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OPTIMIZING THE CAPACITY OF COGNITIVE RADIO NETWORKS WITH POWER CONTROL AND VARIABLE SPECTRUM ALLOCATION

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Cognitive Radio Networks (CRN) were introduced as a means to more efficiently reuse the licensed radio frequency spectrum. One of their salient features is the ability of unlicensed nodes to dynamically adapt their radio parameters according to their needs. This paper investigates the resource allocation problem in CRN by jointly considering power control and bandwidth for a set of secondary users (SU) transmitting simultaneously with a set of licensed users (PU), which transmissions must remain unaltered. The proposed allocation scheme is based on a Genetic Algorithm (GA) where the chromosome's genes represent the reconfigurable interface radio parameters, by defining genetic operations the GA is empowered to find a set of radio parameters that maximize the overall network capacity and under the physical interference model enforced to the transmissions of both PU's and SU's. The numerical results illustrate the prominent effect of adjusting jointly multiple radio parameters on the network capacity.

Keywords: cognitive radio networks, underlay mode, genetic algorithm, spectrum allocation, greedy algorithm, secondary users, shared spectrum, optimization problem

1. Introduction

The notion of spectrum scarcity is directly related to the fixed assignment policy management employed by governmental and international agencies. In its report of 2002, the Federal Communications Commission (FCC) determined that fixed spectrum assignment policies generate non-uniform spectrum utilization. For example, in crowded geographical areas or in rush hours, the average utilization of fixed bands varies between 15% and 85% (FCC. Spectrum Policy Task Force, 2002). In order to exploit the unused portions of spectrum, cognitive radios network, introduced by J. Mitola in (Mitola and Maguire, 1999), constitutes a promising alternative of spectrum management, where unlicensed users are granted the power of dynamically access and allocate underused licensed spectrum. In the so-called underlay access model, secondary users may transmit on some frequency bands at the same time as primary users provided that these transmissions have no or little impact on those of primary users. A good survey of spectrum access models for cognitive radio networks can be found in (Buddhikot, 2007).

In this work, we present a dynamic resource allocation for cognitive radio networks. We assume that unlicensed users are capable of sharing the spectrum licensed bands with licensed users in an underlay mode while keeping the interference level, captured through the signal on interference and noise ratio (SINR), below an acceptable threshold. To capture the interference between the transmissions on different but not necessarily orthogonal spectrum bands, we rely on a channel overlapping factor which captures the fraction of energy that leaks into an adjacent channel. Furthermore, we assume that the frequency band allocated to each secondary link can be variable depending on its needs.

To enable an efficient allocation scheme which exploit various radio parameters, we design an adjustable genetic algorithm (GA) with has as an objective the maximization of the total network capacity or the proportional fairness between competing links. Genetic Algorithm (GA) is an evolutionary optimization technique that imitates natural evolution. It tries to reproduce the biological genetic operations, such as mutation, crossover, and selection, in order to find a high-quality solution. The major benefit of GAs is their ability to make a robust search in large spaces in comparison with other optimization solutions (Goldberg, 1989; Holland, 1975). Within the proposed GA framework, the radio parameters of each cognitive user are mapped to the chromosome's genes forming a potential solution; namely, transmission power, carrier frequency, and channel width (bandwidth). By defining a set of genetic operations on these chromosomes, the GA is tailored to search a set of radio parameters that maximize the fitness function.

To the best of our knowledge, our work is among the firsts in the literature that tackles capacity optimization in CRNs by acting jointly on the transmission power and channel assignment with variable widths. The rest of the paper is organized as follows. In Section 2, the related works on spectrum allocation problems are described. We introduce the system model and state the problem in a formal manner in Section 3. The GA-based spectrum allocation model is presented in Section 4. We present some experimental results in Section 5 and conclude the paper in Section 6.

2. Related work

Power control is a key mechanism to enforce interference constraints of licensed users while maximizing the performance of unlicensed users. In the context of CRNs, this problem has received wide attention in the literature (Tao and Zhisheng, 2003; Clemens and Rose, 2005). In (Naeem *et al*., 2014) a survey of resource allocation in cooperative CRN is presented with a taxonomy of various objectives and protocols defined the literature. More specifically, (Wang *et al.*, 2009) proposed a spectrum sharing strategy based on a throughput model in a CRN. An optimization problem in the form of binary integer linear programming (BILP) is formulated, where it is assumed that every secondary user (SU) can access any available channel with a transmission range than can cover the whole CRN. Note that each SU works in a half-duplex manner. A near-optimal directional search (DS) algorithm was also designed.

