A Multi-objective Genetic Optimization for Spectrum Sensing in Cognitive Radio

Andson Balieiro[1,a], Peterson Yoshioka[1], Kelvin Dias[1], Dave Cavalcanti[2], Carlos Cordeiro[3].

[1]Center of Informatics, CIn
Federal University of Pernambuco, UFPE
Hélio Ramos Av., 50740560, Recife, Brazil.
[2]Philips Research - USA
[3]Intel Corporation - USA

***Abstract*— Cognitive Radio (CR) has emerged as a promising solution to the problem of spectrum underutilization. In CR, spectrum sensing is a key feature. It enables the cognitive user or secondary user (SU) to detect spectrum holes and ensure non-interference to primary communication. Spectrum sensing has its own challenges, such as discovery of opportunities for transmission and sensing overhead. High sensing overhead may impair spectral efficiency as the radio is mostly used for detecting primary users (PUs), rather than transmitting data. On the other hand, a less frequent sensing may result in interference to PU, due to the delay in the detection of the PU´s reappearance and can lead to loss of transmission opportunities. Thus, it is of paramount importance to optimize the sensing periods for each primary channel in order to maximize the number of transmission opportunities and reduce the sensing overhead incurred. This paper extends our previous letter [1] and presents a detailed description of our adaptive sensing optimization scheme for CR Networks based on a multi-objective genetic algorithm (GA) formulation. Our scheme aims at maximizing the spectrum opportunities as well as keeping the sensing overhead always within a user-defined maximum value. The simulation results show that the proposed scheme outperforms the schemes described in the literature, while keeping the sensing overhead within a target value. In addition, it provides different levels of protection to PU communication through the configuration of threshold for sensing overhead.**

***Index Terms*— Cognitive radio; Spectrum Sensing Period; Multi-Objective Genetic Optimization.**

1. Introduction

Nowadays, the number of developed systems based on wireless communications has increased in the world. For deployment of these systems, it is necessary the availability of a scarce resource, the electromagnetic spectrum.

The current static allocation policy for spectrum regulation allocates a given spectrum band to each licensed service/primary user (PU) to ensure that the primary users cause each other minimal interference. However, studies have shown that this system of regulation does not provide an efficient usage of spectral resources, since some licensed spectrum bands are not fully used [2] [3].

Thus, cognitive radio (CR) technology has emerged to enable new wireless services to be employed, and as a result, improve the spectral efficiency, and ensure non-interference to primary user communication. Cognitive radio is a radio that can change its transmitter parameters based on interactions with the environment in which it operates and user requirements. It provides dynamic spectrum access, which can be performed in two main ways, spectrum underlay and spectrum overlay [3].

In the first way, the cognitive radio uses spread spectrum techniques to perform its communication simultaneously with the primary user, such that its transmit power at the shared spectrum does not exceed a predefined threshold, so its signal is considered as noisy by the primary communication. In the last one, the cognitive or secondary users (SU) access the spectrum in an opportunistic way, i.e. while the primary users are not using it. To allow this, the CR senses the surrounding spectral environment to identify spectrum opportunities, i.e. available frequency bands (or channels) for its operation, and then dynamically reconfigure its transmission parameters, such as transmission power, encoding scheme, frequency carrier and so on, so

[a] Corresponding Address: Anibal Fernandes Av., 50740560, Recife, Pernambuco, Brazil. Tel.: +55 8198568611; E-mail address: amb4@cin.ufpe.br

that it can act on the target channel. Cognitive radio networks (CRNs) are composed of a combination of nodes with cognitive radio capabilities.

