Optimization Spectrum Decision Parameters in CR using Autonomously Search Algorithm

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Abstract—In order to solve the contradiction between wireless communication service demand and spectrum resource shortage and enhance the utilization rate of spectrum, Cognitive Radio technology is necessary. Firstly, this paper presents a cognitive engine framework structure, and then the concept of bio-inspired and its application in CR computing were emphatically introduced. Finally, in order to solve spectrum parameters problem, this paper proposed based on autonomously search algorithm. Based on population evolution, ASA algorithm employs the foraging, reproduction, selection and mutation operators, and was tested under the multicarrier simulation environment. The experiment results show that ASA algorithm can better adjust each subcarrier communication parameters according to the requirement of cognitive engine parameters optimization, which include transmitted power, modulation mode, and bit-error-rate and so on, and finally satisfy the channel condition and the dynamic changes of the user service.

Keywords—Cognitive Engine, Bio-inspired Computing, Cognitive Radio, Automously Search Algorithm, multi-objective optimization problem

I. INTRODUCTION

Due to the rapid development and the wide application of wireless communication network and radio technology, the wireless spectrum resource scarcity problem became increasingly serious. Cognitive radio technology is based on cognitive science, computer science and information, and control theory. It can realize effective sharing of resources and optimize the use of them through perception, self-learning and adaptive parameter adjustment function [1-3].

Cognitive engine, as the intelligent core of the cognitive system, can optimize choices according to the environmental information obtained by the sensing module and user needs, thus realize the reconfiguration and optimization of each layer of cognitive system [4, 5]. To a certain extent, the performance of cognitive engine determines the whole performance of cognitive radio. Cognitive engine can use many kinds of artificial intelligence technology, in which, bio-inspired computing as an optimization technology is indispensable.

Reasonable spectrum parameter settings can improve the cognitive radio performance. After analyzed the cognitive radio decision engine, this paper uses a new bio-inspired computing to solve spectrum parameter decision problem.

II. FRAMEWORK STRUCTURE OF COGNITIVE ENGINE

Cognitive engine is the key to realize CR. Structure framework of cognitive engine is shown in Figure 1.

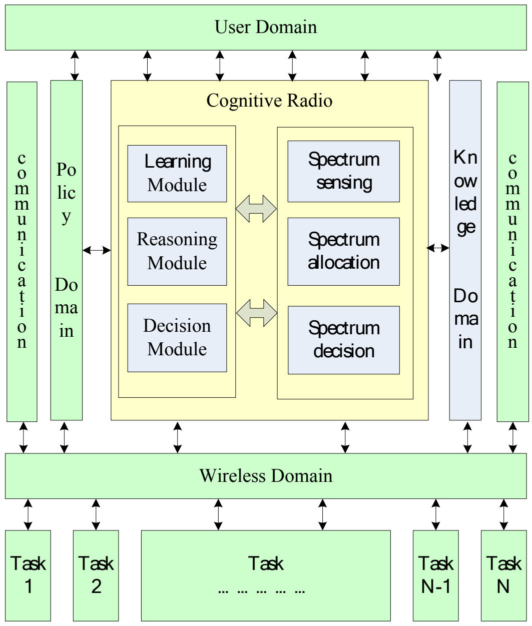


Figure 1. Framework structure of cognitive engine

Outside of the cognitive engine includes user domain, wireless domain, policy domain and the knowledge domain. User domain is responsible for leading the performance requirements of applications and services, such as time delay, transmission rate and other QoS requirements into the cognitive engine. Wireless domain refers to the external environment, and it plays important roles for decision-making optimization and waveform selection; policy domain is responsible for inputting access policy of spectrum resource allocation. Knowledge domain includes short-term knowledge such as wireless environment and internal working parameters, as well as the long-term knowledge, such as rule base and case base. This knowledge is the basis for reasoning and learning.

Within the cognitive engine, there are three modules for fully realization CR: reasoning module, learning module and decision-making module. Reasoning module according to the existing knowledge in the knowledge domain and the current plan makes decisions. Reasoning module mainly includes rule-based reasoning and case-based reasoning. Learning module includes the knowledge accumulation of past behaviors and the results, and constantly enriches the knowledge base and improves future reasoning efficiency of CR. Commonly-used learning methods mainly include neural network, reinforcement learning, Bayesian learning and genetic algorithms. Decision-making module is used to further enhance the performance of parameter configuration, so to maximize customer service requirements. These three modules jointly realize the basic functions of CR. Decision-making module use the optimization method to implementation its function.

