Real-Coded Genetic Algorithm Parameter Setting for Cognitive Radio Adaptation

[1,2]N.Ali Saoucha, [2]A.C.Lammari, [2]K.Benatchba
[1]University of M'sila, M'sila, Algeria
[2]L'École nationale supérieure d'informatique, Algiers, Algeria
n_ali_saoucha@esi.dz, a_lammari@esi.dz, k_benatchba@esi.dz

***Abstract*—Cognitive radio (CR) is an emerging promising technology for future wireless communication networks. For a given status of dynamic wireless channel environment, the radio uses intelligence to optimize user's QoS by adapting the transmission parameters of the radio. Transmission parameters adaptation in a dynamic multicarrier environment has been previously studied using genetic algorithms (GA). The main goal was to select the optimal transmission parameters. When genetic algorithms are applied to complex problems, such as in multicarrier (MC) one, their execution time, to find a solution, increases. In this paper, we propose a new algorithm based on a real-coded genetic algorithm. Several tests have been done to tune the different parameters of the algorithm. The new algorithm is compared to the standard GA, based on De Jong's standard parameter settings and binary coding, used for optimizing QoS for cognitive radio. The tests carried on show that our algorithm gives better performance in terms of convergence speed.**

Keywords—Cognitive radio; multiobjective optimization; genetic algorithm parameter tuning; Real-coded genetic algorithms; convergence speed.

I. INTRODUCTION

These last decades, there has been a great increase for wireless radio spectrum demand due to the fast deployment of new wireless devices. Within the current spectrum regulatory framework, all of the frequency bands are exclusively allocated to specific services, no violation from unlicensed users is allowed and no bandwidth are available for future wireless systems. However, the Federal Communications Commission (FCC) recent survey showed that the actual licensed spectrum is largely underused in vast temporal and geographical dimensions [1]. In order to solve the paradox between spectrum shortage and spectrum underutilization, dynamic spectrum access techniques have been recently proposed [2]. Secondary users, users with no spectrum licenses are allowed to use spectrum holes. Spectrum holes are defined as bands of frequencies assigned to a primary user (licensed users) that are not used at a particular time and in a specific geographic location, by the user [3]. Dynamic spectrum access can be achieved using cognitive radio (CR) technology [3, 4].

One of the basic capabilities of cognitive radio is to adapt its parameters according to the changing environment and user needs [5]. However, autonomous radio adaptation involves having smart artificial intelligence (AI) engine, to make a decision on the best transmission parameters [6]. In this context, the interest in genetic algorithms for optimizing the performance of the radio has already been recognized and demonstrated [7, 8, 9, 10, 11].

There is an obvious interest of using genetic algorithms in cognitive radio as they are able to efficiently explore a wide space of possible configurations to find the most suitable one. However, a poor choice of the algorithm's parameters can affect its performances. In fact, the efficiency of GAs is strongly linked to a judicious choice of its parameters namely: the type of encoding, population size, number of generations, probability and techniques for crossover and mutation. Indeed, the values of these parameters affect the behavior of the algorithm and its ability to find an optimal or near-optimal solution [12]. However, in all the works cited above, the authors used a standard setting for GAs parameters, and no study has been made to adapt them, ignoring that the strength of GAs is based on a good tuning of the algorithm parameters.

Unfortunately, there are no universal rules to setting the parameters of GA, and only experimental results give an idea of the behavior of various components of the algorithms [13]. In 1975 [14], De Jong showed, in his study, that varying parameters affected GA's performance. He tested various combinations of GA parameters on a set of 5 functions, and concluded that for those functions, the following parameters gave good solutions: the best population size was 50–100 individuals, the best single point crossover rate was ~0.6, and the best mutation rate was 0.001. Although, there was no prove that this set of parameters were optimal for every optimization problem, these settings became widely used in the GA community. They are sometimes referred to as standard settings. Theoretical studies have shown that this is a profound mistake [15].

In this work, we propose a new version of genetic algorithms based on a real coding. Moreover a parameter setting is conducted to tune various parameters of the algorithm namely the mutation rate, crossover strategy and rate, selection strategy, number of elites to maintain in a population and size of population. Our algorithm is compared to the algorithm proposed in [8] which is based on a binary coding and a standard parameter setting. Simulation results show that our algorithm has a better convergence speed.