Spectrum sensing [4] is an essential capability for CRNs using spectrum overlay approach for dynamic spectrum access, because the SU must discover available bands for its transmission and be able to detect the presence of the PU. The discovery of spectrum opportunities can be carried out through centralized spectrum databases, which keep track of the PUs and corresponding channel availability within certain areas. For example, incumbent databases are being developed to provide access to TV White Spaces (TVWS) in the US, as required by FCC regulations [5] [6]. The database system requires a central trustworthy entity to store the information. However, it is not the most efficient method for dynamic environments with mobile secondary users and low power incumbents (such as wireless microphones in the US). The discovery of spectrum opportunities can also be achieved through distributed spectrum sensing by secondary users, which is a more scalable and efficient solution for highly dynamic environments. Spectrum sensing has its own challenges, including the problem of sensing reliability and overhead, which is the main focus of this work. Sensing overhead corresponds to the time spent by the SU when it has to stop data transmissions to measure the availability of the communication channel in order to obtain a reliable measurement. High sensing overhead may impair the spectral efficiency as the radio is mostly used for detecting PUs, rather than transmitting data.

Thus, it is of paramount importance to optimize the sensing periods for each channel as a means of maximizing the number of spectrum opportunities (transmission opportunities) and reducing the sensing overhead incurred. In this paper, we extend our previous work [1], where we proposed an adaptive sensing period optimization scheme based on a genetic algorithm (GA) formulation [7]. Our scheme ensures that the sensing overhead is always within a user-defined maximum value. Considering our previous work, this paper presents the following contributions: (1) a comprehensive approach to the sensing period determining problem, considering the sensing overhead versus number of discovered opportunities tradeoff; (2) a detailed description to the sensing period optimization problem based on genetic algorithms and the main differences between our proposal and those ones presents in the literature; (3) we describe the adopted genetic operators, the process carried out for selection of parameters as crossover and mutation probabilities and the flow execution of our scheme; (4) we present the convergence evaluation of our scheme based on GA and new evaluation results obtained in terms of sensing overhead besides those ones presented in [1].

To the best of our knowledge, this is the first GA-based scheme to optimize the scheduling of sensing periods. Although the well-known GA has a large convergence time, a number of solutions to reduce this time have been proposed [8]. In this work, we assume that the GA can be adopted in the first stage of the cognitive cycle during the initialization phase, before the network becomes fully operational. In addition, depending on the dynamic nature of the spectral environment, the GA can also be used to update the sensing periods during the normal operation, such as a background task. Moreover, processing overhead and energy waste in the wireless device can be avoided by carrying out the GA execution in a remote network server or distributing the processing load amongst cooperating secondary devices.

The remainder of this paper is structured as follows. Section 2 describes the challenges raised by MAC layer sensing and related works. The GA based optimization for the sensing period is presented in Section 3. The simulation and analysis are discussed in Section 4. Section 5 concludes this paper.

2. Mac Layer Sensing and Related Works

Spectrum sensing is a dynamic and periodic process of spectral environment monitoring that aims at finding transmission opportunities and to avoid interference to PU transmission. This process can be realized as a two-layer mechanism, PHY and MAC [9]. The PHY-layer sensing focuses on efficiently detecting the primary user´s signals to identify opportunities for spectrum utilization. Energy detection, matched filter and feature detection are well known candidate methods for PHY-layer sensing [4]. At the same time,   MAC-layer sensing aims to determine when the SU has to sense the spectrum, i.e. the sensing periodicity of the channels.

One of the fundamental in spectrum sensing is how to define the channel sensing schedules for the SUs. The tradeoff between the number of discovered transmission opportunities and the corresponding sensing overhead has to be taken into account when determining the sensing time and sensing period. The former refers to the time spent by the SU to determine the signal strength for a certain channel, in the light of the desirable false-alarm and detection probabilities. The latter is the time interval between two consecutive sensing instances; this determines how often a particular band is monitored by SU. The sensing time and sensing period concepts are illustrated in Figure 1.

In this work, as in [9] [10], we adopt the same ON-OFF model (see Figure 1) to represent the PU behavior in the context of MAC layer sensing. In this model, the SU can transmit opportunistically while the channel is in the OFF state, i.e. when no PU is currently transmitting; it must   stop its transmission when the PU is present in the channel, in the ON state.