III. Bio-inspired Computing

Optimization problem, as a very widely-used discipline, has been extensively studied by researcher for a long time, and a lot of optimization methods have been proposed. With the continuous development of science and technology, the optimization problem becomes especially very complicated. Most of the traditional optimization methods aim at some specific problems, and have stricter requirements for the search space, and higher dependency on problems to be solved; even some still need the derivative information of the optimization problems. Thus, it is not applicable for some complex optimization problems despite of the extensive application. Therefore, it is necessary to further research new optimization ideas and methods.

In many optimization methods, bio-inspired computing is the intelligent computing model developed from the inspiration of biological behavior or natural phenomena, such as GA, PSO, ACO, BFO, AIS and ABC and so on [6]. Because these kinds of methods have the characteristics different from the traditional optimization methods, therefor these methods were better fit for solving optimization problem.

(1) Universality

Bio-inspired computing is not designed for a specific problem, but use fitness function evaluates individuals, and drives evolution process on this basis. In the process of optimization, it does not need the knowledge of the search space and other and not dependent on the strict mathematical problem model, such as continuity, conductivity as well as the precise mathematical descriptions of objective function and constraint conditions. Those characteristics make bio-inspired computing has universality and a wide application range.

(2) Parallelism

Its searching process doesn't not start from a point, but takes the population of the workable space as the research object, namely from multiple points at the same time, and it conducts macro regulation and control on the population or training individuals in some probability way. In the process of evolution, the operation of each individual is relatively independent. So the method has natural parallelism, which will greatly improve the efficiency, robustness and rapid response ability of the whole algorithm.

(3) Global

Bio-inspired computing does not depend on the analytic properties of the objective function, but randomly searches in the feasible region space using probability or introducing the mechanism that can avoid the search process being in a certain area. Therefore, it has low convergence speed. However, the search way is more likely to jump from local optimal trap, and find the global optimal solution of problems.

IV. Application of Bio-inspired Computing in CR

These characteristics inspired from biological behaviors make bio-inspired computing are more suitable for solving complex optimization problems in CR [7-11].

(1) Spectrum Sensing

Spectrum sensing is the first link of CR, and its core idea is to make wireless communications equipment have the capacity of finding "spectrum holes" and rationally utilizing them on the premise without causing interference to other users. In order to make unauthorized users reliably perceive and effectively use "spectrum holes", and cause no interference to authorized users, a variety of spectrum detection methods emerge. Base on the number of detection nodes, they can be divided into single node detection and multi-point collaboration detection; based on the detection methods, they can be mainly divided into the matched filtering, energy detection and cycle characteristic detection.

For multi-user collaboration single-point detection problem, assuming that there are M subprime users in the network, they independently perceive certain single frequency band and each of them sends their detection results to center node respectively for data fusion, and perceive model by building energy detection algorithm and the linear weighted joint method on the data received by the center nodes.

For multi-user collaboration multi-point detection problem, people can select problems based on the threshold vectors in the multi-band joint detection method of OFDM system, on the basis of energy detection method, calculate the energy of the signals each channel receives in the frequency domain at the same time, and determine whether there is primary user on sub-channels through a threshold vector. In other words, under interference constraint of certain primary user, full consideration to the characteristics of sub-channels is given, and establish threshold vector optimization model.

(2) Spectrum Allocation

Spectrum allocation refers to the process in which the detected available spectrum is allocated to one or more designated users according to the number of users accessing to the system and their service requirements so as to the cognitive users sharing spectrum resource in rational and fair manner. Its main purpose is to effectively select and use idle spectrums through an adaptive strategy. Using spectrum allocation strategy can effectively improve the flexibility of wireless communication, avoid conflicts between the authorized users and unauthorized users, enable them fairly share the spectrum resources, and meet their different business needs.