A heuristic algorithm is proposed in (Bhardwaj *et al*., 2016) for resource allocation problems in CRNs, where multiple objectives and constraints are considered: sum-rate, fairness, number of active SUs, power consumption, and quality of service requirements. A modified NSGA-II evolutionary algorithm was used and multiple solutions were obtained, representing different trade-offs between conflicting objectives. Authors in (Wang *et al.*, 2015) proposed a fast genetic algorithm (FGA) to solve the problem of jointly allocating bits, sub-carriers and power to maximize the total transmit bit rate in an OFDM based cognitive radio. They assumed an underlay spectrum sharing model, and the allocation problem was formulated as multidimensional knapsack problem (MKP). Also, an evolutionary algorithm based on bio-geography optimization for relay assignment, and a greedy power allocation to maximize the system throughput in shared bands are presented in (Ashrafinia *et al*., 2011).

In (Salehinejad *et al.*, 2010), an approximate non-deterministic ant colony-based algorithm is proposed to solve a set of spectrum allocation problems mapped to well-known NP-hard graph colouring problems (GCPs). This algorithm was casted as a new approach to spectrum assignment problem versus traditional heavy-computational and deterministic methods. Generally speaking, integer and mixed integer non-linear resource allocation in cooperative CRN are considered as computationally-intensive NP-hard problems, which means that their optimal solutions cannot be obtained in polynomial time. For these kinds of problems, generally researchers apply greedy, heuristics or evolutionary algorithms. A three stage heuristic algorithm for joint relay and spectrum selection in CRN is considered in (He *et al.*, 2010), authors mainly focus on the problem of how to allocate resource appropriately to maximize the overall system throughput under the QoS requirements in cooperative CRN. The main objective is to maximize the sum-rate by jointly determining the relay selection, spectrum allocation and power allocation. The authors propose a three-stage heuristic to solve the sum-rate maximization problem. A power allocation scheme using genetic algorithms (GA) is proposed in (Benaya *et al.,* 2016) for a multiple-input-multiple-output (MIMO) system in CRN with the aim to maximize the total secondary throughput. Under interference constraints of multiple SU pairs coexisting with multiple PUs pairs in an underlay spectrum sharing model, the minimal throughput among all SUs is compared with other power allocation schemes, namely, maximum-minimum-throughput-based power assignment (MMTPA) and equal power assignment (EPA). Results show that the proposed scheme maximizes the secondary throughput among all other stated schemes but with additional computational complexity.

A capacity-aware spectrum allocation scheme for CRNs is presented in (Yousefvand *et al.*, 2015) the authors modelled interference constraints relying on the interference temperature model. First, each secondary user increases its transmission power until the interference temperature of one neighbour exceeds its own interference temperature threshold. Then, based on the SINR and bandwidth of potential links, the capacities of the links are calculated using the Shannon formula, taking into account the co-channel interference between potential links on each channel by using an interference graph. Finally, the authors formulated the spectrum assignment problem as a binary integer linear programming to find the optimal feasible set of simultaneously active links among all the potential links in the sense of maximizing the overall network capacity.

Our work can be viewed as an extension of these prior contributions. Whereas some works have focused on power control and others on channel assignment, we adopt a more general approach where each SU can act simultaneously on the transmission power, the carrier frequency, and the channel width. We consider a setting with a high degree of flexibility, where simultaneous and co-channel transmissions of both licensed and secondary users are allowed. However, we assume that primary users are unaware of any parallel transmission, and hence the received signal must be decoded with the same correctness as if no other transmission occurs.

3. The system model

This section introduces some mathematical notations used throughout this paper. Our system model consists in a CRN composed from a set of primary users P_r and secondary users S_c, as shown in Figure 1. We assume that secondary users establish point to point transmission links between them. We denote this set of transmission by L. For $\ell \in L$, t_ℓ and r_ℓ designate the transmitting and the receiving nodes, respectively.

The network is deployed on a two-dimensional region, where each node $u \in S_c$ is specified by its coordinates (x_u, y_u). We assume that each node is equipped with a single radio interface and can dynamically configure the power transmission, the carrier frequency and the channel width. For licensed communications, we assume the existence inside this region of a primary base station (BS) that transmits to a set of primary users disseminated over the cell. This BS is assumed to use a predefined and known frequency band and transmission power. With respect to secondary links, the values of the used bandwidth and transmission power are taken from the discrete sets, W and P, respectively.