The structure of this paper is as follows: In section 2, definitions of the CR parameters are presented and the mathematical expression of the fitness function is given. Section 3 gives a general description of GA for CR. Section 4 describes the implementation of the binary GA, our real-coded

GA. In section 5, discussions on the simulation results are presented. Finally, conclusions are drawn in section 6.

II. COGNITIVE RADIO PARAMETERS

A cognitive radio (CR) is able to detect spectrum holes and adapts the radio's operating parameters to operate in these holes. In fact, a cognitive radio is not only able to adapt to the available frequency spectrum around it, but also to the user needs and channel conditions to enable communications with a certain quality of service (QoS) [5]. To achieve this goal the cognitive radio sense the environmental parameters, used them in conjunction with the radio objectives to determine the optimal set transmission parameters to meet desired QoS [16].

A. Environmental parameters

Environmentally sensed parameters provide knowledge to the CR of the surrounding environment characteristics. These parameters are used as inputs to the fitness function, and help cognitive radio engine make decision. As in [8], three environmental parameters are used in this work; the bit-error-rate (BER), the signal-to-noise ratio (SNR) and the noise power (N). The BER parameter represents the percentage of bits that have errors. The SNR represents the ratio of the signal power to the noise power in decibels. The noise power informs the radio about the approximate noise power in decibels.

B. Transmission Parameters

Transmission parameters determine the output waveform of the radio. The CR receives the input parameters that convey environment sensed data, and upon the requirement, evolves the output transmission parameters towards the goals defined by the objective functions. Similar to [8], the parameters used in this work are the transmitting power (P), the modulation type (MT) and the modulation index (M).

C. Fitness function

Different objective functions for measuring corresponding communication quality metrics need to be defined. These definitions will provide the basis for guiding the cognitive radio's decision making technique. Three wireless communication performance objective functions are considered in this paper [3]: minimizing the BER ($f_{\min\_BER}$), maximizing the throughput ($f_{\max\_throughput}$) and minimizing the power consumption ($f_{\min\_power}$).

In [8], the relationships between the environmental and transmission parameters are expressed as mathematical equations that are defined as the radio objectives for the GA optimization engine as follows:

$$f_{\min\_BER} = 1 - \frac{\log_{10}(0.5)}{\log_{10}(\overline{P_{be}})} \quad (1)$$

$$f_{\max\_throughput} = \frac{\log_2\left(\overline{M}\right)}{\log_2(M_{\max})} \quad (2)$$

$$f_{\min\_power} = 1 - \frac{\overline{P}}{P_{\max}} \quad (3)$$

Where $\overline{P}$ is the average of transmit power on N subcarriers, $P_{\max}$ is the maximum possible transmission power, $\overline{P_{be}}$ is the average BER over N subcarriers, $\overline{M}$ is the average number of bits per symbol over N subcarriers, and $M_{\max}$ is the maximum modulation index.

Unfortunately, these objectives are conflicting. For example, minimizing both BER and power consumption is impossible. So, in order to simplify the problem in [8], these objectives are normalized, weighted, and combined into a single objective function presented below:

$$f_{multiobjective} = [w_1.(f_{\min\_BER})] + [w_2.(f_{\max\_throughput})] + [w_3.(f_{\min\_power})] \quad (4)$$

The weight vector w= [w_1, w_2, w_3] determines the search direction toward the required objective. In [8], three weight vectors representing common scenarios were suggested. The transmission scenarios are the emergency mode, multimedia mode and low power mode. The weighting vector are respectively [0.8,0.15,0.05],[0.05,0.8,0.15] and [0.05,0.15,0.8].

III. GENETIC ALGORITHMS FOR COGNITIVE RADIO

Genetic algorithms [17] are based on an optimization model inspired by the Darwin's theory of evolution to guide progressively a population of potential solutions to the most interesting regions of the search space. The implementation of the binary GA [8] and our proposed real-coded GA for optimizing the QoS for cognitive radio is represented in details below.

