REVIEW OF METAHEURISTIC ALGORITHM FOR COGNITIVE RADIO

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Abstract
Allocation of channel resources in a cognitive radio system for accomplishing minimalized transmission energy with an improved transmission rate is a challenging research area. This paper provides a review of different types of resource allocation algorithm established on the meta-heuristic search belief. The algorithms discussed in the paper are established through replicating the scouting behavior of the animals. Five renowned optimization algorithms, namely, conventional GSO, Firefly Algorithm, Particle Swarm Optimization, Artificial Bee Colony algorithm, and Genetic Algorithm are explained.
Keywords: Combinatorial optimization, Diversification, Genetic Algorithms, Intensification, Meta-heuristics

I. INTRODUCTION

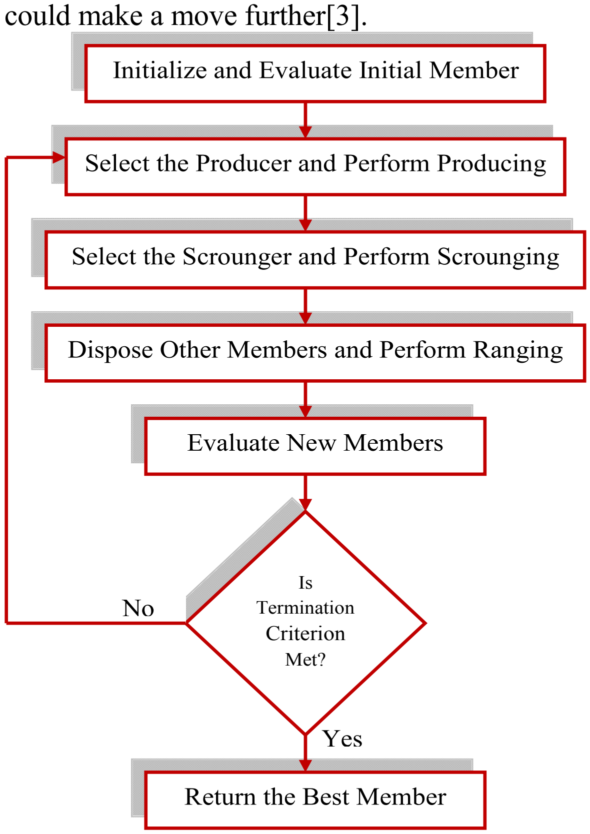
Cognitive Radio (CR) was first introduced by Mitola in 1999 [1], it signifies a core technology that assists service providers, operators and National Regulatory Authorities to drift away from the Command and Control regime and move towards more open access spectrum policies[1]. Basically there are three basic functionalities of a cognitive radio for cognitive behaviour: recognising the spectrum and the environment adjoining the radio, the capability to epitomise and understand knowledge and act consequently through a capacity to reason and learn; and lastly the ability to acclimatize its operating parameters in respond to varying situation[2]. Cognitive radio has moved the paradigm of communications systems designers to focusing on other technical resolutions from other scientific paradigms to tackle traditional problems. In the modern day world wireless networks are required to be efficient, low-cost, robust and flexible. As the number of users increase and with the introduction of new applications and services there is a constant increase in traffic in the network. This has led to rapid growth in the field of metaheuristic related optimization algorithms to cater to the above needs and solve the problems[4]. In this paper, we focus on the ability of the radio terminal to adapt its physical layer parameters to its changing environment. Adaptation involves familiarizing adaptive algorithms that assist the radio terminal from achieving higher spectrum utilization, and better link performance. For this a review of five adaption algorithms are discussed below. We Outline the different components and concepts that are used in the different metaheuristic algorithms in order to analyze their similarities and differences[3].

In this paper the various conventional metaheuristic approaches, which are the Genetic Algorithm, Particle Swarm Optimization, Artificial Bee Colony Algorithm and Firefly Algorithm and they are explained in the following section.