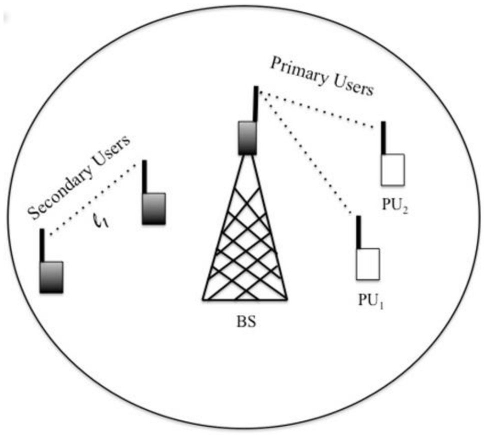

Figure 1. Radio model

In a general manner, a given radio transmission is considered to be successful (i.e., can be decoded correctly at the receiver) if the signal to noise ratio (SNR) is greater than or equal to some minimal threshold β. According to the traditional path-loss radio propagation model, the SNR at the receiver of a link ℓ can be calculated by:

$$SNR_\ell = \frac{P_\ell {D_\ell}^{-\alpha}}{\eta_0} \geq \beta, \tag{1}$$

where D_ℓ represents the Euclidean distance between the transmitter and the receiver of link ℓ, P_ℓ is the power used by the transmitter, α is the path loss exponent, and η_0 is the power of the thermal noise. As a corollary, the maximal distance between the two ends of a link is given by:

$$D_{max} = \left(\frac{P_{max}}{\eta_0 \beta}\right)^{\frac{1}{\alpha}}. \tag{2}$$

Now, let us consider two links ℓ and ℓ' transmitting concurrently on channels c_ℓ and $c_{\ell'}$, where each channel is characterized by its carrier frequency and width. $I_{\ell\ell'}$ ($\in [0,1]$) is a relative measure of the transmission power used by link ℓ that interferes with link ℓ'. In particular, we have the following two extreme values:

- $I_{\ell\ell'} = 0$: there is no channels overlapping between the links ℓ and ℓ'; i.e., the channels c_ℓ and $c_{\ell'}$ are completely disjoint;
- $I_{\ell\ell'} = 1$: links ℓ and ℓ' use the same channel.

The facto r$I_{\ell\ell'}$, similar to the I-factor introduced by Mishra *et al*. (2005), can be obtained in a simplified manner by assuming the transmission energy is spread evenly over the used band. It can be written as:

$$I_{\ell\ell'} = \frac{W_{\ell\ell'}}{W_\ell}, \tag{3}$$

where $W_{\ell\ell'}$ represents the width of the overlapping area (in Hertz) between c_ℓ and $c_{\ell'}$, and W_ℓ the width of channel c_ℓ. In presence of concurrent secondary transmissions on non-disjoint channels, the ability of a primary receiver PU_i to decode successfully the signal coming from the primary BS depends on its SINR level, $SINR_{PU_i}$. This latter must be greater than or equal to β and can be written as:

$$SINR_{PU_i} = \frac{P_{PU_i} G_{(BS,PU_i)}}{\eta_0 W_{BS} + \sum_{\ell \in Sc} P_\ell G_{(t_\ell, PU_i)} I_{\ell,BS}}. \tag{4}$$

With $G_{(BS,PU_i)}$ represents the propagation gain between the BS and PU_i, $G_{(BS,r_{\ell_j})}$ is the propagation gain between the BS and the receiving node of the secondary link ℓ_j, W_{BS} is the width of the channel used by the BS, and η_0 is the density of the thermal noise (given in Watt/Hz). The propagation gains can be further decomposed as follows: $G_{(BS,PU_i)} = d^{-\alpha}_{(BS,PU_i)}$. Where $d_{(BSPU_i)}$ is the euclidean distance between the base station BS and the Primary user PU_i, and $G_{(BS,r_\ell)} = d^{-\alpha}_{(BS,r_\ell)}$.

Where $d_{(BS,r_\ell)}$ is the euclidean distance between the base station BS and the receiver of the link ℓ. Besides, concurrent secondary transmissions may cause interference between the SU themselves. Similarly, the SINR of a secondary receiver of a link ℓ can be written as:

$$SINR_\ell = \frac{P_\ell G_{(t_\ell, r_\ell)}}{\eta_0 W_\ell + \sum_{\ell' \neq \ell} P_{\ell'} G_{(t_{\ell'}, r_\ell)} I_{\ell'\ell} + P_{BS} G_{(BS,r_\ell)} I_{BS,\ell}}, \tag{5}$$

where the propagation gains $G_{(t_\ell,r_\ell)}$, $G_{(t_{\ell'},r_\ell)}$ and $G_{(BS,r_\ell)}$ are defined as mentioned above. Relying on this system model, our aim is to define an optimization model to allocate efficiently the licensed spectrum to the SUs. The spectrum can be divided into partial overlapping channels, in the form of multiple variable width blocks, as shown in Figure 2.