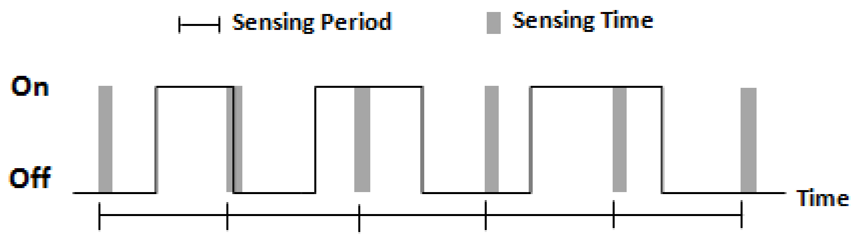

Figure 1. ON-OFF Model and Sensig Time and Sensing Period Concepts

If a shorter sensing period is adopted, many transmission opportunities will be discovered and the PU return can be quickly detected by the SU. However, the SU will spend a lot of time sensing instead of transmitting, owing to the increase in the sensing frequency, which has a negative impact on the spectrum utilization. The increase in the sensing frequency can lead to redundant sensing, i.e. the SU performs the spectrum sensing even though no change in the channel state has occurred, as illustrated in Fig.2.

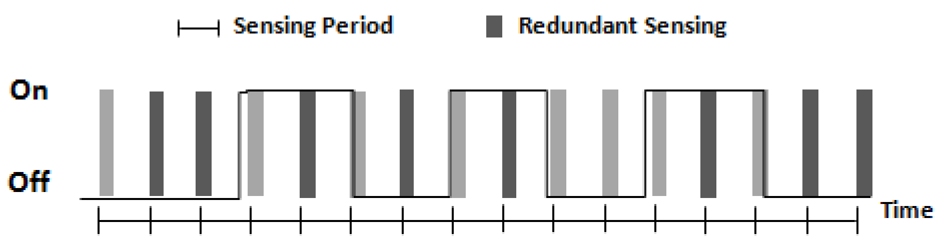

Figure 2. Redundant sensing leads to too much overhead

However, using less frequent sensing may result in interference to the PU, due to the delay in the immediate detection of the PU reappearance. Furthermore, if there is a long sensing period, it can lead to a loss of transmission opportunities (missed opportunities) by the SU, as depicted in Figure 3. A missed opportunity is the time interval when the channel was in the OFF state, but it was not detected by the SU. In Figure 3 the PU activity (ON state) was not detected because the sensing period was too long. Hence, despite the smaller sensing overhead, the PU communication can undergo interference from the SU (interference to the PU).

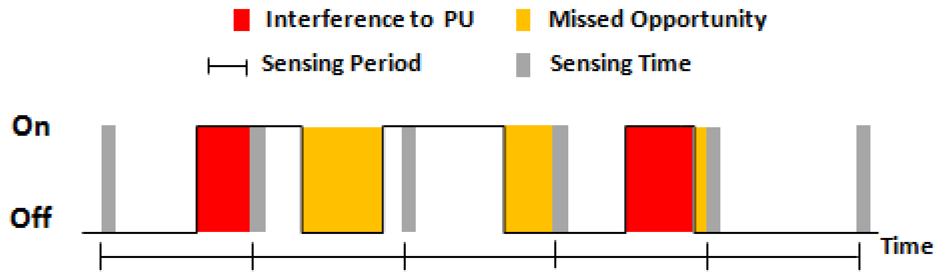

Figure 3. Larger sensing period may result in lower performance and thus interference to PU

In addition, due to the peculiar usage pattern of each channel, defined by the PU activity, a sensing period may result in a good performance, in terms of its ability to minimize the interference to the PU, reduce overhead sensing and detect effective transmission opportunities in one channel (e.g. Ch 1), but not be effective in another one (Ch 2), as shown in Fig.4. Thus, the choice of a single sensing period for all the channels cannot represent a good overall performance.

