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Cognitive Radio Engine Design using Adaptive Multi-Objective GA and PSO

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Abstract – **The radio frequency spectrum is a scarce natural resource, so it is very important to use the spectrum efficiently. Cognitive radio, which can greatly improve the spectrum utilization, is able to adjust the transmit parameters according to the environment. In this paper, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are proposed to design the cognitive radio engine. In order to improve the performance of the algorithm, adaptive mutation mechanism and the elite strategy is introduced into the proposed algorithm. Moreover, the proposed algorithm is used to design a cognitive radio engine in a multi-carrier system with ten sub-carriers. The simulation results show that the proposed algorithm is feasible and effective.**

Keywords –**Cognitive Radio Engine, GA, PSO, QoS.**

I. INTRODUCTION

The available radio resource is getting congested everyday due to enormous increase in wireless applications. With expanding applications there is all of a sudden an extreme lack of available spectrum. The fact is proven that a very small amount of spectrum is being used. The unused spectrum part causes gaps in the spectrum band commonly regarded as spectrum hole. Subsequently, a proposal is made to permit usage of the unutilized spectrum to unlicensed users for a time interval. Thus to use the available electromagnetic spectrum efficiently, Cognitive Radio (CR) is a promising technology to support this solution.

Cognitive radio (CR) is an intellectual radio in which corresponding communication system that has its knowledge internally as well as externally, for example, location and usage on RF range in that area. They can settle on choices about its working conduct by using that data against pre-set targets.

A CR examines its own execution consistently, interpreting its own outcomes; it then uses this data to analyse the radio background, channel state information, system performance etc., thereafter it modifies its radio parameters to fulfil required QoS constraints, operational restrictions, and administrative limitations. They commonly work at frequencies that are initially provided to licensed (primary) radio users, and with that also operate at available frequencies in unlicensed bands [1].

CR points an effective utilization of the available radio resource, maintaining a strategic distance from swarmed unauthorised spectrum bands. Spectrum sensing, Spectrum decision, spectrum sharing and spectrum mobility are some fundamental features of cognitive radio.

Cognitive users should:

- Find the gaps in spectrum i.e. spectrum holes (spectrum sensing)
- Choose the best spectrum option to fulfil the needs of user interaction (spectrum decision)
- Cooperate with other neighbours for accessing selected channel (spectrum sharing)
- Able to switch to other channels when an authorised user claims the band (spectrum mobility)
- Manage non-interruptive communication during handover process
- Keep primary users away from serious interference. These self-adjustable progressive capabilities must include knowledge of previous experience and impacts, present observation and data-types.

The main objective of this paper is to implement an adaptive multi-objective GA and PSO based design to propose the cognitive radio engine.

II. PROPOSED METHODOLOGY

The environment information should be known in time for changing radio behaviour to satisfy the dynamic quality of service, which is described as several environment parameters, such as transmission distance, noise power and available spectrum. The environment parameters will be used to calculate the fitness functions and help cognitive radio engine make decision. The parameters used in this paper are listed in Table 1 [2].

Cognitive radios become possible when the waveform parameters within the cognitive node can be changed adaptively according to the environment. The available waveform parameters should be defined as decision variables for

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evolutionary algorithms calculating generating fitness functions. It's impossible to define a complete list of decision variables to generate a genetic fitness function usable by all radios. The transmission parameters used in this paper is listed in Table 2 [3].

Table 1: Environment Parameters

Parameter name	symbols	Description
Noise power spectral density	n_0	Noise power per bandwidth
Channel loss	Cl	Energy loss of signal transmission in the channel
Transmission distance	T_d	Transmission distance of signal

Table 2: Transmission Parameters

Parameter name	symbols	Description
Transmit power	P_t	Transmit power
Modulation type	M_t	Modulation type
Modulation index	M_i	Number of symbols in a constellation

Fitness Functions

In optimization process, the wireless communication system performance indexes are described as fitness functions to guide the search direction. The individual with a high fitness will have a bigger chance to be selected into the next generation. Some performance indexes are in conflict with each other, for example the minimum of energy consumption usually results in an augment of the Bit Error Rate (BER). Therefore, the actual results of optimization should take balance of these performance indexes, which can meet the communication requirements and improve the other performance as high as possible. Three performance indexes of BER, data rate, and energy consumption are considered in this paper, and the fitness functions in a multi-carrier system are respectively designed as follows:

The fitness function of data rate is defined as [2]:

$$f_{\max\_bit} = 1 - \frac{\sum_{i=1}^{N_c} \log_2(M_i)}{N_c . \log_2(M_{max})} \quad (1)$$

Where N_c is the number of sub-carriers, M_i represents the modulation index and M_{max} is the largest value.

The fitness function of energy consumption is defined as [3]:

$$f_{\min\_power} = \frac{P_t}{N_c \times P_{max}} \quad (2)$$

Where N_c is the number of sub-carriers, P_t is the transmission power and P_{max} is the largest value.

