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Research paper

A Brief Survey on Nature Inspired Metaheuristic and Hybrid-Metaheuristic Optimization Algorithm

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Abstract

The human brains are the ultimate model optimization algorithm, but they are complex in nature. The small microorganism and mammals other than human are do foraging and reproduce to survive in the world by optimizing in a small environment. This leads to a researcher to investigate their lifestyle and foraging behavior in a mathematical model coined as the nature-inspired optimization algorithm. In this brief survey on nature-inspired optimization algorithm related to metaheuristic and hybrid-metaheuristic, we try to show some recent development that is widely used nowadays.

Keywords: *Hybrid-metaheuristic Algorithm, Metaheuristic algorithm, Nature inspired algorithm, Optimization Algorithm*

1. Introduction

The optimization is the process to find the most favorable or the best outcome by making use of a situation or resources. From this point of view, we can say that the optimization is present everywhere, both in nature and the man-made things like searching of nutrients by animals, insects and plants, engineering design, routing on the internet, and searching in the Google. The output of the optimization process depends on the resources present in the specified environment, which can be in terms of the quantity, profit, time, and knowledge. If we use the mathematical tool for representing the optimization process, then it refers to the mathematical optimization.

Most of the mathematical optimization can be formulated with the term design variable, objective function, search space, and solution space. Optimization is a process to find the optimal solution space within the search space with the help of the objective function for the design variable. The optimization algorithm is based on two fundamental principles, one is 'exploration', and the other is 'exploitation'. The exploration expands the search space, so the design variable covers the whole search space in its lifetime. The exploitation is the ability to find the optimal value nearer to the best solution. So, one good optimization method has to the trade-off between the exploration and exploitation to get the superior performance. In the literature [1-11], the optimization algorithm can be classified as:

- Gradient-based optimization algorithm: Whenever we require the gradient information in an optimization to find the optimal value, then it is known as a gradient-based optimization algorithm. The well-known Newton-Raphson algorithm uses the function value and their derivatives to get the optimal value for smooth unimodal problems, so it is a gradient-based algorithm.
- Gradient-free optimization algorithm: Whenever an optimization algorithm uses only the function value, and not the derivative, then the algorithm can be called gradient-free optimization. This optimization can be used when there is a discontinuity of the objective function. One example of the gradient-free optimization algorithm is Nelder-Mead downhill simplex.
- Stochastic optimization algorithm: The meaning of the stochastic is 'random' or 'affected by chance'. Then the stochastic optimization algorithms generate and use random variables for design variations in the search space. Stochastic approximation [12] is the first method related to the stochastic optimization.
- Population-based optimization algorithm: In the population-based optimization algorithm a set of agents are employed to find the optimal solution. Particle swarm optimization (PSO) is one of its kind.
- Trajectory optimization algorithm: The trajectory optimization is the process to design the trajectory to measure some performance within the constrained boundaries. This optimization is extensively used in the aerospace design.
- Evolutionary algorithm: The evolutionary algorithm (EA) is an optimal domain in artificial intelligence. The EA is a subset of the evolutionary computation, which is inspired by the biological evolution. The evolution may consist of the reproduction, mutation, selection, and elimination. As the EA guided by all these processes, it can be applied in any field where we require optimization. Genetic algorithm (GA) and bacterial foraging optimization (BFO) are good choices of evolutionary algorithms. The only constraint in EAs is that the computational complexity is more?
- Swarm intelligence algorithm: The swarm intelligence is the collective behavior of decentralized, self-organizing systems, of a population of agents. The agents may be natural or artificial, communicate locally with each other within their environment. The swarm intelligence is mostly inspired by nature like ant colonies, bacterial growth and birds flocking etc. The author in [6] tries to focus on the swarm intelligence algorithm as the future optimization algorithm.

Altogether, these algorithms except the gradient-based optimization algorithms are coined as the heuristic or metaheuristic algorithms. The meaning of heuristic is 'to find' or 'to discover' or 'learn something for themselves' or 'processing to a solution by trial and error' or 'rules loosely defined'. We can say that the heuristic optimization algorithm discovers an optimal solution with the loosely defined rules by learning themselves through trial and error approach. The 'meta' has a different meaning as 'with', 'across', 'after', and 'beyond'. So, for these reasons, most of the algorithms are known as metaheuristic algorithms. Metaheuristic algorithms can have different forms as stochastic, population-based, trajectory-based, evolutionary, and swarm intelligence.