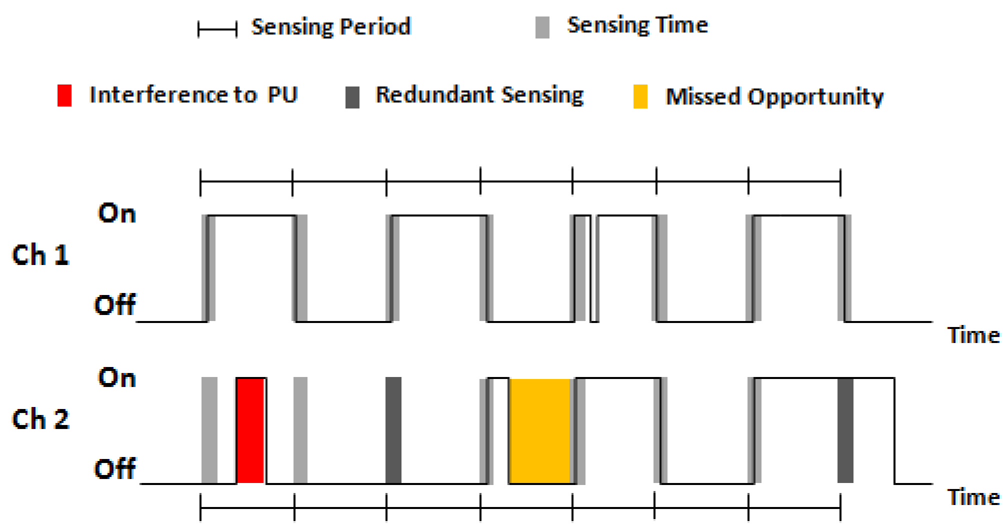

Figure 4. A single sensing period for all channels: effective for channel 1 but not effective for channel 2

As can be seen, the definition of the periodicity of the spectrum sensing phase is challenging. In [11] a sensing system was developed to achieve a better spectral utilization by deciding adaptively whether the CR should be sensing or transmitting user data. The behavior of the PU is modeled as a two-state Markovian process. The decision-making is based on a Partially Observable Markovian Decision Process (POMDP). This scheme avoids unnecessary sensing, but the PU communication becomes susceptible to SU interference. The authors evaluate it in terms of channel utilization and collision probability, but they did not take into account other adaptive methods in evaluation.

In [9] an adaptive algorithm to determine the sensing period for each channel is proposed. Its objective is to maximize the discovery of opportunities for transmission and minimize the delay to find an available channel. The results are obtained in terms of SU´s channel utilization. The authors use information on the average channel behavior to determine the set of sensing periods, unlike our approach that considers instantaneous sensing samples of the channel instead. Furthermore, they fail to take into account the impact of the choice of the sensing period on the interference to the PU and that there are channels/primary users that are less susceptible to interference than others.

Adaptive spectrum sensing schemes to improve the throughput of CR users while maintaining protection to the PU are proposed in [12, 13]. In the first work, the authors consider the channel state keeps constant during each frame, which is not true in cognitive radio scenarios. Moreover, they used just one primary channel and neglected important metrics as interference to the PU and sensing overhead in the evaluation of the proposed scheme. In the second one, the authors define a primary transmission failure probability and use it to derive the sensing interval to be use by CR. For this, they considered that the channel state does not change more than one time in a sensing interval. This assumption, like the previous one, does not apply to dynamic scenarios. Moreover, they do not evaluate the sensing overhead in their approach.

In [14] the authors propose a scheme to define the optimal sensing period that minimizes the transmission delay for cognitive radio. As in [9], this scheme depends of information on the average channel behavior to determine the sensing period. The authors only evaluated their proposal in terms of delay, neglecting metrics as interference to the PU, sensing overhead, for example. So, the overall effectiveness of the scheme is not verified.