The theory based on graph theory model has been increasingly maturely applied in cognitive radio spectrum allocation system, and it is often selected as a kind of mathematical description model by researcher. The spectrum allocation model based on graph coloring theory usually can be described with the available spectrum matrix, efficiency matrix, interference matrix, and no interference matrix. The purpose of spectrum allocation algorithm is to select an allocation criterion, select spectrum allocation plan with the highest target function value from the sets of no interference distribution matrixes satisfying interference matrix, allocate them to different cognitive users, and realize the network utility maximization. Thus, spectrum allocation can be classified as an optimization problem, and it is a typical NP-hard problem.

(3) Spectrum Decision-making

Spectrum decision-making is the descriptions of all the spectrum holes based on spectrum analysis, and it chooses a suitable job spectrum to meet the QoS requirements and the frequency spectrum characteristics of the current transmission. Through spectrum detection, spectrum analysis, and spectrum allocation operation, each cognitive user can use one or more spectrums at one time frame; the frequency spectrums may be composed of a series of continuous or discontinuous spectrums. Cognitive users need to get the different working parameters applicable to different frequency bands, such as modulation method, and transmission power, realize the self-adaption wireless environment on different frequency bands through different working parameters and achieve the best performance of radio.

V. Spectrum Decision Multi-objective Model

CR engine need to adjust *n* decision parameters, including a center frequency, transmitting power, modulation system, symbol rate and so on. Limited by various rules and regulations, electromagnetic environment and hardware facilities, CR parameter adjustment engine has to satisfy certain constraint conditions. Therefore, in order to make proper responses to current external communication environment, CR should optimize some objective functions to meet environmental needs or customer demands. Supposing CR need optimized *m* objective functions, among which m indicates the number of objective function. The objective function selected need to reflect the current link quality, including data rate, BER, average transmitting power, transmission delay, bandwidth, frequency band and so on. Therefore, the adjustment process of adaptive parameter in cognitive engine is a typical multi-objective optimization problem. Adaptive transmission performances of CR need to adjust many parameters, such as Bit-Error-Rate(BER), throughput capacity, computation complexity, power consumption, frequency spectrum efficiency and so on.

This paper considers three important objective functions: maximizing throughput, minimizing power consumption and minimizing BER.

- Minimizing Bit-Error-Rate

$$f_{\min ber} = 1 - L\text{og}_{10} 0.5 \Big/ \frac{1}{N}\sum_{i=1}^{N} \log_{10} P_{ei}$$

where P_{ei} is the *i*th subcarrier BER. In multi-carrier system, the subcarrier number is supposed to be worst BER 0.5.

- Minimizing Power Consumption

$$f_{\min-power} = 1 - \sum_{i=1}^{N} P_i \Big/ N * P_{\max}$$

where P_i is the power transmitted on *i*th subcarrier, $P_{\max}$ is the maximum power consumption.

- Maximizing Throughput

$$f_{\max-throughput} = \log 2(M_i) \big/ \log 2(M_{\max})$$

where M is the *i*th modulation index and $M_{\max}$ is the maximum modulation index.

This paper uses the weighted method to simplify the multi-objective problem.

$$f = \omega_1 \cdot f_{\min power} + \omega_2 \cdot f_{\min ber} + \omega_3 \cdot f_{\max throughput}$$

where, $\omega_i \geq 0 (1 \leq i \leq 3)$ and $\omega_1 + \omega_2 + \omega_3 = 1$. Different weight values combinations represent different communication modes. These modes and weight values are shown in Table 1.

TABLE I. DIFFERENT BUSINESS MODELS WEIGHT SETTING

Mode No.	Meaning	ω_1	ω_2	ω_3
Mode 1	Low-power communication mode, minimizing the transmit power.	0.80	0.05	0.15
Mode 2	Emergency communication mode, minimizing the bit error rate.	0.05	0.80	0.15
Mode 3	Multimedia transmission communication mode, maximizing data throughput.	0.05	0.15	0.80
Mode 4	The weight of each objective is same.	1/3	1/3	1/3

VI. Autonomously Search Algorithm

Biological nature has good adaptability to its survival environment. All various species survive in a kind of competitive environment, and follows the “Law of Survival of the Fittest”, which makes the species continue to evolution, showing breath-taking ability of the natural evolution. After entering the 1960s, being inspired by various natural phenomena or biological behaviour, people proposed many new methods to solve complicated optimization problems. Optimization method inspired by biological behaviour is called bio-inspired computing, such as artificial neural network that simulates human brain tissue structure and information processing, the genetic algorithm that simulates the biological evolution process, artificial immune system that simulates learning and cognition ability of biological immune system, the ant colony algorithm that simulates the ants find the shortest foraging path through individual release and collecting pheromone as well as particle swarm optimization simulating the flock foraging principle. The emergence of these bio-inspired computing methods has greatly enriched the optimization techniques. With the advantages of efficient optimization performance, these methods provide feasible solutions for the complex optimization problems, and have been received extensive attention, thus have been widely used in various fields.