The fitness function of BER is defined as:

$$f_{\min\_BER} = \frac{1}{N_c} \times \sum_{i=1}^{N_c} P_{e_i} \quad (3)$$

Where N_c is the number of sub-carriers, P_e is the error probability of QAM modulation in a Gaussian channel, which can be calculated as [4]:

$$P_e = \frac{2(1-1/\sqrt{M})}{\log_2(M)} erfc \sqrt{\frac{1.5 \log_2(M)}{M-1} \times \frac{E_b}{n_0}} \quad (4)$$

Where E_b is the energy per bit and n_0 is the noise power spectral density.

Proposed Algorithm

The detailed process of the proposed algorithm is as follows:

1. Step 1: Perceive the environment information, if it changes, go to step 2. Otherwise, select a set of parameters from the memory according to the communication requirements.
2. Step 2: Input the cognitive radio parameters, and perform multi-objective optimization process to obtain a pareto-optimal set.
   a. Step 2.1: Initialize the population according to the knowledge of previous cognitive cycle, and make P' empty.
   b. Step 2.2: Calculate the fitness value and the crowding distance of the individuals according to the formulas from (1) to (4).
   c. Step 2.3: Update the memory library and judge whether the termination condition is met. If it satisfies, then stops, the individuals of the memory library form the Pareto-optimal set, otherwise, continue.
   d. Step 2.4: Add the individuals into mating pool based on the fitness and crowding distance. The individuals with bigger value may have a bigger chance to be added. If the fitness value is same, the individuals with greater crowding distance will be added. Put the individuals with biggest fitness into population P'.
   e. Step 2.5: Perform crossover and mutation with probability P_c, P_m respectively, where the mutation probability P_m can change according to the crowding distance.
   f. Step 2.6: Calculate the fitness and crowding distance of all the individuals (the new individuals, the parents individuals and the individuals in P'), and select excellent individualwith bigger fitness and greater crowding distance to form the new population, go to Step 2.3.
3. Step 3: Select a set of parameters from the Pareto-optimal set according to the communication requirements.

The fitness function is optimized using following optimization techniques:

1. Genetic Algorithm
2. Particle Swarm Optimization

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Genetic Algorithm

Genetic Algorithm is an optimization tool that lies on the platform of Heuristic Approaches. Based on the proposal of Darwin principle of fittest survival, this method was introduced to commence optimization problems in soft computing [5]. The first category of results is termed as initial population and all the individuals are candidate solution. Simultaneous study of the population including all candidates and next phase of solutions are generated following the steps of GA [6].

An iterative application of operators on the selected initial population is the initiative process of GA. Further steps are devised based on valuation of this population. The typical routing of GA is described in following pseudo code:

1. Randomly generate initial population.
2. Employ fitness function for evaluation.
3. Chromosomes with superior fitness are valued as parents.
4. New population generation by parent's crossover with probability function.
5. Chromosome mutation with probability to defend system from early trap.
6. Repeat step 2.
7. Terminate algorithm based on satisfaction criteria.

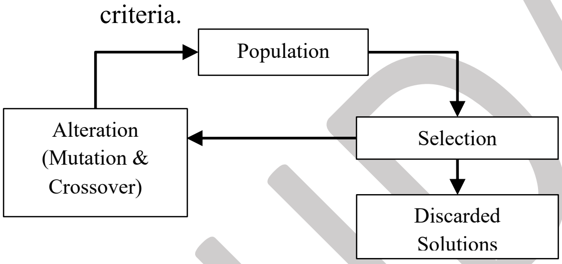

Figure 1: Genetic algorithm evolutionary cycle

Particle Swarm Optimization (PSO)

PSO is a heuristic method [7]. The evaluation of candidate solution of current search space is done on the basis of iteration process (as shown in Figure 2). The minima and maxima of objective function is determined by the candidate's solution as it fits the task's requirements. Since PSO algorithm do not accept the objective function data as its inputs, therefore the solution is randomly away from minimum and maximum (locally/ globally) and also unknown to the user. The speed and position of candidate's solution is maintained and at each level, fitness value is also updated. The best value of fitness is recorded by PSO for an individual record. The other individuals reaching this value are taken as the individual best position and solution for given problem. The individuals reaching this value are known as global best candidate solution with global best position. The up gradation of global and individual best fitness value is carried out and if there is a requirement then global and local best fitness values are even replaced. For PSO's optimization capability, the updation of speed and position is necessary. Each particle's velocity is updated with the help of subsequent formula:

$$v_i(t+1) = wv_i(t) + c_1 r_1[\hat{x}_i(t) - x_i(t)] + c_2 r_2[g(t) - x_i(t)] \quad (5)$$