Although the analytical models provide an elegant and efficient way of defining the sensing period, in general they are based on a set of assumptions(e.g. specific traffic models and probability distributions, channel idealization) and do not evolve as the scenario changes [15]. Thus, the solutions [9, 11, 12, 13, 14] discussed earlier are not flexible enough to be applied to dynamic environments, since they are heavily dependent on the analytical models and stochastic distributions adopted. So, for any change in the environment, a new analytical model needs to be developed off-line and loaded into the CR system. This is a big drawback if we consider that a CR is expected to be highly reconfigurable and modular, and that developing a new analytical model may require significant human effort.

Computational intelligence solutions are naturally candidates for the optimization of CR functionalities [16] in dynamic scenarios. Genetic Algorithms (GA), in particular, are powerful tools for finding satisfactory answers to the problem of large search spaces and could be an alternative to allowing a sensing period to be scheduled in dynamic environments by taking into account the channel behavior.

In [17, 18] are proposed schemes based on GA to choose transmission parameters to be used by CR. However, they do not take into account the impact of the choice of the sensing period on their results and they only evaluate the proposal in terms of the best fitness for individuals and convergence rate, respectively

In [19] a mechanism for cooperative sensing is proposed for cognitive radio systems. The sensing information of each CR terminal is sent to a central entity and carries out the weighted data fusion to determine the available spectrum bands. The weight of the received information of each cognitive user is defined by the GA and aims at improving the overall performance of the cooperative proposal. Unlike our proposal, which focuses on sensing period optimization, this work is concerned with a physical layer sensing algorithm. Despite the differences, both our work and the one referred in [19] could be adopted in the same system, since they act in different layers and are complementary.

Various suggestions have been put forward in the field of spectrum sensing for CR. However, our work, which extends [1], is unique in proposing the adoption of GA as a multi-objective strategy for optimizing the sensing period, with the aim of finding a maximum number of spectrum utilization opportunities, subject to a user-defined upper sensing overhead. Different from previous studies, our work analyzes the amount of time that SU spends on spectrum sensing, which has significant impact on both number of discovered transmission opportunities and amount of interference caused to primary communication. Moreover, our scheme based on Genetic Algorithms can be applied in scenarios with other traffic models, since it is not dependent of analytical or stochastic assumptions to its derivation, which is not true for [9, 11, 12, 13, 14]. Furthermore, it takes into account the interference caused to PU to determine the sensing periods and it provides different levels of protection to PU communication, defined by user, and a good number of transmission opportunities for SU.

3. Our Scheme

3.1. Channel Model

We assume an SU must sense a channel during a sensing time in order to determine its availability for use. The sensing period of channel i will be represented by x_i .An idle channel discovered (OFF state) by the periodic sensing becomes a new transmission opportunity that can be utilized by the SU. As in [9, 10], the duration of the ON/OFF period for each channel is given by an exponential distribution with mean $1/\lambda^i_{TON}$ and $1/\lambda^i_{TOFF}$, respectively.

Let $S^i(t)$ be the state of channel i , at time instant t. $S^i(t)=1,$ if the channel state is ON and $S^i(t)=0,$ when the channel state is OFF; the sensing process consists of channel sampling at regular time intervals. To determine the optimal set of sensing periods for the channels, our scheme uses instantaneous sensing samples as input to the GA.

3.2. Genetic Algorithm and the Optimization Problem

The GA is a search algorithm based on the principles of natural selection and genetics. It relies upon evolving a set of solutions, represented by the so-called chromosomes, over a period of time. Eventually, through the GA operators (selection, crossover and mutation) a good solution will be found by combining different possible solutions [8]. In the proposed GA formulation, each individual or chromosome j, represented by $X^j=[x_1, x_{2,} x_3, ..., x_N]$, is formed by N parcels as depicted in Fig 5, where $j=1,2,3,...,N$; N and L are the number of channels and population size, respectively. Each parcel x_i , with binary encoding, represents the sensing period for channel i. Thus, our proposal takes into account the intrinsic parallelism of the GA to find an optimal or sub-optimal sensing period for each channel