This paper simulates life cycle behavior characteristics and proposed an autonomously search algorithm (ASA). Biological life cycle includes four behavior characteristics, are born, grow, reproduce and recession. ASA employs four search operators corresponding to these four behavior characteristics, namely foraging, reproduction, selection and mutation. In them, foraging behavior refers to the GSO algorithm [12]. Reproduction, selection and mutation refer the GA algorithm

VII. Experiments Setting and Results Discussion

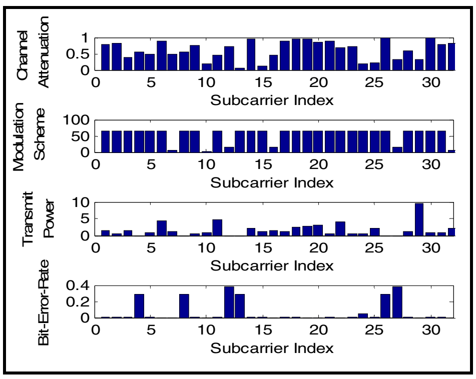
Simulation testing environment uses multi-carrier system; its parameters refer to reference [13]. For ASA, each of the experiments was repeated 30 times, and the max iterations in a run $T_{\max}$ =3000; the population size S=30; foraging parameters refer to reference [12]; selection operation performs elitist selection strategy; reproduction operation use single point crossover and the crossover probability is 0.8; mutation operation use dimension-mutation strategy and the mutation probability is 0.1. In order to further test the performance of ASA, this paper compares it with GA and PSO. Experimental results can be seen from the Table II to III and Figure 2 to 3. The ASA algorithm can adaptively optimize the transmission parameters according to channel conditions and customer service type of change, and obtained better parameters decision scheme than GA and PSO.

VIII. Conclusion

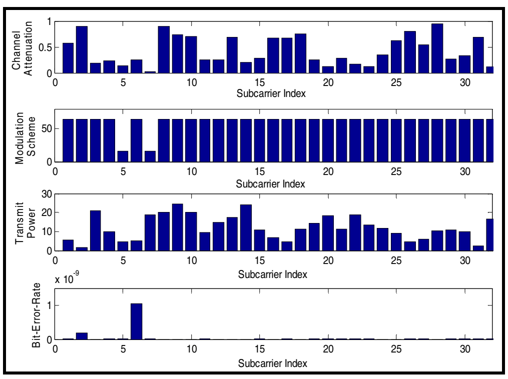
This paper designs the cognitive engine research framework of CR, and then the application of bio-inspired computing in decision-making module is emphatically introduced. Spectrum decision is an important part of the cognitive radio. Adaptive adjustment of spectrum decision parameters can improve the service efficiency of cognitive radio. In this paper, multiple parameter transmission is modeled as a multi-objective optimization problem, which includes minimize the transmission power, minimize the bit error rate and maximize data throughput. Inspired by biological behavior, this paper proposed an autonomously search algorithm. The experimental results show that the proposed algorithm can meet the communication demand and has better optimization performance.