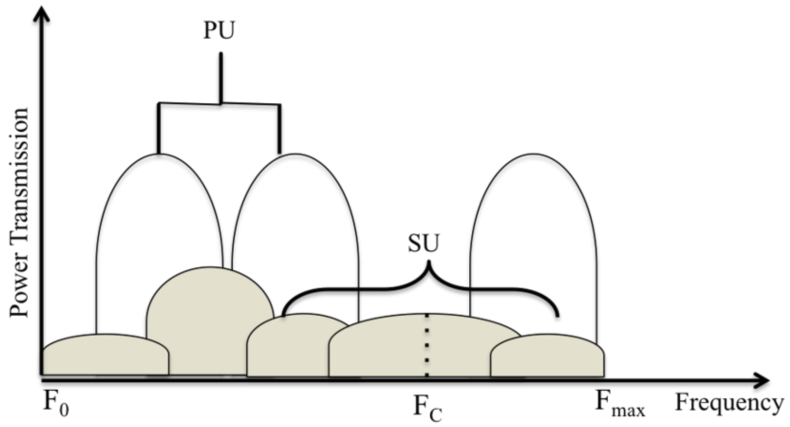

Figure 2. Spectrum usage

The opportunistic assignment of the channels to secondary users has to achieve some throughput objective without degrading the quality level the PU's activity. Thus, SUs must create no or limited interference to licensed users and should also kept mutual interference as minimum as possible. To this end, we assume that secondary users have full acknowledge of the radio spectrum state (lower/upper carrier frequencies, respectively(F_0/F_{max}), and the PUs configurations: locations, carrier frequency, transmission power.

This can be done for example through a centralized spectrum management entity. Secondary links compete for M contiguous channels, numbered from 1 to M. The throughput of each link ℓ is calculated using the well-known Shannon formula:

$$\theta_\ell = W_\ell log(1 + SINR_\ell). \tag{6}$$

4. Genetic algorithm for spectrum assignment in CRNs

As stated previously, the reuse of licensed bands provide the ability to increase significantly the overall cognitive network throughput through an appropriate configuration of the radio interfaces with respect to selected carrier frequency, channel width or transmission power. An appropriate tuning of these parameters would increase the throughput of each link while reducing interference to other users in the network. But these wide set of possibilities makes at the same time the optimization problem much harder than with basic configurations.

We provide now the details of our genetic algorithm (GA) to maximize the sum of throughputs of the set of secondary links. The chromosome's gene represented in Table 1 is a set of parameters which define the power transmission, frequency range and bandwidth for each link ℓ_i. Through a number of genetic operations on these chromosomes, the GA is designed to search the set of parameters that optimize the spectrum allocation scheme with the aim of maximizing the overall throughput of the network, called also the fitness function.

Table 1. Chromosome representation

Power	Central Frequency	Bandwidth

4.1. Fitness functions

They play a central role in shaping the GA, it allows measuring the relevance of solution and getting the best solution in a large search space. For our problem, we use the following two alternative formulations:

$$f_1 = Max \sum_{\ell \in L} \theta_\ell, \tag{7}$$

which maximizes the overall throughput of the set of secondary links;

$$f_2 = Max \sum_{\ell \in L} \log\theta_\ell, \tag{8}$$

which aims to achieve proportional fairness between the competing secondary links.

4.2. Chromosome encoding

Typically, for each link we need to represent the power, the carrier frequency of the channel and the bandwidth. Encoding is one of the most critical tasks in the development of a GA; it is used to represent a different set of variables in a gene form, giving rise to chromosomes (individuals). In our case, we use two alternatives: binary and decimal encoding. Note that the former is the most common used method in literature.

Link ℓ_1			Link ℓ_2		
7	40	20	10	70	40

Figure 3. Decimal coding

Link ℓ_1																							
0	0	0	0	0	1	1	1	0	0	1	0	1	0	0	0	0	0	0	1	0	1	0	0

Figure 4. Binary coding

4.3. Population initialization

GAs needs a set of initial solutions called population. Hence, we generate randomly a set of solutions where the parameters of each link $\ell \in L$ are selected according to the following process:

- transmission power p_ℓ is generated randomly from a discrete range of 7 values within the set P;
- the carrier frequency f_ℓ is generated randomly between $F_0 + \left(\frac{W_{min}}{2}\right)$ and $F_{max} - \left(\frac{W_{min}}{2}\right)$, where W_{min} is the minimum bandwidth allocated to a link;

- the channel width w_ℓ is selected randomly such that it is less than or equal to $(F_0 + \frac{F_{max}-F_0}{2})$. It also verifies $f_\ell + \frac{w_\ell}{2}$ and $f_\ell - \frac{w_\ell}{2} \in [F_0, F_{max}]$.

The initial population can be represented as a matrix of dimension $(|L| * 3) * (pop)$ where pop the population size. See an example with two links in Figure 5.