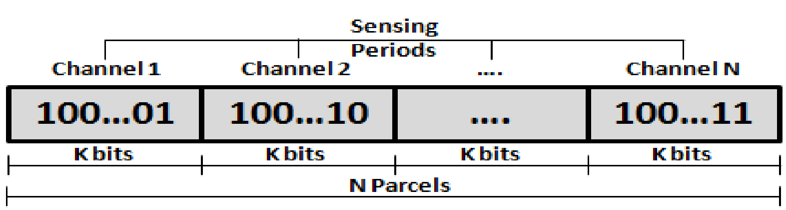

Figure 5. Chromosome structure

The binary encoding for each parcel with resolution of P decimal dots uses K bits, according to Eq. 1. Where, $X_{\max}$ and $X_{\min}$ are the upper and lower limits for the sensing period, i.e. $x_i \in [X_{\min}, X_{\max}]$. Thus, the individual encoding is given by N x K bits.

$$2^K \geq (X_{\max} - X_{\min}) x 10^P \tag{1}$$

We used the Pareto strategy to evaluate the solutions to the problem (i.e. the individuals) during the evolutionary process, since the determination of the set of sensing periods is a multi-objective problem. Thus, optimization is based on the concept of dominance [7].

In our approach, the dominance evaluation function $f(\,.\,)$ is based on the number of discovered transmission opportunities (Op), as defined in equation (2). Moreover, the individual's evaluation takes into account the sensing overhead incurred (Ov), which is given by Eq. (3).

$$Op(X)=\sum_{i=1}^{N}\sum_{h=1}^{M} S^i(x_i h) \tag{2}$$

$$Ov(X) = \sum_{i=1}^{N} \frac{t_s}{x_i} \tag{3}$$

Where $S^i(x_i h)$ is the state of the channel i at the time instant $x_i h$, with h varying from 1 to M. M is the total number of samples of channel i with a sensing period x_i; and t_s is the sensing time.

During the evaluation process, the fitness value for each individual j is defined by computing the number of individuals dominated by j in the population ($DN(X^j)$), as described in Eq. 4, where $\equiv$ ($\cong$) means dominance (non-dominance). Moreover, an evaluation is carried out to determine whether this particular individual has an overhead rate equal or less than a user-defined threshold (Th_{ov}), as defined in Eq. 5. Where $\delta_{ov}(X^j)$ is equal to zero if individual j has an overhead rate greater than Th_{ov} and equal to one otherwise.

$$DN(\mathrm{X}^j) = \sum_{r=1, r\neq j}^{L} \begin{cases} 1, & \mathrm{X}^j \equiv X^r \\ 0, & \mathrm{X}^j \cong X^r \end{cases} \tag{4}$$

$$\delta_{ov}(X^j) = \begin{cases} 1, & \mathrm{Ov}(\mathrm{X}^j) \leq \mathrm{Th}_{ov} \\ 0, & \mathrm{Ov}(\mathrm{X}^j) > \mathrm{Th}_{ov} \end{cases} \tag{5}$$

Thus, the fitness value of each individual X^j is given by Eq. 6.

$$fitness(X^j) = \delta_{ov}(X^j) + DN(X^j) \tag{6}$$

Hence, the sensing period optimization problem can be formulated as in (7):

$$\begin{aligned} &\underset{j\in\{1,2,3,\dots,L\}}{Max}\ fitness(X^j) \\ &subject\ to \quad \begin{cases} x_i > 0,\ x_i \in X^j,\ i = 1,2,3,\dots,N \\ Ov(X^j) \leq\ Th_{ov} \end{cases} \end{aligned} \tag{7}$$

Though there are classical GA approaches for solving multi-objective problems, in our multi-objective problem presented in Eq. 7, we used the aggregating functions approach to deal with multiple objectives, because this one does not require any changes to the basic mechanism of a GA and it is therefore very simple and easy to implement. Moreover, the literature presents studies that have successfully used this approach in multi-objective optimization [18]

3.3. Genetic Operators

For the selection operator, where the individuals are selected for the crossover process, we adopted the roulette wheel, which is based on the individual fitness value. This process simulates the natural selection mechanism, which acts on biological species [7].