TABLE II. ASA EXPERIMENT RESULTS

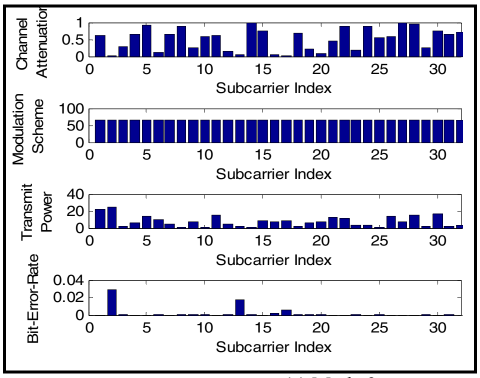
Mode 1				**Mode 2**			
weight		experiment result		weight		experiment result	
Index	value	Index	value	Index	value	Index	value
w1	0.8	power	**1.6(1)**	w1	0.05	power	12.1
w2	0.05	pber	0.0618	w2	0.8	pber	**3.95e-11 (1)**
w3	0.15	throughput	53.8	w3	0.15	throughput	61
Mode 3				**Mode 4**			
weight		experiment result		weight		experiment result	
Index	value	Index	value	Index	value	Index	value
w1	0.05	power	7.7	w1	0.4	power	5.07**(2)**
w2	0.15	pber	0.00169	w2	0.3	pber	0.000749**(2)**
w3	0.8	throughput	**64(1)**	w3	0.3	throughput	62.5**(2)**



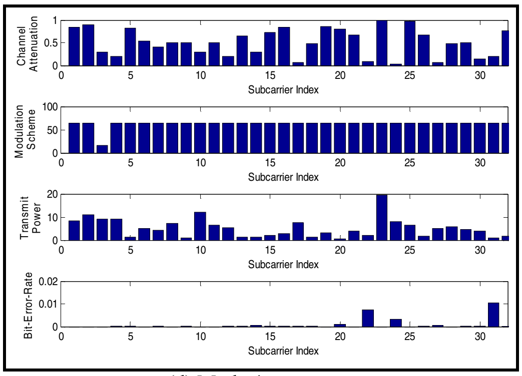
(a) Mode 1



(b) Mode 2



(c) Mode 3



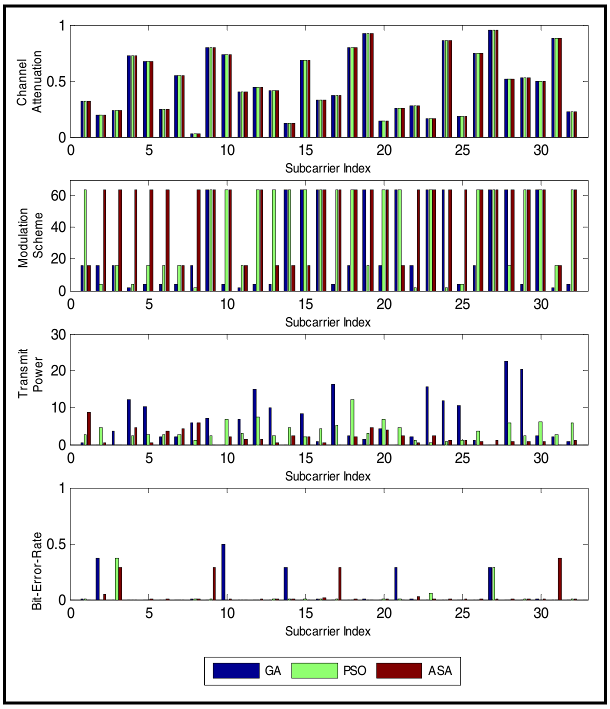
(d) Mode 4

Figure 2. Performance of ASA

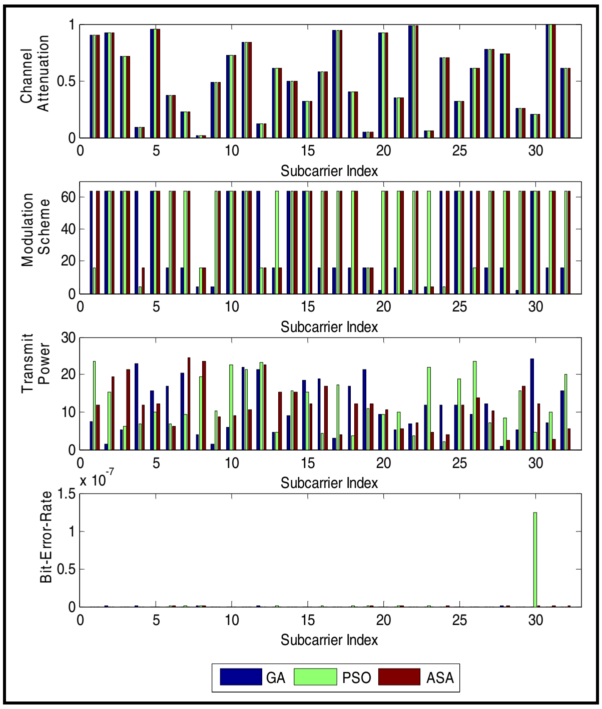
TABLE III. THREE ALGORITHMS EXPERIMENT RESULTS

