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Swarm Optimization and an Overview of the Optimization Algorithms

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A B S T R A C T

Swarm Intelligence (SI) involves collective study of the individual's behavior of population interaction with one another. It is an area of research of Artificial Intelligence. Swarm intelligence applications have helped various industries solve their problems such as in Logistics and Transportation Business, telecommunications, robotics, network security, data mining and machine learning. SI is inspired by natural behavior to solve optimization problems. In this paper few of the latest SI based optimization algorithms have been discussed. More specifically, we focus on the algorithms inspired by whale, bees, moth, grasshoppers, wolves, birds, dragonfly and pelicans

Keywords: Swarm Intelligence (SI), Natural Behavior, Optimization, Pelican Optimization Algorithm (POA), Particle Swarm Optimization (PSO), Hunting Behavior.

1. Introduction

Optimization refers to the process of finding the best possible solution(s) for a particular problem. As the complexity of problems increases, over the last few decades, the need for new optimization techniques becomes evident more than ever. The optimization algorithms provide the best performance in terms of optimized output and quality products that effectively improve the overall efficiency of algorithms, the overall execution time, and also solving memory management issues to a greater extent. The optimization can be to find minimum and maximum of a function, minimizing transportation costs, maximizing profits, lowest time duration for finishing a project.

A swarm is a large number of similar, simple agents cooperating locally with each other, and their environment. Swarm intelligence(SI) is an artificial intelligence approach which is inspired by natural behaviour to solve optimization problems. SI is in the field of artificial intelligence (AI) and is based on the collective behaviour of elements in decentralized and self-organized systems. SI algorithms are well established and applied in well-known aptitude-based problems where real-time actions are handled efficiently inspired from natural systems.

The concept of SI was firstly proposed in the 1980s. Since then, it has attracted increasing attention from the scientific community in a variety of fields, including engineering, economics, computer science, artificial intelligence, and many others. SI was inspired by the observation of the collective behavior in societies in nature such as the movement of birds and fish. The collective behaviour of such ecosystems, and their artificial counterpart of SI, is not encoded within the set of rules that determines the movement of each isolated agent, but it emerges through the interaction of multiple agents.

The main disadvantage of swarm intelligence optimization algorithm is that it is prone to premature convergence and poor local optimization ability. It is difficult to predict the behaviour from the individual rules. Moreover the functions of colony could not be understood with the knowledge of functioning of an agent and even a small change in the simple rules results in different group level behaviour. This group possess Swarm Intelligence if the following principles are true.

- Each member of the group should be able to manage and achieve space and time computations in response to natural changes. Activities may vary, depending on the group specific functions such as searching for food may be the main activity of ants..
- Parameters and factors for determining quality such as. safety, energy efficiency need to be verified.
- There should not be any response by the group in orderly manner. There should be a backup for it to exist in case of unexpected changes in the environment and all resources should not depend on a single point of focus.
- There should not be a complete change in the groups behaviour when an unexpected event occurs as it leads to wastage of resources such as energy.
- However, the group should also be able to switch its behavioural mode, provided this change is a positive one and the group has ways of knowing so.[5]

2. Related Work

The comprehensive survey of Wedde and Farooq [6] focuses on routing algorithms for wired networks. The main objective of the survey is to understand the basic design principles and the core differences existing between routing protocols proposed by researchers belonging to different communities, namely the communities of artificial intelligence, SI, and networking. In the survey, the authors discuss how the different protocols address the main challenges of routing in wired networks. This work aims to bridge relevant work of different research communities to propose novel intelligent routing solutions for future networking systems.

Saleem et al. [7] have presented a rather extensive survey of these SI-based algorithms for routing in WSNs and have pointed out a number of methodological flaws in the way these algorithms are commonly presented and empirically evaluated. Sim and Sun [8] presented a review of ACO approaches for routing and load balancing in wired networks. The authors of the review made some confusion in interpreting the existing work, since they present ACO-based routing and load balancing as two different aspects, while, in more general terms, in SI-based routing they are the two faces of the same coin. In fact, SI design intrinsically favours the spreading of the data over multiple paths, automatically resulting in load balancing. The review also discusses in some depth the different mechanisms devised to avoid the situation in which the system is unable to adapt the entries of a node routing table in spite of changing network conditions (this potential problem is indicated in the ACO literature as stagnation or locked decisions).