We note that we will take almost the same range of parameters used in [8] as follows: we simulate a multicarrier system with 64 subcarriers. Each subcarrier is assigned a random attenuation value, N, to simulate a dynamic channel. We consider three different QAM constellations as the modulation types of the system (e.g., 16-QAM, 128-QAM, 1024-QAM). The transmit power ranges from 0.1 to 2.56mW increasing by 0.0256mW. The maximum power value is selected since it is close to the specified maximum transmit power level of 2.5mW for a 1MHz bandwidth, allowed in the lower UNII band (5.15–5.25 GHz).

A. Encoding

A particular configuration of the radio is encoded as a chromosome, where each gene represents a signal processing function (transmission power, modulation). All the works that has been done until now [7, 8, 9, 10, 11], have chosen to use a binary encoding without justifying this choice. In the case of binary encoding, each real value is encoded as a binary one.

This type of coding is simple to implement, and the operators of mutation and crossover are easily constructed. But it requires an encoding / decoding mechanism. This is the major disadvantage of this type of representation [19]. Taking into account the real-time aspect of cognitive radio systems, moving towards a real coding seems logical since no transcoding (binary to real) is needed. In the following, we present the implementation of the GA using binary and real coding.

1) Real representation: In this encoding, the chromosome is a real vector and the search space is the set of allowed values.

- $M \in \{8, 16, 32, 64\}$.
- P: between 0.1 mW and 2.4808 mW with a step of 0.025.

2) Binary representation: With transmit power ranging from 0.1 mW to 2.4808 mW and a step size of 0.025 mW, this provids a total of 94 values where each value is represented by an integer value.The minimum 0.1 mW would be represented by the integer value "0". The integer value keeps increasing with a step size of 0.025 mW. The highest power is 2.4808 mW. It would be represented by integer value "93". The representation of 94 integer values will require a total of 7 bits. Whereas two bits are required to represent the 4 types of constellations in QAM.

B. The generation of the initial population

In this step, an initial population is randomly generated to promote the heterogeneity of the population.

C. Selection

Once the initial population is generated, the next step is to evaluate the fitness function (objective function) for each individual in the current population. An individual classification is made based on the value of the objective function. Individuals with higher fitness value will have higher probability of being selected for reproduction. There exist a number of selection methods in the literature. The most popular methods are:

1) Roulette-Wheel Selection: Individuals are assigned a probability of being selected based on their fitness.

2) Rank Selection: Each individual is assigned a rank based on fitness, and selection is based on this ranking.

3) Tournament Selection: q individuals are randomly selected from the population and the best of the q individuals is selected as parent.

D. Reproduction

The population is diversified by applying random variation operators, such as mutation and crossover. The crossover operator generates new chromosomes by crossing two parents (chromosomes). Some individuals may also experience mutation. Even though, the selection is the same for both types of coding, the crossover and mutation must be adapted to the type of coding used. In what follows, we will present the implementation of these two operators according to the adopted coding.

E. Crossover

Once the selection phase is completed, reproduction operators (crossover and mutation) are applied. The crossover combines two parents to form two children. The idea behind this operator is that the new solutions may be better than both of the parents if they take the best characteristics from each one. Moreover, and in order to preserve some of the good solutions already in the population, not all solutions are used in crossover. As a result, a crossover probability, defined here as Pc, is used. Only 100*Pc per cent of the population is used for crossover, and 100*(1-Pc) per cent remains in the current population.

In both cases whether binary or real encoding, a random position is chosen, then the resulting parts are swapped between the two parents. However, In the case of binary encoding, a validation phase is necessary. All produced solutions are checked for invalid values. For example, the binary representation of a power value of 2.4552 mW and a power value of 2.4296 mW is respectively "1011011" and "1011100". A crossover that takes a place in the fifth bit generates invalid children, since a gene value of "1011111" is undefined.

F. Mutation

The mutation operator is a random change in genes and occurs with a low probability Pm. In our problem, this operator is:

- For real coding: Replacement of the current value of the gene by a random value in the interval defined for the gene.
- For the binary coding: Flipping the current value of the bit.