	Link ℓ_1			Link ℓ_2		
Individual $_1$	7	40	20	10	70	40
Individual $_2$	10	30	60	13	20	20
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Individual $_{pop}$	17	120	40	2	50	40

Figure 5. Population initialization

Each row represents a possible spectrum assignment for a set of links. The spectrum assignment for PU is generated randomly and fixed during all the genetic process and at this point all individuals (feasible solution) must verify the constraint (5) and if an individual does not satisfy the constraint, a new random allocation will be done for this individual following the process cited above.

4.4. Genetic operators

GAs usually implement the selection, crossover and mutation operators. The fitness values of the chromosomes in the initial population are firstly calculated, and depending of the selection method a set of chromosomes (individuals) will be selected under a certain percentage. We have implemented two selection methods:

- Random selection: a set of individuals are selected randomly.
- Elitist selection: individuals with the largest fitness are selected.

In order to maintain the population diversity, we applied crossover operator. Two individuals are randomly selected from the current population and are chosen as parents. Crossover is performed on a single point chosen uniformly on the two parents. Then, we swap the remaining two parts of these to create two children. Note however that validation phase is necessary to verify that the new individuals remain in the space of valid solution. If a child contains a radio configuration for a link violating the radio specification, such as a carrier frequency outside the interval $[F_0, F_{max}]$, or a channel width with invalid power transmission value, the solution is rejected and an new crossover point must be selected.

Mutation is another operator where a single point is chosen uniformly from a single individual. To accomplish this operation, we select first one gene from the individual, then:

- The selected gene represents the power transmission: mutation consists on selecting a new power transmission value within the set P.
- The selected gene represents the channel width: mutation consists on selecting a new bandwidth within the set W.

For binary-encoded chromosomes, the mutation consists simply to flip the current value of one bit. Mutation may also generate invalid solutions and a verification phase is needed as for the crossover operator.

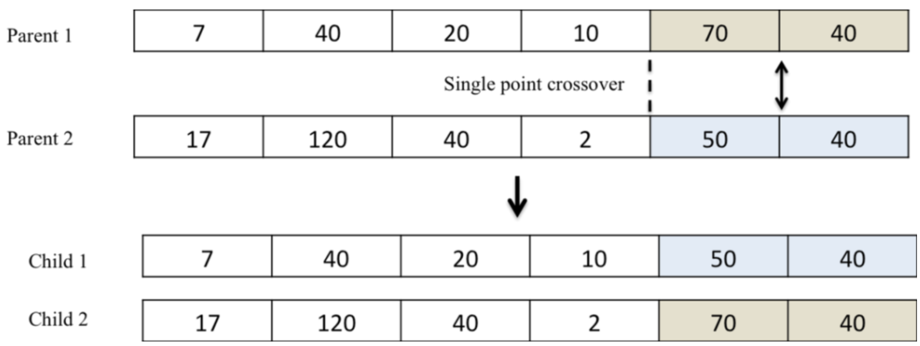

Figure 6. Crossover

As a generational replacement policy, we use the elitist replacement method, where, according to the fitness value, the best child replaces the worst parent in the next generation. Finally, as a stopping criteria, we define a maximum number of iterations.

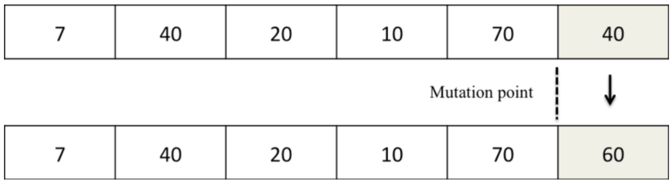

Figure 7. Mutation

4.5. Greedy heuristic for channel allocation in CRNs

In order to evaluate the performance of our GA, we designed for comparison purposes, a simple greedy algorithm that assigns in a sequential manner the radio parameters. As a heuristic, we sort these links from largest to smallest length, as these latter have more allocation possibilities. This algorithm is described in below.

Algorithm 1. Greedy Algorithm

$\theta \leftarrow 0$
L: set of secondary links
Sort links according to their Euclidean length distance from the largest to the smallest ones;
For $\ell \in L$ **do**
Select power, carrier frequency and channel width for ℓ, such that:
θ_ℓ is maximized ($\theta_\ell \leftarrow w_\ell \log_2(1 + SINR_\ell)$, where w_ℓ is the channel width and $SINR_\ell$ is calculated as in (5));
$\forall u \in Pr, SINR_u \geq \beta$
$\theta \leftarrow \theta + \theta_\ell$ (overall throughput of SUs).
End For

5. Experimental results

In this section, we present and discuss various simulation results for the optimization of the spectrum allocation in CRNs for secondary users while enforced hard constraints on the interference level experienced by primary users.

Our experiments were conducted using both GA and Greedy algorithm. Each network instance is obtained by randomly generating one primary BS which generates downlink traffic, and a number of PU and SU nodes over a $1000 \times 1000\ m^2$ area.