Ren and Meng [9] have briefly surveyed some existing ACO algorithms, genetic algorithms (GAs), PSO algorithms, reaction–diffusion mechanisms, and other biologically-inspired methodologies proposed for MANETs and wired networks, and have investigated how they could be used in WSNs for routing, clustering, and security. Iyengar et al. [10] have investigated a couple of algorithms based on genetic algorithms as well as various versions of antbased algorithms, and have considered their use in WSNs. The review mainly focuses on algorithms developed for routing in wired networks and MANETs, while the specific characteristics of WSNs are only marginally considered.

More recently, Ducatelle et al. [11] have made an extensive survey of ACO approaches for best-effort and quality-of-service (QoS) routing in wired networks and in MANETs. The authors of the survey also discuss the relative benefits and the features of classical top-down design vs. bottom-up design, which is typical of SI approaches. S. A. Arunmozhi et al.[12] proposed spider monkey approach to optimize the routing path in MANET under Black Hole attack to achieve routing optimization in MANETs. This experiment was designed to achieve better performance in terms of packet delivery ratio, throughput and end-to-end delay.

3. Swarm Optimization Algorithms

3.1 Whale Optimization algorithm

The Whale Optimization Algorithm (WOA) simulates the intelligent hunting behaviour of humpback whales called bubble-net feeding method. The whales create the typical bubbles along a circle path while encircling prey during hunting. Simply, bubble-net hunting behavior could describe such that humpback whales dive down approximation 12 m and then create the bubble in a spiral shape around the prey and then swim upward the surface following the bubbles [13]. In the context of WOA, a swarm refers to a number of potential solutions to the optimization problem, where each potential solution is referred to as a search agent. The aim of the WOA is to find the search agent position that results in the best evaluation of a given objective function.

Application:

It can be used as an appropriate algorithm for solving different constrained or unconstrained optimization problems for practical applications without structural reformation in the algorithm.

3.2 Grey Wolf Optimization algorithm

It is a population-based meta-heuristics algorithm that simulates the leadership hierarchy and hunting mechanism of grey wolves in nature, and it's proposed by Seyedali Mirjalili et al. in 2014. The main phases of grey wolf hunting are Tracking, chasing and approaching the prey. They then Pursue, encircle, and harass the prey until it stops moving and finally attack the prey. They follow a very strict social dominance hierarchy. The Fittest solution is considered as an Alpha wolf (α)*,*Second best solution as a Beta wolf (β)*,*Third best solution as a Delta wolf (δ) *and* Rest of the candidate solutions as Omega wolves (ω).[14]

Applications:

Classification of sonar data set using neural network trained by gray wolf optimization.[15]

Spatial Prediction of Landslide Susceptibility [16]

3.3 Artificial Bee Colony (ABC) algorithm

The Artificial Bee Colony (ABC) algorithm is a swarm based meta-heuristic algorithm that was introduced by Karaboga in 2005. The ABC optimization algorithm is based on the foraging behaviour of a colony of bees. The model consists of three essential components: employed and unemployed foraging bees, and food sources. The first two components, employed and unemployed foraging bees, search for rich food sources, which is the third component, close to their hive. The model also defines two leading modes of behaviour which are necessary for self-organizing and collective intelligence: recruitment of foragers to rich food sources resulting in positive feedback and abandonment of poor sources by foragers causing negative feedback. In ABC, a colony of artificial forager bees (agents) search for rich artificial food sources (good solutions for a given problem). To apply ABC, the considered optimization problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbour search mechanism while abandoning poor solutions.

