle pbest and $X_{gb}(t) - X_i(t)$ describes the social component of the particle where, $X_{gb}(t)$ denotes the particle gbest. The new velocity and position of a particle, $V_i(t+1)$ and $X_i(t+1)$ respectively can be calculated over many iterations to get our desired solution.

Over the years researchers have been proposing new methods to the PSO algorithm due to the simplicity of the algorithm, its low computation cost and effectiveness as compared with traditional optimization algorithms, many algorithms has been proposed which improve the PSO algorithm further. Some of the proposed modification are in the form of hybridization with other nature based optimization algorithms like Genetic Algorithm, ACO [42,43,44] etc., modification of the PSO algorithms like fuzzy PSO, QPSO [45] etc. and even extension of PSO algorithms to fields like discrete [46] and binary optimization. Some of the modification done to the PSO algorithm over the years are given in table 2.

Table 2: Some modified algorithms based on the PSO algorithm

Year Published	Algorithm Name	References
2018	PSO-CATV	Time-varying Cognitive avoidance PSO [47]
2013	PSOCA	Cognitive avoidance PSO [48]
2013	MOPSO	Multiple objective PSO [49]
2013	PSO-RANDIW	Random weighted PSO [50]
2013	PSO-GA	Hybridization of PSO with GA [43]
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Year Published	Algorithm Name	References
2013	PSO-SA	Hybridization of PSO with SA [44]
2013	QPSO	Quantum-behaved PSO [45]
2012	DPSO	Discrete PSO [46]
2011	PSO-ACO	Hybridization of PSO with ACO [42]
2011	CPSO	Chaotic PSO [51]

4.2 Firefly Algorithm

Inspired by the flashing pattern and behavior of fireflies at night, Yang proposed the Firefly algorithm (FA) [3] in 2008. The flashing light in fireflies serves two purposes; one is to attract the mating partners and the other is to warn of predators. Yang formalized the Firefly algorithm based on the flashing lights and how each firefly is attracted to one another based on the flashing lights. To formalize the FA algorithm Yang idealized some characteristics of the fireflies as:

1. The fireflies are considered as unisex i.e. fireflies are only attracted to one another based on the flashing pattern not on the gender of the firefly.
2. The attractiveness of the firefly is directly proportional to the light intensity i.e. a firefly will move towards a brighter one and if there is no light intensity, it will perform a random walk.
3. The light Intensity of the fireflies are determined from the objective function.

With these assumptions, Yang proposed the updated position of a firefly say i to a brighter firefly j at iteration $t + 1$ is given as:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha \epsilon_i^t, \quad (3)$$

In the above equation, x_i^t represents the initial position of the firefly i , $\beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t)$ represents the attractiveness of the firefly x_i to another firefly x_j , β_0 represents the brightness at $r=0$ and $\alpha \epsilon_i^t$ represents the randomization term with α representing a randomization parameter in which ϵ_i^t is a vector of random numbers derived from a Gaussian, uniform or others distribution.

As the FA algorithm is based on the attraction and attractiveness decreases with the distance between fireflies, the whole population can be divided into sub groups which in turns provides an efficiently and faster way of searching for the global best and local best in the search landscape. Other important aspect of FA algorithm is that can be reduced to other meta-heuristic algorithms such as SA, DE, APSO thereby having the characteristics of all these algorithms. Over the years FA algorithm has either been modified or hybridize to obtain better results, low computation cost etc. A detailed survey on firefly algorithm and its variants are done by Fister et al. [52].

4.3 Bacteria Colony Algorithm

The Bacteria Colony Optimization is based on how bacteria move about in the environment. The major inspiration comes from a certain bacteria called *E. Coli*. This method of optimization follows how bacteria move with their flagellum, how only the ones better at searching survive and with the change of environment, the weaker ones die, and how new offsprings are made from the stronger ones and the cycle continues as bacteria search for more optimal conditions to survive longer.

There are four major characteristics of bacteria which make up the bacteria colony optimization.

- **Chemotaxis:** This model very uniquely reproduces how bacteria, especially *E. Coli* move in the environment by the movement of their flagellum, or whip-like structures present in the bacteria. Thus, a better individual means that it has better chances to survive and reproduce.
- **Elimination, reproduction and migration:** We said that natural selection offers the survival of only the bacteria that can search better for the nutrition around. The weaker ones will be eliminated, and the stronger ones reproduce to give better offspring and this cycle will repeat. Chemotaxis, elimination and reproduction is followed by a process called migration. After the nutrition of a place has depleted, the bacteria have to migrate to a newer place with abundant nutrition to continue the former three processes.
- **Communication:** In the bacteria colony model, we find individuals communicating with its neighbours, random individuals in the group, and also with the whole group. This makes the search for better nutrition more efficient.