II. REVIEW OF DIFFERENT METHODOLOGIES

A. *Standard GSO Algorithm*

Sufficient meta-heuristic search algorithms are available in the literature of various publishers. However in comparison to all of those algorithms GSO embraces the top level in providing effective solutions to the standard test set. Yet, the effectiveness of GSO in providing solutions to practical problems is much constrained. The flowchart of the standard GSO is represented in Fig. 1, where the principal processing stages are producing, scrounging dispersion. In producing, the producer that is assessed as the best member examines at zero degree followed by lateral scanning at three unsystematic points of the scanning view. The producer passages to new position, only if it finds a better position in its scanning operation. Under a situation of remaining in the same position for a fixed number of repetitions, the producer turns back its head to zero degree. In the dependent process, 80% of the rest of the members are being carefully chosen and imperilled to a joining process, similar to the crossover operation of the genetic algorithms. The remaining members are disseminated for ranging, in which the random head angles are spawned to determine a random distance for finding a new position, where the members could make a move further[3].



Fig(1) Flow-chart of Standard GSO Algorithm[3]

B. Genetic Algorithm

Genetic Algorithm is an Adaptive Strategy and a Global Optimization technique. It is an Evolutionary Algorithm and belongs to the wider study of Evolutionary Computation. The Genetic Algorithm is a sibling of other Evolutionary Algorithms such as Learning Classifier Systems, Evolutionary Programming, Evolution Strategies and Genetic Programming. The Genetic Algorithm is a parent of various number of different techniques and sub-fields The Genetic Algorithm is motivated by population genetics and evolution at the population level and Mendelian understanding of the configuration and apparatuses such as recombination and transmutation. This is the new fusion of evolutionary biology.

The aim of the Genetic Algorithm is to exploit the various candidate solutions in the population against a cost purpose from the problem domain. The strategy of the Genetic Algorithm is to recurrently employ substitutes for the recombination and transmutation of genetic mechanisms on the population of candidate solutions, where the cost objective are applied to a decoded representation of a candidate administers the probabilistic contributions. A given candidate solution can make to the succeeding generation of candidate solutions[5].

For a maximization problem, the brightness is proportional to the objective function's value. Other forms of the brightness could be defined in same way to the fitness function as in genetic algorithms[4].

C. Particle Swarm Optimization

Particle swarm optimization was developed by Kennedy and Eberhart in 1995 based on swarm behavior of flocking of birds or schooling behavior of fish. Operators such as crossover or mutation are not used in swarm optimization making it similar but simpler than genetic algorithms and ant algorithms.

For optimization it relies upon real number randomness and communication amongst the swarm particles. This makes it easier to implement as there is no need of encoding or decoding of parameters.

Just like flocking of birds particles in swarm algorithm flow through the environment behind the fitter members of the group. These particles move towards historically good areas of the environment they are in. The aim of the algorithm is to locate the optima in a multi dimension hyper volume. This goal is achieved by assigning random positions and random velocities to all the particles in the space. The algorithm advances the position of each particle based on its velocity and position in the space till the best position is known[5].

Over time and through a combination of explorations and exploitations in search space the particles gather around and optima. Velocity alterations were based on a crude inequality test: ifpresentx > bestx, make it smaller; ifpresentx < bestx, make it bigger. Some investigation revealed that further reviewing the algorithm made it easier to understand and improved its performance. Relatively simply testing the sign of the inequality, velocities were accustomed according to their variance, per dimension from best locations: Mathematically it can be proved from the below formula.[6]

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vx[][] = vx[][] + rand()*p_increment*(pbestx[][] - presentx[][])
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Fig (2) Formula to calculate velocity alterations [6]

D. *Artificial Bee Colony Optimization*

The Artificial Bee Colony (ABC) algorithm is used for improving numerical problems. Artificial Bee Colony optimization algorithm is an global optimization algorithm, which had been proposed for numerical optimization. However it can be also used for constrained and unconstrained optimization problems and combinatorial optimization problems, with just three control factors. Artificial Bee Colony optimization algorithm is inspired by the intelligent foraging behavior of honey bees. The model consists of three vital constituents: employed and unemployed searching bees, and food sources. The first two constituents, employed and unemployed searching bees, search for rich food sources close to their hive. Similarly a group of agents search for good solutions for a given problem[6].