Applications:

- Training an artificial neural network is an optimization task since it is desired to find the optimal set of weights of a neural network in the training process. [17]
- Structural analysis of beam. [18]
- Approaches for numerical optimization. [19]

3.4 Particle Swarm Optimization

The particle swarm optimization (PSO) algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock, to discover patterns that govern the ability of birds to fly synchronously, and to suddenly change direction by regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm. The PSO optimizations integrated three concurrent objective functions, the contact pressure uniformity, the film thickness stability, and the maximum load capacity. The Particle swarm optimization and genetic algorithm combination (GA) have been utilized to determine the Cluster Head (CH) depending upon the cluster formed. For the selection of CH, factors like energy, degree and mobility are estimated. Also estimate the position of the selected CH using the GA algorithm. After the selection process, the selected CH location is calculated using the cluster center based GA method. The placement process depends on the energy value of CH.

Applications:

- In wave scattering problems.[20]
- Energy-Storage Optimization. [21]
- PSO can simulate the movement of a particle swarm and can be applied in visual effects like those special effects in the Hollywood film.

3.5 Moth flame optimizer

It is applied to solve complex real-world optimization problems in numerous domains**.** The main inspiration of this optimizer is the navigation method of moths in nature called transverse orientation. Moths fly in night by maintaining a fixed angle with respect to the moon, a very effective mechanism for travelling in a straight line for long distances. However, these fancy insects are trapped in a useless/deadly spiral path around artificial lights. Since the moon is so far away from the moth, the moth uses this near-parallel light near the surface to stay in a straight line. Although lateral orientation is effective, moths are often observed to circle the source repeatedly until they are exhausted. In fact, moths are fooled by the fact that there are many artificial or natural point light sources

Applications:

- MFO is considered one of the promising metaheuristic algorithms and successfully applied in various optimization problems in a wide range of fields, such as power and energy systems, economic dispatch, engineering design, image processing and medical applications.
- Avishek Das [3] used the moth-flame optimization algorithm to determine the optimal set of current excitation weights and determine the optimal spacing between array elements in the three-ring structure of the improved concentric antenna array (CCAA).
- Satomi Ishiguro [4] proposed a new method to optimize the loading mode of nuclear reactors—a multi-group moth-flame optimization algorithm with predators.
- Hegazy Rezk [5] studied the hybrid moth-flame optimization algorithm and the power condition of the maximum solar photovoltaic/hot spot system with incremental conductance tracking under different conditions.

3.6 Dragonfly algorithm

Dragonfly algorithm (DA) is a novel swarm intelligence meta-heuristic optimization algorithm inspired by the dynamic and static swarming behaviors of artificial dragonflies in nature. [22] In fact, the two required phases of optimization, exploration and exploitation, are represented by the static and dynamic swarming behaviours. Also, dragonflies form sub-swarms and fly over different areas in a static swarm. This is similar to exploration, and it aids the algorithm in locating appropriate search space locations. On the other hand, dragonflies in a dynamic swarm fly in a larger swarm and in the same direction. In addition, this type of swarming is the same as using an algorithm to assist it converges to the global best solution.[23]

Generally the swarms follow following principles:

- Separation: which indicates the avoidance of neighbouring static collisions
- Alignment: which returns the speed of individuals paired with neighbouring individuals
- Cohesion: which indicates the individual tendency toward the centre of the herd

Applications:

- The Dragonfly algorithm has the advantage of optimizing task scheduling and resource allocation in a cloud computing.
- Widely used in the field of image processing, machine learning, Aadil et al. [24] proposed a new method called the dragonfly-based clustering algorithm (CAVDO) to focus on the scalability of IoV topology.
- Daely and Shin [25] utilized a dragonfly algorithm in two scenarios: (a) to predict the location of randomly deployed nodes in a designated area and (b) to localize different noise percentage of distance measurement

3.7 Grasshopper Optimization Algorithm (GOA)

Grasshopper Optimization Algorithm (GOA) is a recent swarm intelligence algorithm inspired by the foraging and swarming behavior of grasshoppers in nature. The GOA algorithm has been successfully applied to solve various optimization problems in several domains and demonstrated its merits in the literature. Their life cycle includes two phases called nymph and adulthood. The nymph phase is characterized by small steps and slow movements, while the adulthood phase is characterized by long-range and abrupt movements [30]. The movements of nymph and adulthood constitute the intensification and diversification phases of GOA.