Binary mutation may, also, generate invalid solutions and a verification phase is needed. For example, the binary representation of a power value of 2.4808 would be "1011101". A mutation that flips the sixth bit would generate an invalid chromosome, since a gene value of "1011111" is undefined. So once again, the verification of the validity of the mutated genes is required.

IV. SIMULATION RESULTS

To adjust the various parameters, we performed several tests varying, each time, only one parameter. At each step, we fix the value of the tested parameters to their best one. The values tested for each parameter are given in Table I.

Genetic Algorithms are non-deterministic methods. As a result, for each parameter, 10 simulations are performed and the average is shown in Tables II, III and IV.

The results given in Table II show the effectiveness of our algorithm based on real-coding to find solutions as accurate as the standard binary coded GA for the three modes of transmission and with a considerable gain in term of computation time. Taking into consideration that a cognitive radio communication is menaced by the appearance of the primary user, these results provide great deal of improvement to the performance to the radio.

It is clear from Table III and Table IV that the following standard parameters (population size, crossover rate for multimedia mode and emergency mode) are the best choices. However, for the remaining parameters (mutation rate, number of break points and crossover rate), we note the domination of adapted settings. This confirms the need to adapt the parameters of the genetic algorithm to our problem.

TABLE I. TESTED VALUES FOR EACH PARAMETERS

Parameter	**Tested values**
Representation	Binary coded / Reel coded
Mutation rate	0.000,0.001,0.002,0.003,0.004,0.005,0.006, 0.007,0.008,0.009,0.010,0.011,0.012,0.013, 0.014,0.015,0.016,0.017,0.018,0.019,0.020,1 .000
Crossover point	1,2,3,4,5,6,7,8,9,10
Crossover rate	0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1
Selection	Roulette-WheelSelection/Rank Selection /Tournament Selection
Population size	10,20,30,40,50,60,70,80,90,100
Elit	00, 01, 02, 03,04, 06,07, 08,09,10, 15, 20, 25

TABLE II. BINARY CODED VS. REEL CODED

Mode	**GA based Binary coded**		**GA based Reel coded**	
	Best score	Time (s)	Best score	Time(s)
Emergency	0.7639	892.1283	0.7619	349.5160
Low power	0.8959	681.3715	0.8651	316.8155
Multimedia	0.9700	629.2242	0.9591	351.6860

TABLE III. RESULT USING STANDARD SETTING AND BINARY CODED

Parameter	**Standard**		
Mode	Emergency	Low power	Multimedia
Mutation rate	0.001	0.001	0.001
Crossover point	2	2	2
Crossover rate	0.6	0.6	0.6
Selection	Tournament	Tournament	Tournament
Population size	50	50	50
Elit	0	0	0
score	0.76	0.89	0.97
Time (s)	892.12	681.37	629.22

TABLE IV. RESULT USING ADAPTED SETTING AND REEL CODED

Parameter	**Adapted**		
Mode	Emergency	Low power	Multimedia
Mutation rate	0.014	0.012	0.012
Crossover point	3	7	7
Crossover rate	0.6	0.7	0.6
Selection	Tournament	Tournament	Tournament
Population size	50	50	50
Elit	1	1	1
Score	0.76	0.89	0.97
Time (s)	349.51	316.81	351.68

V. CONCLUSION

This paper proposes a genetic algorithm based on a real-coding for optimizing QoS for cognitive radio. Moreover a tuning of the different parameters of the algorithm has been done. Our algorithm is compared to the GA algorithm based on De Jong's standard parameter settings and binary coding for optimizing QoS for cognitive radio [8]. The results that we have obtained allow us to confirm that De Jong setting are not always the best choice for the problem of optimizing the QoS for cognitive radio. Increasing the mutation rate and the number of crossover points has a good influence on the quality of the obtained solution. Our GA, based on a real coding, is more powerful in terms of convergence speed.

REFERENCES

[1] Federal Communications Commission, “Spectrum Policy Task Force,”Rep. ET Docket no. 02-135, Nov. 2002.