Besides, network parameters are set as follows: $\alpha = 2$ (path loss exponent); $\eta_0 = 10^{-15}$ (thermal noise power per Hz). F_0 and F_{max} are fixed respectively to 20 MHz and 220 MHz, the minimum bandwidth W_{min} equals to 20 MHz, whereas the channel widths are in$\{20,40,60\}$ MHz, and the power levels are in $\{2,7,10,13,15,17,20\}$ mWatt. All the solution approaches were implemented using Java and performed on a Intel i5 core with 2.80 GHz CPUs.

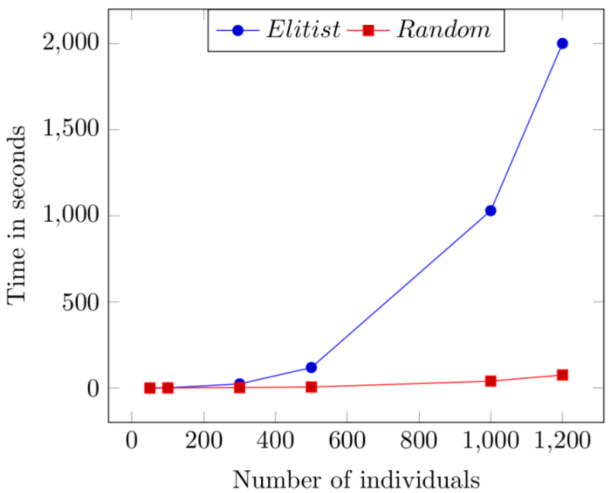

Figure 8. Comparison between Elitist and Random selection

5.1. Performance of the GA

As genetic algorithms are non-deterministic methods, we averaged the results of 6 simulations in all our experimentations. First, we discuss the impact of varying the selection methods used in our GA approach.

It appears from the results reported in Figure 8 that random selection is more efficient in term of time compared to the elitist method, which may require additional processing such as sorting the initial population according to the fitness of the individuals. Although the configuration of the genetic operators plays a central role in the generational process, there are no universal rules to set the parameters of GA and only experimentations can give an idea of their impact.

Following this statement, we can observe that the number of individuals and the size of the initial population greatly influence the objective of maximizing the throughput of the SUs as we see on Figure *9*. This is due to the diversity of the candidate solutions in the initial population. Also, the probability of having an individual with the greatest fitness increases proportionally with the initial population size.

Results shown in Figure 10 demonstrate that the number of iterations in the GA is not a good indicator of achieving the high-quality solution. In our case we select as the best solution the individual with the best fitness among all the generational process until the last iteration.

Results given in Figure 11 and Table 2 show the effectiveness of our genetic algorithm based on a decimal-coded chromosomes to find solutions as accurate as the standard binary-coded method with a considerable gain in term of computational time compared to the binary-coded GA, this can be explained by the fact that decimal-coded GA doesn't requires an encoding / decoding mechanism as for the binary coding. Figure 12 shows the performance of proposed genetic spectrum assignment algorithm as a function of the number of secondary users. We can note that our GA globally achieves the objective of maximizing the overall SU throughput using the different system utilities defined in section 4.

In some cases, the throughput cannot be maximized as we can see for 14 secondary users and this can be explained by the fact that some SUs have not satisfied the SINR constraints.

Table 2. Comparison between Decimal and Binary coding

Number of individuals	Number of iteration	Decimal GA Thr. (Mbps)	Binary GA Thr. (Mbps)
20	50	4.43	4.70
50	50	7.58	7.30
100	50	8.84	8.51
300	50	5.54	5.92
500	50	8.45	8.67