The application of the metaheuristic algorithm for an optimization problem may not guarantee the optimal solution. That means, one metaheuristic algorithm can't be suitable for all problems [13]. To overcome this problem, the first approach can be modifying the searching pattern within the original algorithm, and it is known as the modified metaheuristic or modified heuristic algorithm. The second approach can be combining the different metaheuristic algorithms that can supplement each other [1-3, 5, 6, 11]. These types of algorithms are known as hybrid metaheuristic algorithm.

2. Nature Inspired Metaheuristic Algorithms

The human approach of solving a problem be heuristic or metaheuristic by trial and error. In the modern era, metaheuristic algorithms are treated as scientific methods for problem-solving. It is very difficult to say when the heuristic algorithm was stated. Most of the metaheuristic algorithms are developed taking inspiration from nature. Nature teaches us how to survive within the constrained environment. The nature-inspired metaheuristic optimization algorithms must have a fundamental principle of self-adaptation, cooperation, and competition in each iteration (or generation). The self-adaptation improves the performance, cooperation helps in information exchange between the agents, and competition helps the agent to survive among other agents. Then, the main concern is to, how we can formulate the natural process to a mathematical tool. Development of mathematical modelling of natural search phenomena is a challenge in nature-inspired metaheuristic algorithm [14].

One of the oldest and most used metaheuristic algorithms is the genetic algorithm (GA), which is based on Darwinian evolution and natural selection in the biological system with the help of crossover, mutation, and selection of fitness. The GA was developed by Holland in between 1960's to 1970's, and he published a book "Adaptation in Natural and Artificial Systems" [15] on summarizing the development of genetic algorithms. The potential of GA was tested with different objective functions by Jong during his PhD [16].

Some researchers try to use the concept of mutation only, without a crossover to reproduce the offspring and kept the superior solution at each generation to solve the optimization problem. This category of metaheuristic algorithm is widely classified as evolutionary algorithms, which is a subset of the evolutionary computation (EC). Initially, the Fogel and its group developed the evolutionary programming (EP) technique [17-19]. The memetic algorithm is one of the recent growing areas in evolutionary algorithms, which was introduced by Moscato technical report in the year 1989 [20]. The memetic algorithm is one of the population-based approaches to individual learning and incorporates the local improvement procedure for searching. The memetic algorithm also referred to as cultural algorithms and genetic local search. The most recent advancement of memetic algorithms is given in [21, 22].

The next phase of metaheuristic algorithm is interesting, and they are more inspired by the collective behavior shown in the natural process or organism. The collective behavior of decentralized, self-organized system is known as the swarm intelligence, which is the most prominent metaheuristic algorithm domain at present and future. The swarm intelligence was first proposed by Beni and Wang in 1989 [23] and apply in the cellular robotic system. After this, many researchers showed an interest in the development of swarm intelligence metaheuristic algorithms. In the year 1992, Dorigo proposed ant colony optimization (ACO) [24] in his dissertation 'Optimization, Learning and Natural Algorithms' which can find the shortest path, inspired by ant behavior. The detailed survey of ACO has been reported in the book 'Ant Colony Optimization' [25]. The next development was particle swarm optimization (PSO) [26] in the year 1995, which is inspired from birds flocking, fish schooling, and swarm theory. Storn developed a differential evolution (DE) [27] in the year 1996, which is well suited for robust and parallel computation. Further enhancement on DE are proposed in [28] and proves that this algorithm is more efficient than GA. The more details of function optimization on DE are reported in the book [29, 30], and advancement of DE is presented in the book [31].

Until 1997, the researcher compares the algorithm with the average function result and expresses algorithm A1 will better than A2 or algorithm A2 outperform A1. In the year 1997, Wolpert and Macready published 'no free lunch theorems for optimization' [13] send a shocking message to the optimization community. The theorems state that if algorithm A1 is superior to algorithm A2 for some optimization problem, then A2 will outperform A1 for other optimization function. Now the researchers realized that there is no universal algorithm. This leads to more focus on finding better and more efficient algorithm related to a specific problem.