Thus, individuals with the highest fitness values are suitable for surviving to the next generation. For the crossover operation, which selects genes (bits) from parent's chromosomes and creates a new offspring (the individual), we adopted a uniform operator. For the mutation operator, which randomly changes the new offspring, we used bit mutation [7].

Defining correct parameters for setting up the GA is important to obtain good results and two main parameters in the GA are the crossover (pc) and mutation (pm) rates (probabilities) since they express the frequency with which the crossover and mutation operations are carried out. The adoption of a high mutation rate may result in the loss of good solutions during the GA evolutionary/evolving process, because of the increased likelihood that these solutions may be altered, especially when elitist techniques are not being used. On the other hand, a lower mutation rate for a big population may cause a lack of diversity in the solutions as well as premature convergence via GA.

The crossover rate impacts on the number of chromosomes that comprise a crossover pool. Thus, if it is adopted a very small crossover rate, it could generate insufficient number of new offspring (solutions). In contrast, with a high crossover rate, a large amount of new chromosomes could be added to the population, which could result in the loss of good blocks inside a chromosome, and the destruction of good schemes [7].

We conducted multiple instances tests to define these probability values. We adopted 10 test values within the interval [0.01, 0.95] for each probability (pc and pm) as shown in Table 1. We combined all these values and we evaluated 100 test cases.

Table 1. Test case values

pc	0.05/0.1/0.2/0.3/0.4/0.5/0.6/0.7/0.8/0.9
pm	0.01/0.0325/0.055/0.0775/0.1/0.3/0.5/0.7/0.9/0.95

The case test we selected was the one that provides the greatest average fitness value for the population. Figure 6 depicts the results for the tests. As can been seen, case test #5 shows the best performance for the GA, which had crossover and mutation rates equal to 0.1 and 0.001, respectively.