Applications:

M. Kaur and E. R. Kumar[31] prevented the overloading of transmission lines using GOA.

3.7 Pelican Optimization Algorithm (POA)

The main idea in designing the proposed POA is simulation of the natural behaviour of pelicans during hunting for their prey(fish, frog, turtles and crustaceans). In POA, search agents are pelicans that search for food sources[26]. The behaviour and strategy of pelican hunting is a sharp and intelligent process that made the birds skilled hunters. POA simulates the strategy of pelicans while attacking and hunting its prey to update candidate solutions, widely employed for dimensionality reduction. The POA starts by randomly initializing a population of pelicans, each representing a potential solution to the optimization problem. Each pelican then evaluates its fitness based on the objective function of the problem, and the fittest pelicans are selected to form the "elite" group. The elite pelicans then fly to search for food, representing the search for better solutions. The POA also incorporates a mechanism for exploring new areas in the search space. This is achieved by randomly selecting a subset of non-elite pelicans, which are then used to generate new candidate solutions through a random walk process. These new solutions are then evaluated and may potentially join the elite group. The POA continues to iterate through the search process until a stopping criterion is met, such as a maximum number of iterations or a desired level of solution quality is achieved.

The hunting strategy of Pelicans is called cooperative hunting strategy. They work together to lock up the fish in a tight group.then they dive into water to catch fish with their bills. The two phases in POA are the Exploration Phase and the Exploitation Phase. The Exploration phase is used to find target location and the Exploitation Phase deals with prey hunting and diving as in Fig 1.

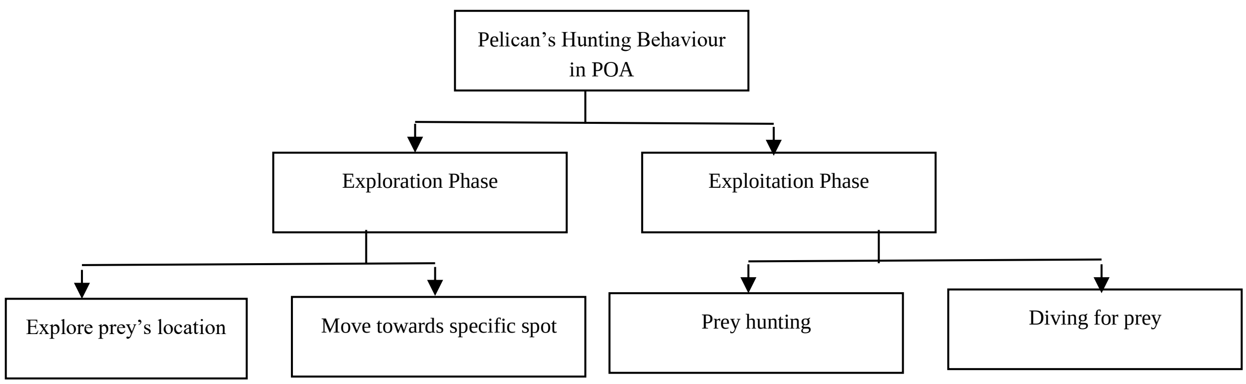

Fig 1. Pelican's hunting behaviour as in POA

The steps followed in POA are as follows:

Step 1: Initialize all the important parameters such as population size (Number of agents), lower bound, upper bound, design variables and objective functions.

Step 2: Initialize population randomly for N search agents.

Step 3: Evaluate agents performance by calculating fitness values for N agents.

Step 4: Generate target location randomly and move agents towards prey (Exploration phase)

Step 4.1: Explore the search space to find the target

Step 4.2: Update the agents position by comparing the current Fitness value with the earlier position fitness value.