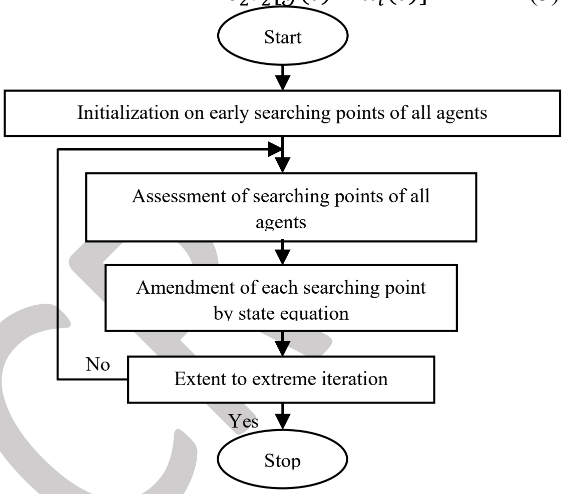

Figure 2: Flow chart of PSO algorithm

III. Simulation and Results

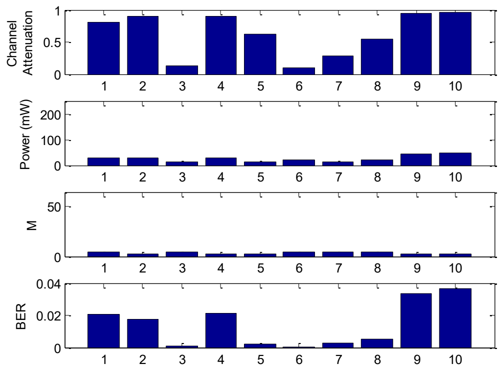

Figure 3: Simulation of balance mode using genetic algorithm

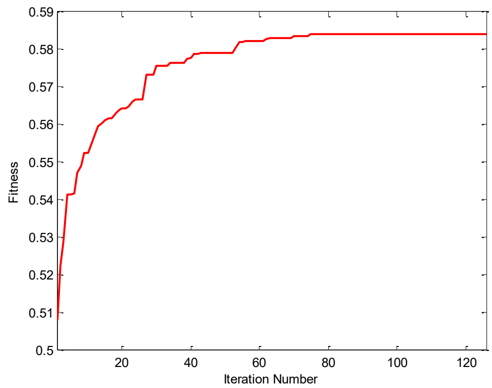

Figure 4: Iteration count of genetic algorithm for balance mode

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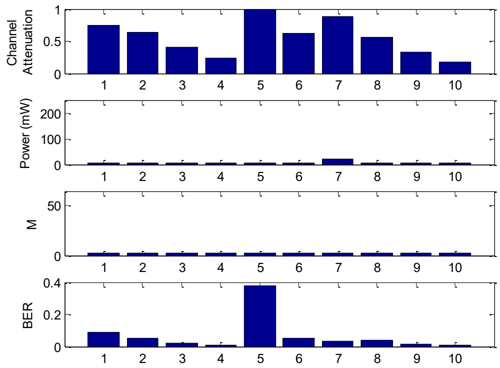

Figure 5: Simulation of balanced mode using particle swarm optimization

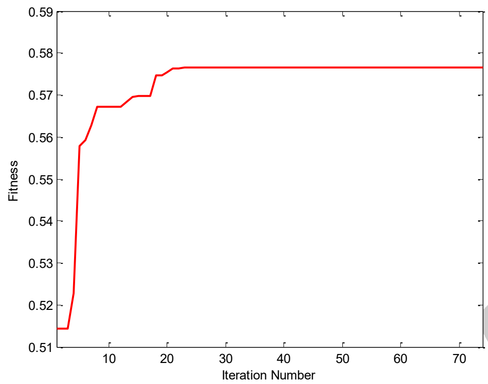

Figure 6: Iteration count of particle swarm optimization for balanced mode

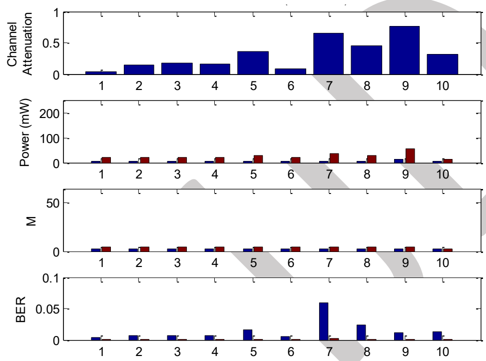

Figure 7: Comparison of GA and PSO simulations for balanced mode

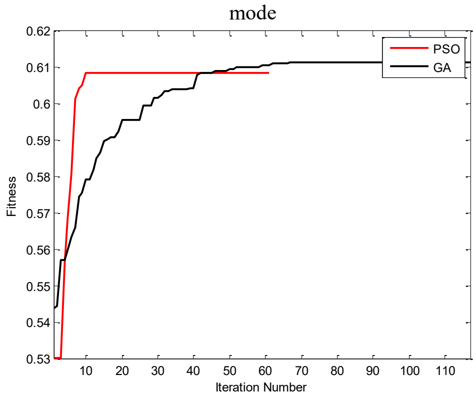

Figure 8: Iteration count comparison of GA and PSO for balanced mode

IV. Conclusion

This paper introduced an approach to design cognitive radio engine based on GA and PSO in a multi-carrier system. An important aspect of these techniques is the designing of fitness function, which guides the searching of the parameter sets to the optimal set. This paper has introduced how to design fitness function by using cognitive radio parameters and simulate a multi-carrier system with 10 sub-carriers. Furthermore the simulation results shown that the proposed algorithm is feasible and effective.

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