The bacteria optimization model can be formulated combining three sub-models:

- In the Chemotaxis and Communication model, bacteria run and tumble and communicate with each other. The position of the bacteria can be formulated using the formula:

$$Position_i(T) = Position_i(T - 1) + R_i * (Ru_{Infor}) + R\Delta(i), \quad (4)$$

$$Position_i(T) = Position_i(T - 1) + R_i * (Tumb_{Infor}) + R\Delta(i) \quad (5)$$

- The Elimination checks that only the bacteria that has an energy level greater than a given energy level can survive. Mathematically, it can be determined as:

$$if L_i > L_{given}, and i \in healthy, then i \in Candidate_{repr}, \quad (6)$$

$$if L_i < L_{given}, and i \in healthy, then i \in Candidate_{eli}, \quad (7)$$

$$if i \in unhealthy, then i \in Candidate_{eli}. \quad (8)$$

- Migration model tells the bacteria to move to a newer location with better nutrition, using the formula:

$$Position_i(T) = rand * (ub - lb) + lb \quad (9)$$

4.4 Crow Search Algorithm

With recent advances in the field of swarm intelligence, the Crow search algorithm, as its name suggests, is a novel method which mimics how crows act in the environment. It is majorly inspired from the fact that crows are intelligent and how they are very efficient in hiding their food in different places. They can remember the location of the food they have hidden for months. Also, interestingly, it has also been observed that crows also keep track of the hiding places of other crows so that they can steal food. To counter this, whenever a crow finds that another crow is following it, they fly away far from the hiding place to trick the other crow and save its food. The crow search algorithm, very cleverly mimics these behaviours of crows to create a very efficient algorithm.

While implementing this algorithm, two matrices, one for the crows, and the other for the memory of the hiding places of the crows are kept. These keep track of the location of the crow and also the location of the hiding place in the search space.

$$\begin{bmatrix} x_{11}^t & x_{12}^t & \dots & x_{1d}^t \\ x_{21}^t & x_{22}^t & \dots & x_{2d}^t \\ \vdots & \vdots & \vdots & \vdots \\ x_{N1}^t & x_{N2}^t & \dots & x_{Nd}^t \end{bmatrix}$$

During the movement of crow i towards crow j , two things can happen - If crow j is unable to discover that crow i was following it, then crow i updates its position as follows:

$$x_i(t+1) = x_i(t) + r_i * fl_i(t) * (m_j(t) - x_i(t)) \quad (10)$$

Where r_i is a random number, and fl decides if the search will be local or global. If $fl > 1$ then the crow i moves far away from crow j , and vice versa. If crow j is able to detect crow i following it, then it moves away from its hiding place. The new position of crow j is now a random position on the search space.

This whole equation can be summarised into two parts based on a value which is called *Awareness Probability*. If it is high, then the search happens to be global, and if it is lowered then the search is local. This happens because if a crow can search for another crow better then it can track long distances better and search for more optimal food.

4.5 Grey wolf optimization

Grey wolf optimizer (GWO) [26] was proposed by Mirjali in 2014 after taking inspiration from hunting patterns of grey wolves in nature. He also observed the hierarchy of leadership among grey wolves in a pack. Grey wolves live and hunt for prey together in a group. First, the pack tracks the prey and chases

it, after which it encircles the prey and starts attacking until the prey stops moving. Taking inspiration from this he proposed the GWO which offers high convergence speed, simple and greater precision as compared to other nature based optimization algorithms. In GWO Mirjali categorize the wolves in the pack into four groups namely the alpha (), beta (), delta (), and lastly the omega (). The alpha () is considered as the individual which has the highest authority followed by the beta () and the delta (). The rest of the grey wolves are collectively considered as the omega () of the pack.

- **Encircling prey:** In GWO the grey wolves first track and surrounds the prey. This is the encircling part of the algorithm. The mathematical equations representing this is given below:

$$D = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (11)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (12)$$

where \vec{A} and \vec{C} are coefficient vectors, t denotes the current iteration, \vec{X}_p is the position vector of prey, and \vec{X} denotes the position vector of a grey wolf. The vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (13)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (14)$$

where components of \vec{a} are linearly decreased from 2 to 0 over the course of iterations and \vec{r}_1 and \vec{r}_2 are random vectors in $[0, 1]$.

- **Hunting:** After the encircling phase is done, the hunting phase of the algorithm is started. The alpha of the pack leads the pack in hunting for prey followed by the beta and the delta. In GWO to simulate these conditions, it assumes that the alpha has better knowledge about the prey location. The mathematical equations regarding the hunting phase are given below:

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right|, \vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right|, \vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\gamma - \vec{X} \right| \quad (15)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \quad (16)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (17)$$

After the hunting phase, the grey wolves start attacking the prey. To briefly explain the process of how GWO works, we first start by creating a random population of grey wolves/ individuals. Over many iterations, the individuals based on their hierarchy start to approximate the prey's expected location. The individuals in the population interact with each other and shared information regarding the prey location till the optimal solution is found.