Step 5: Perform agents hunting (Exploitation Phase)

Step 5.1: Update agents position.

Step 5.2: Save best agent position and value.

Step 6: Compare current iteration with maximum iterations

Step 6.1: if current iteration is not equal to maximum iterations then go back to Step 4

Step 6.2: If equal then stop.

Applications

- POA has been implemented in Ovarian Tumour Detection [27]
- To design a wind Turbine Fault classification model[28].
- To design a decision support tool for aquatic invasive species.[29]

Table 1: Comparative analysis of SI Algorithms

Sl. No.	**Optimization Algorithm**	**Working Principle**	**Merits**	**Demerits**
1.	Whale Optimization Algorithm	Simulates the intelligent hunting behaviour of humpback whales called bubble-net feeding method .	Population-based WOA has an ability to avoid local optima and get a global optimal solution.	Slow convergence rate and poor exploitation capability. This may prove to be problematic when applied to optimization problems requiring high precision results.
2.	Artificial Bee Colony (ABC) algorithm	Is based on the foraging behaviour of a colony of bees. The model consists of three essential components: employed and unemployed foraging bees, and food sources.	• The ABC optimization technique is simple in structure. • Strong robustness, fast convergence and high flexibility	• A poor exploitation capability. • Premature convergence in the later search period. • The accuracy of the optimal value cannot meet the requirements sometimes.
3.	Particle swarm optimization	It is based on the simulation of the social behavior of birds within a flock.	PSO has a main advantage of having fewer parameters to tune. PSO obtains the best solution from particles' interaction,	• Through high-dimensional search space, it converges at a very slow speed towards the global optimum. It shows poor-quality results in complex and large datasets. • It is easy to fall into local optimum in high-dimensional space and has a low convergence rate in the iterative process.
4.	Moth flame optimizer	It is inspired from the navigation method of moths in nature called transverse orientation.,	It is applied to solve complex real-world optimization problems in numerous domains such as power and energy systems, economic dispatch, engineering design, image processing and medical applications	Slow convergence and low-quality solutions.

5.	Grey Wolf Optimization	Simulates the leadership hierarchy and hunting mechanism of grey wolves in nature	Fewer parameters, simple principles, and implementing easily.	Slow convergence speed, low solution accuracy, and easy to fall into the local optimum
6.	Dragonfly algorithm	It is a novel swarm intelligence meta-heuristic optimization algorithm inspired by the dynamic and static swarming behaviours of artificial dragonflies in nature.	• It is very simple and easy to implement. It can be seen that it suits applications in different areas. • It can be merged with other algorithms	It does not have an internal memory that can lead to premature convergence to the local optimum. It is easily stuck into local optima because it has a high exploitation rate.
7.	Grasshopper Optimization Algorithm	Inspired by the foraging and swarming behaviour of grasshoppers in nature	• Major advantage is its simplicity, flexibility, scalability and robustness. • It has reasonable execution time and easy to implement.	Easy to fall into local optimum Slow convergence speed.
7.	Pelican Optimization Algorithm	Simulation of the natural behaviour of pelicans during hunting for their prey(fish, frog, turtles and crustaceans).	• Has the advantages of adjustment parameters such as fast convergence speed and simple calculations. • POA has better competitive performance via striking a proportional balance between exploration and exploitation to provide optimal solutions.	Performance depends heavily on the problems characteristics and the chosen parameter settings. Not much research is done in its applications for network efficiency

Conclusion

This paper compiles the .research in the field of Swarm Intelligence with a classification of various Swarm Optimization algorithms with an emphasis on Pelican Optimization Algorithm, their drawbacks and merits. These algorithms are derived from the occurrences in nature, by the behavior of birds and animals while they hunt for their prey, move in groups for their security and efficiency. These mechanisms can be implemented in improving the energy efficiency and security for networks such as MANET, WSN etc. The study attempts to provide an initial understanding for the exploration of the practical attributes of the algorithms and their future purview by the research scholars.

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