Mode 1					
weight		experiment result			
Index	value	Index	GA	PSO	ASA
w1	0.8	power	6.18	3.58	**1.93(1)**
w2	0.05	pber	0.0548	0.0225	0.0423
w3	0.15	throughput	27.4	40.6	52
Mode 3					
weight		experiment result			
Index	value	Index	GA	PSO	ASA
w1	0.05	power	13.6	12.6	9.43
w2	0.15	pber	0.00952	6.1e-06	2.53e-08
w3	0.8	throughput	49.3	59.1	**64(1)**

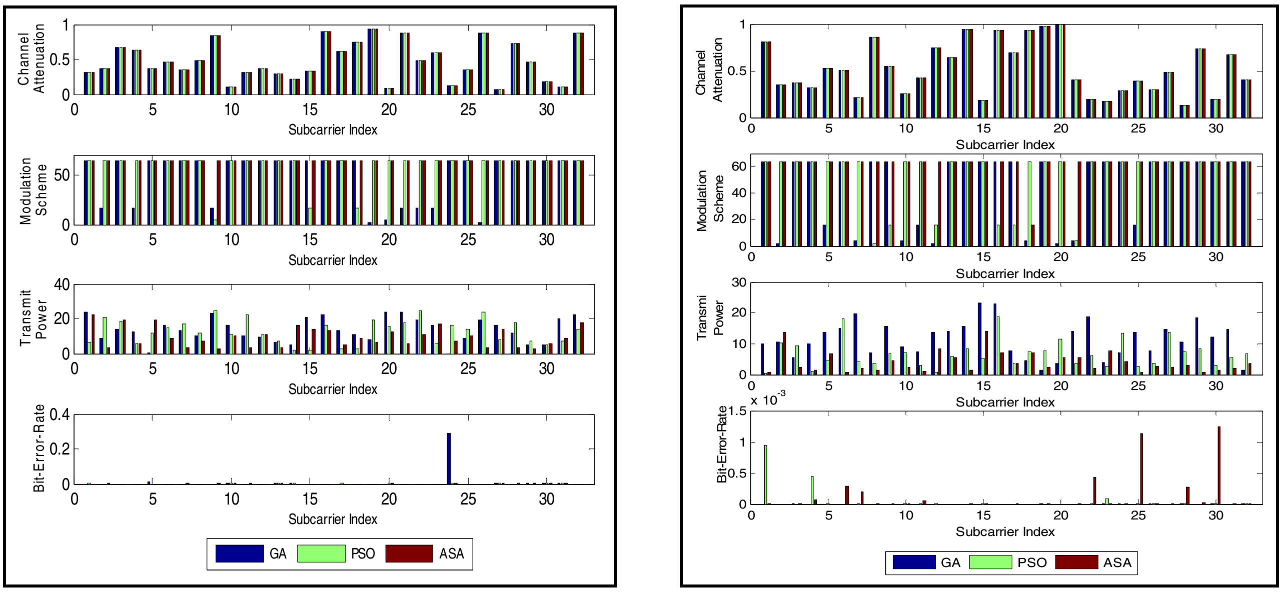
Mode 2					
weight		experiment result			
Index	value	Index	GA	PSO	ASA
w1	0.05	power	11.5	12.6	11.8
w2	0.8	pber	4.57e-12	3.94e-09	**8.59e-14(1)**
w3	0.15	throughput	34.6	52.8	54.6
Mode 4					
weight		experiment result			
Index	value	Index	GA	PSO	ASA
w1	0.4	power	11.5	6.73	**4.05(1)**
w2	0.3	pber	4.04e-07	4.61e-05	0.000117
w3	0.3	throughput	46.2	54.2	**62.5(1)**



(a) Mode 1



(b) Mode 2



(c) Mode 3 (d) Mode 4

Figure 3. Performance comparison of GA, PSO and ASA

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