Study of Nature Inspired Algorithms

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***Abstract* -** *Solving optimization problems becomes a central theme not only on operational research but also on several research areas like robotic, medicine, economic, Data-Mining etc. The number of support decision problems that can be formalized as an optimization problem is growing rapidly. In the communities of optimization, computational intelligence, and computer science, bio-inspired algorithms, especially those SI-based algorithms, have become very popular. In fact, these nature-inspired metaheuristic algorithms are now among the most widely used algorithms for optimization and computational intelligence. This survey discusses the various nature inspired meta-heuristic algorithms, and analyses the key components of these algorithms in terms of three evolutionary operators: crossover, mutation and selection.*

Keywords: *Artificial Bee Colony, Ant Colony Optimization, Bat Algorithm, Cuckoo Search Algorithm.*

I. INTRODUCTION

Optimization is paramount in many applications, such as engineering, business activities, and industrial designs. Obviously, the aims of optimization can be anything—to minimize the energy consumption and costs, to maximize the profit, output, performance, and efficiency. It is no exaggeration to say that optimization is needed everywhere, from engineering design to business planning and from Internet routing to holiday planning. Because resources, time, and money are always limited in realworld applications, one has to find solutions to optimally use these valuable resources under various constraints.

The term optimization can be defined as:

- To make as perfect, effective, or functional as possible.
- Make optimal; get the most out of; use best.

In Mathematics, to optimize means finding the best solution to a problem, where best is considered an acceptable (or satisfactory) solution, which must be absolutely better than a set of candidate solutions, or all candidate solutions.

Optimization can be applied to solve problems of engineering and other branches of science. Rao described in [1] several examples of optimization problems in different engineering disciplines (chemical, civil, electrical, etc.).

An optimization algorithm can be analysed from different perspectives. In this paper, algorithms are analysed against three evolutionary operators i.e. crossover, mutation and selection operator.

- Crossover: the recombination of two parent chromosomes (solutions) by exchanging part of on chromosome with a corresponding part of another so as to produce offsprings (new solutions)
- Mutation: the change of part of a chromosome to generate new genetic characteristics.
- Selection: the survival of the fittest which means the highest quality chromosomes will stay within the population and pass on to the next generation.

The role of these operators can be defined as follows:

- Crossover is mainly for mixing within a subspace. It will help make the system converge.
- Mutation provides a main mechanism for global search.
- Selection provides a driving force for the system to evolve toward the desired states

Next section discusses thekey steps of various popular nature-inspired algorithms and then analysed in terms of above mentioned evolutionary operators and their ways of exploration and exploitation.Last section concludes briefly.

II. Nature Inspired Algorithms

Nature inspired meta-heuristic algorithm have received great interest and attention in the literature. In the communities of optimization, computational intelligence, and computer science, bio-inspired algorithms, especially those SI-based algorithms, have become very popular. In fact, these nature-inspired metaheuristic algorithms are now among the most widely used algorithms for optimization and computational intelligence. SI-based algorithms such as ant and bee algorithms, particle swarm optimization, cuckoo search, and firefly algorithms can possess many advantages over conventional algorithms.There are over a dozen popular, nature inspired algorithms for optimization. Each algorithm is discussed briefly.

Genetic algorithm

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution [4]. The genetic algorithm repetitivelyadjusts a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. GApractises three main types of rules at each step to generate the next generation from the current population: Selection rules select the individuals, called parents that contribute to the population at the next generation. Crossover rules combine two parents to form children for the next generation. Mutation rules apply random changes to individual parents to form children. Over successive generations, the population "evolves" toward an optimal solution.

Simulated Annealing

In 1983, Kirkpatrick et al. developed a simple stochastic algorithm called simulated annealing. The method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy. A new point is randomly generatedin every iteration of algorithm. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm admits all new points that lower the objective with a certain probability threshold, points that raise the objective. Strictly speaking, simulation annealing is not an evolutionary algorithm, and thus there is no crossover operator in this algorithm and also the exploitation is weak because the acceptance is carried out by a probability condition. It finds the global optimality at the expense of a large number of function evaluations.

Ant colony optimization

Ant colony optimization (ACO) is a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems [6]. In ACO, a set of software representatives called artificial ants search for good solutions to a given optimization problem. To apply ACO, the optimization problem is transformed into the problem of finding the best path on a weighted graph. The artificial ants progressively build solutions by moving on the graph. The solution construction process is stochastic and is biased by a pheromone model, that is, a set of parameters associated with graph components (either nodes or edges) whose values are modified at runtime by the ants. ACO uses only mutation and fitness related selection and can have good global search ability but convergence may be slow because it lacks crossover and thus the subspace exploitation ability is limited.