4.6 Sperm Whale Algorithm

This Sperm Whale Algorithm [20] as the name suggests, makes use of how sperm whales interact in nature. This algorithm is based on how sperm whales use their incredibly good hearing to spot food and enemies, and how they use sound to communicate with one another. The main features of this algorithm can be stated as follows:

- Sperm whales come across two opposite poles in their cycle of breathing and feeding – the land for breathing and the sea for food. This feature has been used in the algorithm as two poles of answers, the Best and the Worst answers.
- The sperm whales travel in groups of 6-9 with males and females in the same group. When it's the mating season, the males fight among themselves and the strongest male gets to mate with the females in the group. This has been used in the algorithm to choose better children for the next generations. Obviously, the candidates with higher Objective score wins the fight, and thus, the solution converges towards the optimal value with every generation.

The best and worst individuals in the population of the whales in each gathering are the X_{best} and the X_{worst} , individually, showing the following relationships:

$$X_{center} = X_{worst} + c \times X_{best} \quad (18)$$

$$X_{reflex} = 2X_{center} - X_{worst} \quad (19)$$

X_{reflex} is situated outside the inquiry space, c should diminish thus:

$$c = r \times c_i \quad (20)$$

where c_i is the beginning focus factor and r is the constriction coefficient that is less than 1.

5 Applications of SI Techniques

The applications of Swarm Intelligence are limitless to be honest. It has put its name in various fields of research and other real-world usage. One of the biggest advancements in recent years has obviously been machine learning or deep learning and SI techniques have been extensively used to achieve greater results in the field. SI techniques have also shown development in Networking improving the cost of Wireless Sensor Networks (WSNs) [53] and also topological issues, energy issues, energy issues, connectivity and coverage issues and localization issues. SI techniques have been very useful in speech processing [54] as well and have found significant reduction in background noise in audios for recordings. This is important because audio clips with background noises and echo is unintelligent speech and SI techniques have improved a lot in this field. Techniques like PSO, ABC were seen to give better signal to noise ratio.

Techniques like ACO are useful in image processing specifically in feature extraction from images [55]. It has been seen that these techniques give a better perceptual graph while doing feature extraction from images. These techniques also have proved detrimental in image segmentation and also been very useful in bioinformatics [56] by the use of automatic cluster detection and has been extensively used in computer vision for mammography in cancer risk detection and breast cancer detection. Swarm intelligence has also been very useful in data mining in healthcare for better results in finding previous cases of diseases such as cancer, heart diseases, tumors and other health related problems. Swarm Intelligence has also been useful in logistics and transport, in efficient routing of cargo from different one destination to another, especially ACO, with its pheromones have very efficiently given desired outputs from the source to destination nodes. Similarly, for telecommunication as well, ACO has optimized the routing of different telecom networks and the efficient management of users in different networks has been handled. Beehive Algorithm are also useful in segmenting tasks for basic factory operations like transport from one portion to another, packaging etc. Different SI techniques have been useful for mass recruiting for any company because they use pheromones to attract and automatically cluster in more advantageous spots.

Furthermore, SI techniques have been used for automated machine learning by creating Deep Neural Networks (DNNs) [57], which usually require severe expertise to be designed manually, social network analysis for detecting communities [58],[59],[60], [61]. They have also shown better results in Resource Allocation; better processing of resources and managing assets in a strategic way. Swarm Intelligence also probably has countless other feats in several other fields like structural engineering [62]. To describe them all would be a very lengthy task to continue, which we will discuss in later chapters, in more detail. To summarize in one sentence, Swarm Intelligence has definitely found its way to every field of study in this world.

6 Discussions and Conclusion

In this chapter, we have presented the various population based swarm intelligence techniques that have been developed so far including particle swarm intelligence, firefly algorithm, bacteria colony algorithm, crow search algorithm, grey wolf optimization, sperm whale algorithm and their fundamental structures along with their mathematical models. SI based search technique and working of a few of these algorithms are highlighted. A brief explanation of applications of swarm intelligence techniques is done. Some major deductions from this chapter are listed below:

1. The major component that differentiates SI optimization algorithms from traditional optimization algorithms is the stochastic nature. Adaptive nature [63] of the algorithms provide a tremendous potential to solve large scale, multi dimensional, complex problems more efficiently.

2. Exploration and exploitation are the fundamental operations that in a SI search. The success rate of finding optimal solutions depend on the balance between exploration and exploitation.
3. As the nature of the optimization problem is different with one another, we need to choose which SI techniques to use based on various factors like working mechanism of the SI techniques, its parameters tuning capabilities, setting of parameters etc.
4. While one or some SI algorithms may perform well on some optimization problems, it might not perform well on other optimization problems. So, according to our requirements we may need to modify parts of SI techniques, hybridize with other algorithms so that we can get the desired solution.
5. Prior analysis of usage of SI techniques is crucial for applications. Though, statistical measures are available, but mostly lacks direct comparison [64]. Alternative techniques like visual analysis, which considers direct comparison of solutions would be useful [65,66].

As different swarm intelligence based algorithms provide a way to overcome different optimization problems efficiently and effectively as compared to traditional techniques, Swarm Intelligence techniques are becoming more popular to solve various complex optimization problems. It has several advantages over traditional algorithms in terms having stochastic nature, efficient search of the search space using exploration and exploitation and faster convergence.

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