ABC Algorithm Pseudocode

Begin
Initialize the population of solutions
Evaluate the population
Cycle=1
Repeat
Produce new solutions for the employed bees
Apply greedy selection process
Calculate the probability values
Create the new solutions for the onlookers
Apply greedy selection for the onlookers
Define abandoned solution
Memorize best food source position
Cycle=cycle+1
Terminate cycle number, when reaching maximum cycle number

Fig (3) Pseudocode for Artificial Bee Colony Optimization.

To apply ABC, the measured optimization problem is first transformed to the problem of finding the best parameter vector which lessens an objective function. Then, the artificial bees arbitrarily discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbor search mechanism while abandoning poor solutions. . At first, all food source locations are revealed by scout bees[8]. Thereafter, the nectar of food sources are oppressed by employed bees and onlooker bees, and this repeated exploitation will ultimately cause them to become exhausted. Then, the employed bee which was misusing the drained food source becomes a scout bee in search of additional food sources once again. In other words, the employed bee whose food source has been exhausted becomes a scout bee. In ABC, the position of a food source represents a possible solution to the problem and the nectar sum of a food source corresponds to the quality (fitness) of the associated solution. The number of employed bees is equal to the number of food sources (solutions) since each employed bee is associated with one and only one food source.[7]

E. *Firefly Algorithm*

The bioluminescence processes is accountable for blinking light of fireflies. There are many concepts regarding purpose and significance of blinking light in firefly's life cycle but many of them congregate to breeding phase. The basic objective of blinking light is to appeal breeding partner. The form of these recurring flashes is exclusive and is based upon the rhythm of flashes, rate of blinking and amount of time for which flashes are witnessed. This pattern appeal both the males and females to each other and female of a species retort to specific pattern of male of same kind . Conferring to the inverse square law, intensity of the light I, keeps on decreasing as the distance r increases in terms of I α 1/r2. Air also acts as absorbent and light gets feebler with aggregative distance. Merging these two factors diminish the perceptibility of fireflies to a limited distance usually few hundred meters at night which is adequate for fireflies to converse with each other[8].

Firefly algorithm is based upon idealizing the blinking characteristic of fireflies. The idealized three rules are:-

- All fireflies are considered as unisex and regardless of the sex one firefly is attracted to other fireflies

- The Attractiveness is proportionate to their brightness, which means for any two blinking fireflies, the movement of firefly is from less bright towards the brighter one and if no one is brighter than other it will move randomly. Furthermore they both decrease as their distance increases.
- The landscape of the objective function directly affects the brightness of the firefly [3] [7].

FA Pseudocode

Objective function f(x), x=(x1,x2,…,xd)T
Initialize a population of fireflies xi(i= 1,2, . . , n)
Define light absorption coefficient γ
While (t<MaximumGenerations)
For i=1:n (all n fireflies)
For j=1:i
Light intensity Ii at xi is determined by f(xi)
If (Ii > Ij)
Move firefly i towards j in all d dimensions
Else
Move firefly i randomly
End If
Attractiveness changes with distance r via exp[-γr2]
Determine new solutions and revise light intensity
End for j
End for i
Rank the fireflies according to light intensity and find the current best
End while

Fig (4) Pseudcode for Firefly Algorithm.

For a maximization problem, the brightness is proportional to the objective function's value. Other forms of the brightness could be defined in same way to the fitness function as in genetic algorithms[8].

III. CONCLUSION

It can be concluded that each metaheuristic algorithm has its own advantages and disadvantages like Genetic Algorithm and Particle Swarm Optimization have the Ability to determine an unknown system's performance with least knowledge while they lack in convergence to the global optima due to poor parameter settings, indefinite search space and imprecise objective model. While PSO algorithm are simple and have fast converging behaviour it Sticks with local optima under multimodal scenarios. Particle Swarm optimization algorithm Ability to handle the constrained mixed integer problem model of channel allocation while selecting the degree of approximation is complex. ABC Algorithm is simple and efficient but requires more and correct information about the problem model. Firefly algorithm has a straightforward selection and produces substantial allocation but it Inability to handle multimodal search space is the main disadvantage.

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