Particle swarm optimization

Inspired by swarm behaviour, such as fish and bird schooling in nature, Particle swarm optimization algorithm is given in [7].. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no crossover operator. PSO consists of mainly the selection and mutation which means that PSO can have high mobility in particles with a high degree of exploration.

Differential evolution

Differential evolution (DE) is a method developed by R. Storn and K. Price in [8]. DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means DE does not require for the optimization problem to be differentiable. DE optimizes a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimization problem at hand.

Shuffled frog leaping algorithm

In 2005, MuzaffarEusuff et al. proposed a meta-heuristic algorithm called shuffled frog-leaping algorithm (SFLA) for solving combinatorial optimization problems [9]. SFLA is a population based cooperative search metaphor inspired by natural memetics. The SFLA consists of a set of interacting virtual population of frogs partitioned into different memeplexes. The algorithm performs at the same time an independent local search in each memeplex. To ensure global exploration the virtual frogs are periodically shuffled and reorganized into new memeplexes. Random virtual frogs are produced and replaced in the population.

Cat swarm optimization

CSO is based on cat's behaviour [10]. Applying CSO to solve problems of optimization, the first step is to decide how many individuals to use. The entities in CSO is called cats, and every single cat has its own position poised of M dimensions, velocities for each dimension, a fitness value representing the accommodation of the cat to the benchmark function, and a flag to identify whether the cat is in seeking mode or tracing mode. The concluding solution would be the finest position of one of the cats in the solution space. CSO keeps the best solution until it reaches the end of the iterations. CSO has two sub modes, namely seeking mode and tracing mode. These two modes individually represent different procedures in the algorithm to imitate the behaviours of cats, and they are dictated to join with each other by a mixture ratio MR.

Weed colonization

Weeds are the plants whose vigorous invasive habits of growth pose a serious threat to desirable cultivated plants making them a threat for agriculture. Weeds have shown to be very robust and adaptive to change in environment. Thus capturing their properties would lead to powerful optimization algorithm. To mimic the robustness, adaptation and randomness of colonizing weeds, a novel numerical stochastic optimization algorithm was proposed by A.R. Mehrabian and C. Lucas in 2006, called invasive weed optimization (IWO) [11].

Artificial bee colony algorithm

In 2007, D. Karaboga proposed an optimization algorithm called artificial bee colony based on the intelligent foraging behaviour of honey bee swarm [12]. In the ABC framework, the society consists of three clusters of bees: employed bees, onlookers and scouts. It is assumed that there is only one artificial employed bee for each food source. In other words, the total of employed bees in the colony is equal to the number of food sources around the hive. Employed bees go to their food source and come back to hive and dance on this area. The employed bee whose food source has been abandoned becomes a scout and starts to search for finding a new food source. Onlookers watch the dances of employed bees and choose food sources depending on dances. As ABC uses only mutation and fitness-related selection and can explore the search space effectively, but convergence may be slow because it lacks crossover.

Monkey Search Algorithm

Monkey search algorithm was developed by Antonio Mucherino and OnurSeref in 2007 [13]. This algorithm is inspired by the behaviour of a monkey climbing trees in its search for food. Monkey search discovers a tree of solutions where branches contain neighbour solutions on their end. The monkey marks these branches on its way climbing down whenever a better solution is found such that these marks can be used to choose branches to climb on the way up. This algorithm simply used the selection and mutation mechanism, no explicit crossover used.

Firefly algorithm

The firefly algorithm (FA) was developed by Xin-She Yang in 2008 and is based on the inspiration from natural behaviour of tropical fireflies [14]. FA tries to mimic the flashing patterns and behaviour of tropical fireflies. Since local attraction is stronger than long-distance attraction, the population in FA can automatically subdivide into multiple groups, and each group can potentially swarm around a local mode. Among all local modes, there is always a global best solution that is the true optimality of the problem. FA can deal with multimodal problems naturally and efficiently. By closely examining the algorithm it is observed that mutation is used for local search as well as global search.