In the 21st century, the researchers are more focused to design the metaheuristic algorithms inspired by nature. In the year 2002, Passsino developed bacterial foraging optimization algorithm (BFOA) [32] taking inspiration from E-coli bacteria found in the human intestine and swarm intelligence [33-35]. The Karaboga presented a technical report on artificial bee colony (ABC) in the year 2005 [36] taking inspiration from honey bees. Further, in [37], the ABC algorithm was compared with the well-known algorithm GA and PSO, it has been shown that it can work for the high-dimensional problem. Rashedi [38] proposed a novel metaheuristic search method named as the gravitational search algorithm (GSA) based on the principle of laws of gravity and mass interaction in the year 2009. In this publication, the author reported that GSA method of function optimization was outperforming, when compared with the PSO, and the real genetic algorithm. The GSA algorithm shows faster convergence as compared with another. Then in the year 2008, Yang proposed a firefly algorithm (FA) in his book 'Nature-Inspired Metaheuristic Algorithms' [9] based on the behavior of the male-female firefly on light flashing and light intensity. Further, the potential of FA was discussed in [39] related to the multimodal function optimization. Again, Yang proposed a cuckoo search (CS) algorithm [40] in the year 2009, and bat-inspired algorithm (BA) [41] in the year 2010. The CS algorithm is based on the behavior of Cuckoo birds and a random walk inspired using Levy flight [42-45]. The more developments in CS and FA are reported in [46, 47]. The BA is based on the echolocation behavior of bats. The human brain is more efficient in the heuristic search process than the collective behavior of insects like ant, bee etc. So, Shi proposed a brainstorm optimization (BSO) algorithm [48] in the year 2011. In addition, more metaheuristic algorithms have been reported in the recent past. These are teaching-learning-based optimization (TLBO) algorithm [49], and bacterial colony optimization (BCO) [50] in the year 2012. Mirjalli et al propose grey wolf optimizer (GWO) [51] inspired by grey wolf (canis lupas) leadership hierarchy and hunting mechanism in the year 2014. In the same year, Pham, et al. propose bee's algorithm [52] inspired by the foraging behavior of honey bees and Salcedo-Sanz propose coral reefs optimization (CRO) algorithm [53].

3. Hybrid Metaheuristic Algorithms

The objectives of the metaheuristic algorithms are to find the optimum value for a given problem. According to Wolpert and Macready [13], there is not a single universal optimization algorithm that can be suitable for all optimization problems. That means algorithm A1 can perform better than algorithm A2 for some applications, but for other applications, A2 may perform better than A1. For this reason, the optimization community tries to think in a different angle to enhance the performances of the algorithms. The performance can be improved by:

- Modifying the searching pattern of the individual algorithm by analyzing the energy space of the optimization problem related to the modification of optimization algorithms.
- By combining the thinking ability of one algorithm with another reference to parallel hybridization.
- First, we run an optimization algorithm and get the solution. Using this solution as the initial solution, we run another optimization algorithm to get the optimal value. These categories can be referred to as the sequential hybridization.

The performance can be improved by somehow doing hybridization of optimization algorithms. The meaning of 'hybrid' in the literature referred as 'the offspring of two plants or animals of different species or varieties' or 'mixed character'. So, when we can't get good performance by one algorithm, we provide some supplement for better performance that exploits and combines the advantages of the classical optimization algorithms. Preux and Talbi [2] shown the researcher a way towards the hybrid evolutionary algorithms. Again, in the year 2001, Talbi described a more formal way of the taxonomy of hybrid metaheuristic optimization algorithm [5]. There are so many hybrid optimization algorithms present in the literature, but in a true sense, the 21st century brings us nature inspired hybrid metaheuristic algorithms, that show their ability to provide the optimal solution. Sometimes, the hybridization of the algorithm shows better results through experimentation. Some of the nature-inspired hybrid metaheuristic algorithms are described below.

In the beginning year 2001 of the 21st century, an orthogonal genetic algorithm with quantization (OGA/Q) [54] was proposed by applying the orthogonal design and quantization techniques to form a new crossover operator in GA. From the observation, the most common dominant algorithm for hybridization is PSO, for its evolutionary approach. Some other evolutionary metaheuristic algorithms are also used for hybridization, such as GA, ACO, ABC optimization, DE, BFO, memetic algorithm, and many more [1, 3, 4, 6-8, 55-57].