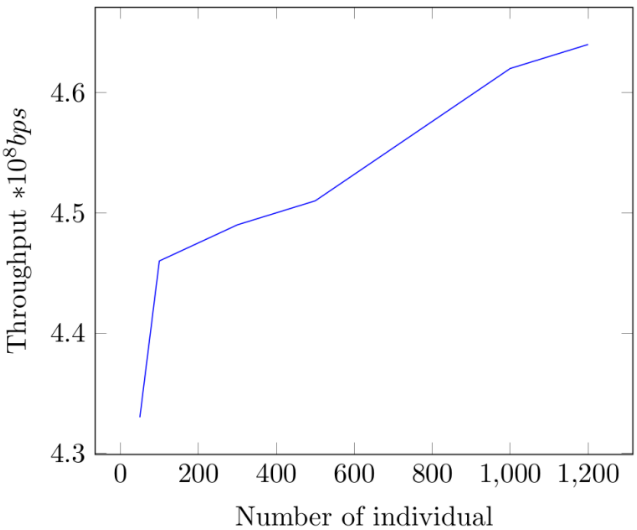

Figure 9. Throughput and population size

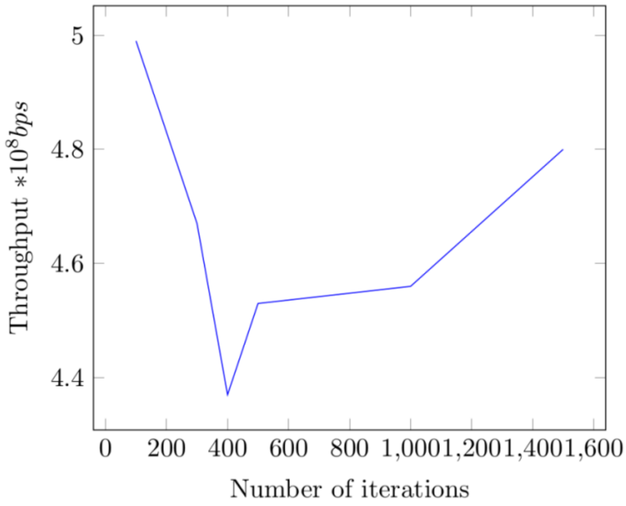

Figure 10. Throughput and number of iterations

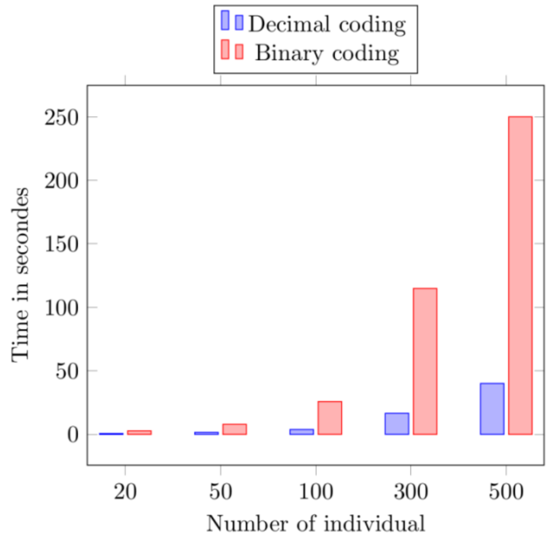

Figure 11. Comparing Decimal and Binary coding

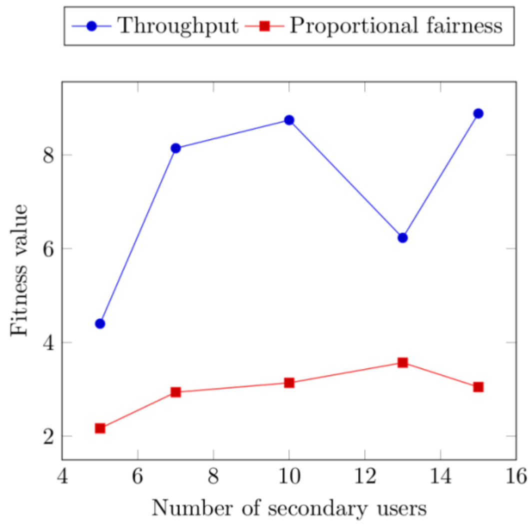

Figure 12. System utility with an increased number of SU

5.2. Comparing GA with the Greedy algorithm

Figure 13 shows the throughput performance of the GA algorithms compared to the greedy approach. For each problem instance, the overall objective is higher with the GA algorithm. At each step, the GA produces a radio assignment for all secondary users and verifies all the constraints with a global point of view. Whereas, the greedy algorithm builds a step-by-step solution for the SUs without considering a global solution for the entire system network and without reversing its decisions.

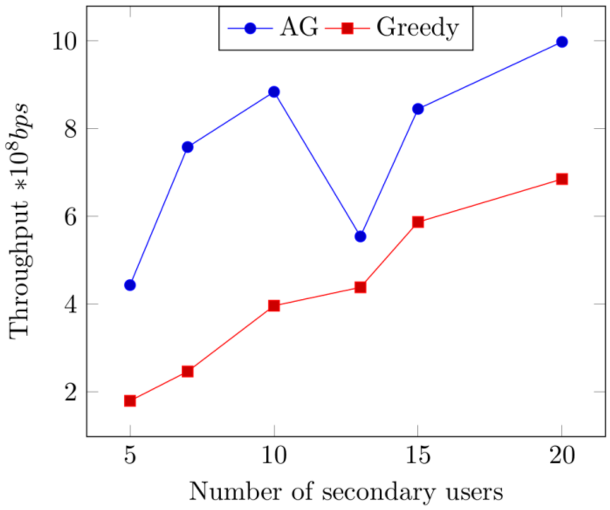

Figure 13. Throughput performance (GA vs Greedy)

5.3. Impact of varying multiple radio parameters

Here we report the results of six experiments, where in each experimentation we used 6 SUs and 2 PUs trying to transmit on a radio band of 200 Mhz in an underlay mode. We alternatively fix the bandwidth and the power transmission of the SUs, and then we compare it to our GA scheme which allows variable powers and bandwidth values. The results are shown in Figure 14. We can see that varying power transmission and bandwidth offer a more efficient spectrum use with a significant increase of SU throughput compared to fixed radio parameter experimentations.