Glow-worm search optimization

The GSO algorithm was developed and introduced by K.N. Krishnanand and DebasishGhose in 2009 for optimizing multi-modal functions [15].The behaviour pattern of glowworms which is used for this algorithm is the apparent capability of the glowworms to change the intensity of the luciferin emanation and thus appear to glow at different intensities. The intensity of luciferin is associated with the objective function of glow-worm’s location, and a greater luciferin mean better location and objective function value of glowworms. GSO used only mutation and fitness-related selection. Absence of crossover results in poor convergence rate of GSO.

Bumblebees algorithm

In 2009, FrancescComellas and Jesus Martinez Navarro developed a multiagent optimization algorithm inspired by the collective behaviour of bumblebees [16]. In this algorithm, each agent encodes a possible solution of the problem to solve, and evolves in a way similar to real life insects. This algorithm can easily be adapted to solve other problems by adapting the cost function and mutation to the new problem. Like ABC algorithm bumblebees algorithm used only selection and mutation. No explicit crossover used.

Cuckoo search algorithm

Cuckoo search is an optimization algorithm developed by Xin-she Yang and Suash Deb in 2009 [17]. It was inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds (of other species). Some host birds can engage direct conflict with the intruding cuckoos. For example, if a host bird discovers the eggs are not their own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. Some cuckoo species such as the New World brood-parasitic Tapera have evolved in such a way that female parasitic cuckoos are often very specialized in the mimicry in colours and pattern of the eggs of a few chosen host species. In addition, this algorithm was enhanced by the so called levy flights rather than by simple isotropic random walks. By examining this algorithm it is observed that CS has strong mutation at both local and global scales while good mixing is carried out by using solution similarity, which also plays the role of equivalent crossover. And again this algorithm also lacks the explicit crossover mechanism.

Bat Algorithm

The Bat algorithm is a metaheuristic algorithm for global optimization. It was inspired by the echolocation behaviour of microbats, with varying pulse rates of emission and loudness. The Bat algorithm was developed by Xin-She Yang in 2010 [18]. The idealization of the echolocation of microbats can be summarized as follows: Each virtual bat flies randomly with a velocity $v_i$at position (solution) x_i with a varying frequency or wavelength and loudness A_i. As it searches and finds its prey, it changes frequency, loudness and pulse emission rate r. Search is intensified by a local random walk. Selection of the best continues until certain stop criteria met. There was no explicit crossover; however, mutation varies due to the variations of loudness and pulse emission that's why exploitation becomes intensive as the search approaches the global optimality.

Termite colony optimization

In 2010, Ramin et al. proposed Termite colony optimization (TCO) algorithm based upon intelligent behaviours of termites [19]. Termites moves randomly in search space but their trajectories were biased towards regions with more pheromones. Different types of movement pattern were introduced into the TCO algorithm to maintain the balance between global and local search because TCO lacks the crossover mechanism.

Brain Storm Optimization algorithm

In 2011, Yuhui Shi proposed Brain Strom Optimization (BSO) algorithm inspired from the human brainstorming process [20]. The BSO algorithm has two major operators: convergent operator and divergent operator. In the BSO algorithm, the solutions were clustered into several categories, and the new solutions being generated by the mutation of cluster or existing solutions. The best solution selected based upon the fitness function value. Explicit crossover mechanism is also missing from this algorithm.

Wolf Search algorithm

In 2012 Rui-Tang et al. proposed a new bio-inspired heuristic optimization algorithm called the wolf search algorithm (WSA) that imitates the way wolves search for food and survive by avoiding their enemies [21]. Each searching agent simultaneously performs autonomous solution searching and merging. Local optima were overcome when the searching agent leap far away upon being triggered by the random emergence of an enemy. As like other meta-heuristic algorithm this algorithm uses the selection and mutation mechanism only. No explicit crossover mechanism used.

Flower pollination algorithm

Flower pollination is a fascinating process in the natural world. Based upon the evolutionary features of the flower pollination, Xin-She Yang proposed an algorithm called flower pollination algorithm (FPA) [22]. In principle, Flower pollination activities occur at all scales, both local and global. But in reality, adjacent flower patches or flowers in the not-so-far-away neighbourhood are more likely to be pollinated by local flower pollen than by those far away. This feature was mimicked in the flower pollination algorithm by using a proximity probability to switch between common global pollination to intensive local pollination. Selection was achieved by choosing the best solutions and passing them on to the next generation. There is also no crossover mechanism in this algorithm.