As we know, the PSO is swarm evolutionary metaheuristic algorithm based on the evolution. The PSO and DE are hybridized to form a particle swarm with differential evolution operator termed as DEPSO [58]. The DEPSO provide bell-shaped mutation from DE applied to the PSO for evolution. The local search and communication ability of the multi-swarm by dividing the whole population into small sizes of swarm using PSO for developing hybrid metaheuristic algorithms as dynamic multi-swarm particle swarm optimizer (DMS-PSO) is presented in [59]. The PSO as a mutation operator in the GA was investigated in the power flow problem using the hybrid genetic algorithm/particle swarm optimization (GA/PSO) in [60, 61]. By the combining of bird flocking or fish schooling behavior of PSO with the foraging behavior of ACO gives rise to a new hybrid algorithm called particle swarm and ant colony optimization (PSACO) [62] and solve the non-convex optimization problem. In [63], researchers proposed bacterial swarm optimization (BSwO) by hybridizing the PSO operator in BFOA. In [64], the researcher proposes some modification in the position rule of PSO to improve the convergence speed as particle swarm optimization with randomized pbest (PSO-RPB). Again, in the context of improving the convergence speed, authors [65] proposed dispersed particle swarm optimization (DPSO), where each particle decides its own direction towards the personal memory or swarm memory. In [66], a multi-strategy ensemble particle swarm optimization (MEPSO) was proposed by segmenting the swarm in two groups, one for the Gaussian local search serve exploitation behavior, and another one for differential mutation who serves exploration behavior of optimization theory. The Changsheng Zhang et al in [67] proposed a hybrid differential evolution and particle swarm optimization (DE-PSO) for updating the particle using the DE operator and the mechanism of the PSO algorithm. The researchers in [68] proposed a hybrid particle swarm optimization (HPSO) algorithm by employing the opposition-based learning and modifying the velocity equation. In [69], Seyedali Mirjalili et al. combine the exploration property of the GSA and exploitation behavior of PSO to form hybrid PSOGSA algorithm for function optimization. Wang Fan et al. [70] proposed CS-PSO algorithm and Amirhossein Ghodrati et al. [71] proposed CS/PSO algorithm by hybridizing the CS and PSO algorithm. Some more PSO based hybrid algorithms are cellular particle swarm optimization (CPSO) [72] by combining cellular automata (CA), PSO-BFGS strategy [73] by combining modified Broyden-Fletcher-Goldfarb-Shanno (BFGS) method, hybrid PSO-BFO based algorithm in [74], and hybrid artificial bee colony and particle swarm (ABC-PS) algorithm [75] for function optimization.

Now a day's researcher is also investigating new hybrid techniques inspired by nature heuristic methods beyond PSO. In 2007, a hybrid genetic algorithm and bacterial foraging (GA-BF) [76] approach for function optimization were reported by involving the principles of GA in BFO algorithm. In [77], the researchers proposed an adaptive chemotaxis size for BFO algorithm known as ABFOA. In the year 2012, R. Panda et. al. proposed a new hybrid metaheuristic algorithm known as crossover bacterial foraging optimization algorithm (CBFOA) [78] by incorporating the crossover mechanism of GA into the reproduction step of bacteria foraging in BFO. Kong et al. proposed Hybrid artificial bee colony (HABC) [79], which improved the performance than ABC algorithm via exploring an orthogonal initialization. One memetic algorithm-based hybrid algorithm was proposed in [80] known as a memetic algorithm with double mutation operators (MADM) to deal with the global optimization problem. In this paper [81], a hybrid cuckoo search algorithm based on Solis and Wets local search technique is proposed for constrained optimization that counts on an augmented Lagrangian function for constraint-handling. A hybrid artificial bee colony and differential evolution (hABCDE) [82] optimization algorithm based on the information exchange behavior of the artificial bee and the faster convergence of DE. In the year 2015, R. Panda et. al. proposed an adaptive crossover bacterial foraging optimization algorithm (ACBFOA) [83] making the CBFOA step size adaptive. In the year 2015, M. K. Naik et. al. proposed adaptive cuckoo search (ACS) algorithm [84, 85] making the cuckoo search (CS) to decide its step size adaptively from its fitness function. M. K. Naik et. al. proposes a new hybrid cuckoo search – gravitational search algorithm (CS-GSA) [86, 87] by combining the exploiting capability of the GSA and exploration capability of CS. From the point of hybrid metaheuristic algorithm [1, 3, 4, 7, 111-113], the PSO seems to be dominant in recent days, but the future will be with the other swarm optimization techniques [6].

4. Conclusion

The research on the optimization algorithm is not new, but still, the researcher tries to get an original algorithm from the inspiration from nature. The other way is to hybridize the algorithm to get the better result if someone carefully studies the search pattern of the individual algorithm. So, if we compare the number nature-inspired algorithm reported by the researcher based on the life of mammals, and microorganism or natural phenomenon in nature is negligible in the sense of what exists. So, there may be many more natures inspired algorithm can be explored in the future.

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