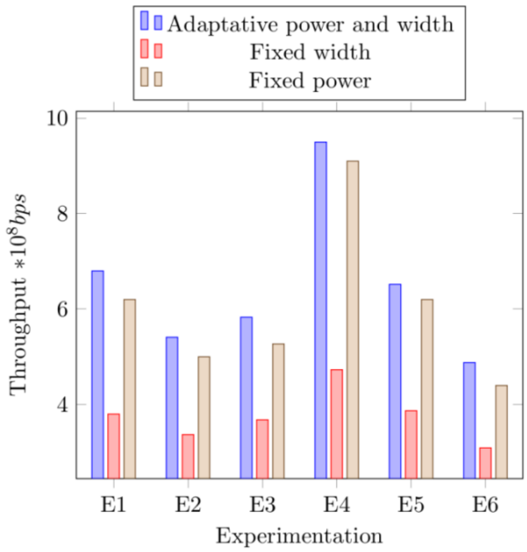

Figure 14. Throughput results with variable radio parameters

In Figure 15 we investigate the number of violations (i.e. the number of SUs which did not obtain a minimal throughput using fixed power, fixed bandwidth and variable power and bandwidth setting). We can see that the allocation scheme with fixed bandwidth at W_{min} offers the lowest number of unserved SUs.

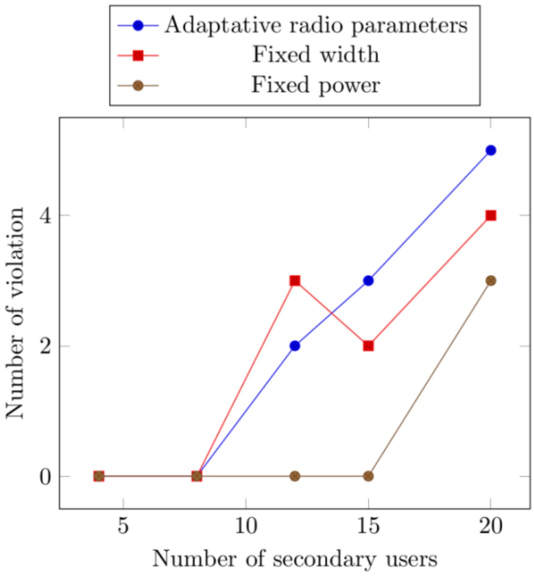

Figure 15. Number of violation

However, Figure 16 illustrates that with the same radio model, the joint power and bandwidth allocation scheme we obtain the best throughput values.

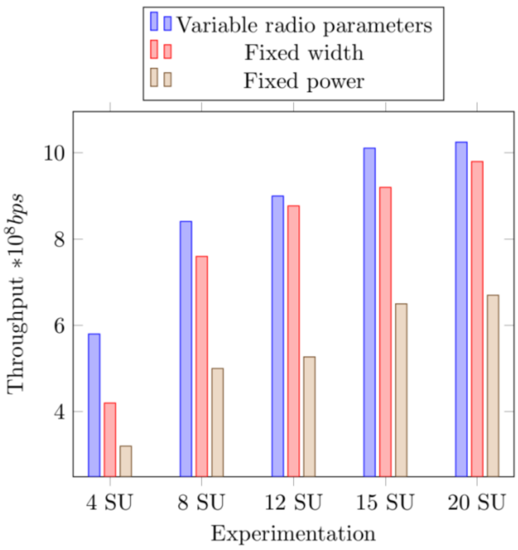

Figure 16. Throughput results with variable number of SUs

6. Conclusion

We presented in this paper a genetic algorithm for optimizing the capacity and the overall throughput of cognitive radio networks in the presence of primary or licensed transmissions. We adopted an underlay access scheme under the SINR interference constraints. Our main contribution is to define a spectrum assignment model with variable power transmission and variable channel width. The population of the GA represents a set of a feasible spectrum allocation solution and can reach acceptable solution in reasonable time comparing to a simple greedy allocation algorithm. Numerical results show that network capacity can be significantly increased with varying multiple radio parameters at the same time. Also, results showed the superiority of the GA algorithm compared to a greedy algorithm where links are configured in a sequential manner. As a future work, we plan to apply our GA in a more realistic. In particular, the IEEE 802.11af standard constitutes a very promising solution for exploiting unused TV white spaces to provide high throughput network services to mobile users.

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