Krill Heard Algorithm

Krill heard algorithm was proposed by Amir HosseinGandomi and Amir HosseinAlavi in 2012 [23]. KH simulates the herding behaviour of krill individuals. The minimum distance of each individual krill from food and from the higher density of the herd were considered as the objective function for the krill movement. The time-dependent positions of the krill individuals were formulated by three main factors: movement induced by the presence of other individuals, foraging activity, and random diffusion. Two genetic operators (Selection and Mutation) were added to the algorithm for precisely modeling of the krill behaviour. KH was tested using several benchmark problems. The performance of KH was compared with GA, ACO, DE, PSO algorithms. The results showed that the performance of KH algorithm was good.

Egyptian vulture optimization algorithm

In 2013, Chiranjib Sur et al. proposed a new metaheuristic algorithm called Egyptian vulture optimization algorithm [24]. This algorithm primarily used for combinatorial optimization problems Tossing of pebbles and the ability of rolling things with twigs were the two main activities that used in Egyptian Vulture algorithm. Tossing of pebbles used in this meta-heuristics for introduction of new solution in the solution set randomly at certain positions. And ability of rolling things with twigs considered as rolling of the solution set for changing of the positions of the variables to change the meaning and thus create new solutions which may produce better fitness value and also better path when it comes for multi-objective optimization. Only selection and mutation used in this algorithm and no explicit crossover introduced.

Atmosphere Clouds model optimization algorithm

In 2013, a novel atmosphere clouds model optimization algorithm (ACMO) which was inspired by the move behaviour, generation behaviour, and spread behaviour of the clouds in the natural world [25]. Search method composed by move behaviour and spread behaviour of clouds which disperses the whole population to the search space. The ACMO algorithm was tested on a set of benchmark functions in comparison with two other evolutionary-based algorithms: particle swarm optimization (PSO) algorithm and genetic algorithm (GA). The results demonstrated that the proposed algorithm has certain advantages in solving multimodal functions, while the GA algorithm has a better result in terms of convergence accuracy.

Dolphin echolocation

A. Kaveh and N. Farhoudi proposed a new optimization method named Dolphin Echolocation (DE) [26]. This algorithm was adopted from hunting dolphins.Dolphin can send sound in the form of click in different orientations and when this sound strikes an object, some part of the energy of the sound is reflected back to the Dolphin as echo. Then, the Dolphin hears them and decides to make a decision at this time. Hunting stage is started and dolphin moves to bait, sending sound and receiving echo continue until Dolphin hunts the bait. Obviously, during this approach, the probability of hunting increases every time and search space decreases continuously. Looking closely at DE algorithm, it shows that random route generation is primarily mutation, whereas reflected sound based selection provides a mechanism for selecting any particular solution. There is no explicit crossover mechanism in this algorithm.

Lion Optimization

MaziarYazdani and FariborzJolai developed a new population based algorithm called Lion Optimization Algorithm (LOA) [27]. This algorithm is inspired from the special lifestyle of lions. The basic structure of LOA grouped into four major components based on the nature of its functions. They are,

- Pride Generation, which is responsible for generating solutions,
- Mating: that refers to deriving new solutions and
- Territorial Defence : that refers to the process of evaluating the existing solution and
- Territorial Takeover: intends to find and replace worst solution by new best solution.

Territorial takeover resembles to selection operation that keeps better solution and vanishes the worst solutions. Mating used for randomly generating new solutions and this resembles the mutation process. Again there is no explicit crossover in this algorithm.

III. CONCLUSION

Many nature inspired algorithm is briefly discussed in this study. Most of them are based on the swarm intelligence and use population based search. Through study it is found that most algorithms use mutation and selection to achieve exploration and exploitation. Some algorithm use crossover as well, but most do not. Mutation helps us explore on a global scale, whereas crossover explores in a subspace and thus is more likely to lead to convergence. Selection provides a driving mechanism to select the promising states or solution. This implies that there is a room for improvement. By introducing crossover operator the performance of these algorithms can be improved.

Through study, it is found that setting of algorithm dependent parameters can significantly affect the performance of an algorithm. To get good performance, there is need to find the right values for parameters. In other words, parameters need to be fine-tuned so that the algorithm can perform to the best degree.

Related to parameter tuning, there is another issue of parameter control. The idea of parameter control is to vary the parameters during iterations so that the algorithm of interest can provide the best convergence rate and thus may achieve the best performance. In the BAT algorithm, parameter control has been attempted and found to be very efficient.

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