[2] Federal Communications Commission, “Facilitating opportunities for flexible, efficient and reliable spectrum use employing cognitive radio technologies: notice of proposed rule making and order, ” FCC Document ET Docket No. 03-108, December 2003.

[3] S. Haykin, “Cognitive radio: brain-empowered wireless communications,” IEEE J. Sel. Areas Commun., vol. 23, pp. 201–220, Feb. 2005.

[4] J. Mitola and G. Q. Maguire, “Cognitive radio: Making software radios more personal,” IEEE Personal Commun., vol. 6, pp. 13–18, Aug. 1999.

[5] Z. Zhao, S. Xu, S. Zheng, and J. Shang, “Cognitive radio adaptation using particle swarm optimization,” Wireless Commun. Mobile Comput., vol. 9, no. 7, pp. 875-881, July 2009.

[6] S.E El-Khamy, M.A. Aboul-Dahab, M.A. Attia, “A hybrid of particle swarm optimization and genetic algorithm for multicarrier cognitive radio, ” 26th National Radio Science Conference (NRSC 2009),March 2009,pp.1-7.

[7] T. R. Newman, “Multiple Objective Fitness Functions for Cognitive Radio Adaptation”, Ph.D.dissertation, Virginia Polytechnic Institute and State University, August, 2004.

[8] T. R. Newman, B. A. Barker, A. M. Wyglinski, A. Agah, J. B. Evans, and G. J. Minden, “Cognitive engine implementation for wireless multicarrier transceivers”, Wireless Communications & Mobile Computing, vol. 7, no. 9, pp. 1129 -1142, Novembr 2007.

[9] C. J. Rieser, “Biologically inspired cognitive radio engine model utilizing distributed genetic algorithms for secure and robust wireless communications and networking”, Ph.D.dissertation, Virginia Polytechnic Institute and State University, August 2004.

[10] T. W. Rondeau, B. Le, D. Maldonado, D. Scaperoth, and C. W. Bostian, “Cognitive radio formulation and implementation”, 1st International Conference on Cognitive Radio Oriented Wireless Networks and Communications, Mykonos, Greece, June 2006.

[11] T. W. Rondeau, “Application of artificial intelligence to wireless communications”, Ph.D. Dissertation, Virginia Polytechnic Institute and State University, September 2007.

[12] D. H. Wolpert and W.G. Macready, “No free lunch theorems for optimization, ” IEEE Transactions on Evolutionary Computation, vol. 1, no. 1, pp. 67-82, 1997

[13] B. Yuan and M. Gallagher, “Statistical racing techniques for improved empirical evaluation of evolutionary algorithms,” In X. Yao et al., editor, Proc. Parallel Problem Solving from Nature (PPSN VIII), volume 3242 of Lecture Notes in Computer Science, pages 172–181. Springer, 2004.

[14] K.De Jong, “The Analysis of the Behavior of a Class of Genetic Adaptive Systems, ” PhD thesis, University of Michigan, 1975.

[15] D. H. Wolpert and W. G. Macready, “No free lunch theorems for optimization, ” IEEE Transactions on Evolutionary Computation, vol.1, pp. 67–82, 1997.

[16] A.A.El-Saleh, M.Ismail, M.A.M.Ali, “Pragmatic trellis coded modulation for adaptive multi-objective genetic algorithm-based cognitive radio systems” 2010 16th Asia-Pacific Conference on Communications (APCC), 2010 , pp: 429 – 434.

[17] D. E. Goldberg, “Genetic Algorithms in Search, Optimization and Machine Learning,” Addison-Weley, Reading, MA, 1989.

[18] A. E. Eiben, Z. Michalewicz, M. Schoenauer, and J. E. Smith. Parameter Control in Evolutionary Algorithms. In F.G. Lobo, C.F. Lima, and Z. Michalewicz, editors, Parameter Setting in Evolutionary Algorithms, pp. 19-46. Springer Verlag, 2007.

[19] T. Hiroyasu, M. Miki, and S. Watanabe, “Distributed genetic algorithms with a new sharing approach in multiobjective optimization problems”, IEEE Proc. Congress on Evolutionary Computation, vol. 1, pp. 69 – 76, July, 1999.