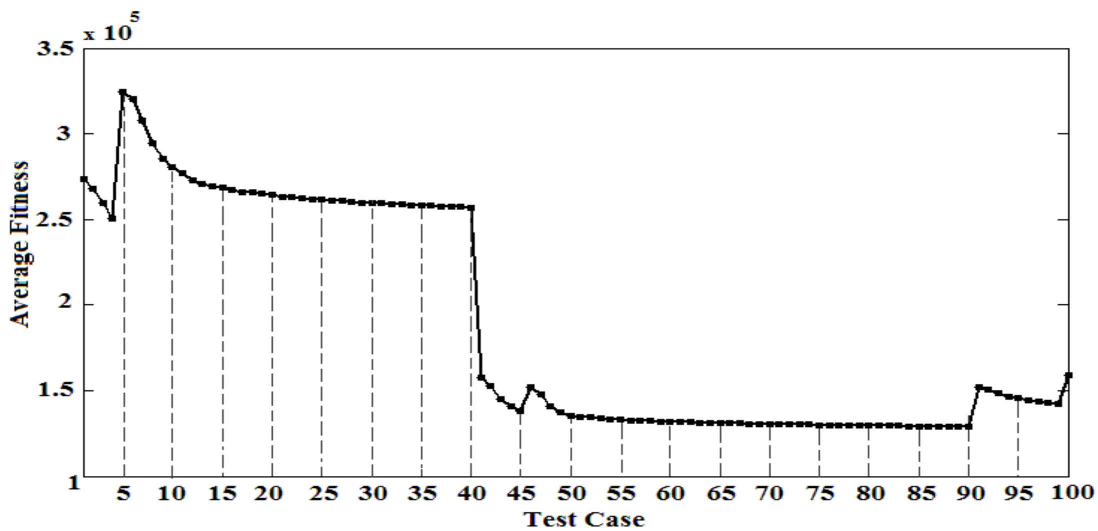

Figure 6. Test case results

3.4. Execution flow of the scheme and GA parameters

The execution flow of our sensing period optimization based on the GA is as follows (see Figure 7). Initially, the population (sets of sensing periods) is randomly generated to provide candidate solutions to the problem. Next, the channels are sensed with each sensing periods set generated in the first stage. Following the sensing, the individuals (set of sensing periods) are evaluated in accordance with the fitness function defined in (6), which takes into account the sensing overhead and number of transmission opportunities. Afterwards, the individuals are submitted to the selection, together with the crossover and mutation operators. Moreover, we employ the elitist strategy to ensure that the individuals with best fitness will not be lost during the selection process, but are carried over to the next generation to form a new population. After these operations have been completed, a new generation of sensing periods will be created and the stop criterion, which is determined by the number of generations (G), is evaluated. If the stop criterion is not satisfied, the process is repeated in the channel sensing stage. Otherwise, the best individual is chosen as the solution for the problem. It contains a specific sensing period for each channel as illustrated in Fig. 7.

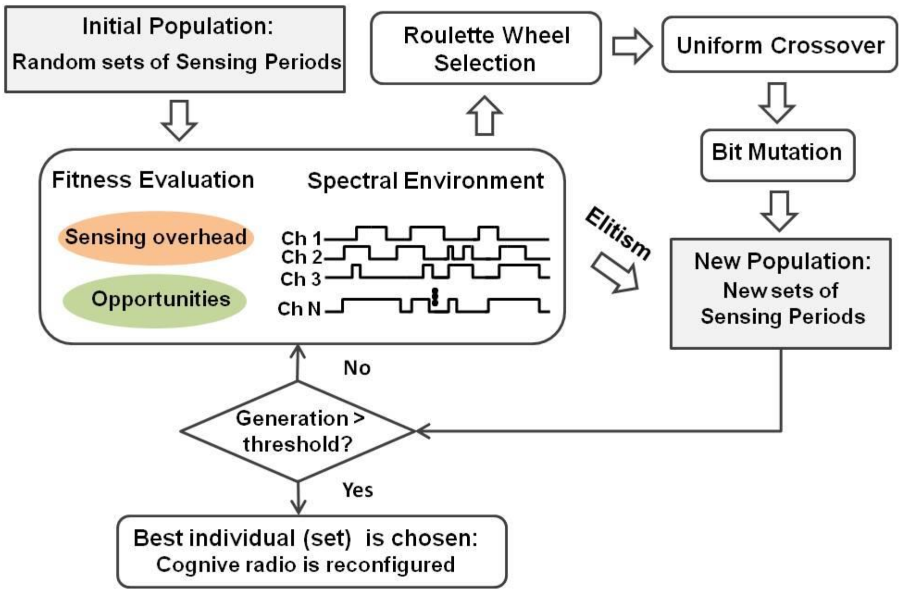

Figure 7. Execution Flow of the Scheme Based on GA.

The sensing periods can vary at a configurable interval $(X_{\min}, X_{\max}]$, for example $(0, 10]$ seconds. The resolution used to represent the individuals was set to 10^{-10}, i.e. $P = 10$. Thus, each parcel belonging to an individual, i.e. a channel sensing period, is encoded in 75 bits, according to (1). The population size (L) and number of generations (G) were defined as 100 and 300, respectively, as in [17]. Table 2 summarizes the GA parameters employed in this work.

Table 2. GA Parameters

Parameter	Value
Number of generations (G)	300
Population size (L)	100
Crossover rate (pc)	0.6
Mutation rate (pm)	0.001
Resolution (P)	10
Number of bits	75

4. Scheme Evaluation

4.1. Evaluated Metrics

Three metrics were used to evaluate our scheme. The first is the sensing overhead that impacts on the spectral efficiency, as discussed in Section 2. This metric is calculated according to Eq. 3. The number of discovered transmission opportunities is the second metric, as described in Eq. 2. It is an important metric since the larger the number of discovered transmission opportunities, the greater the chance the SU has to transmit its data. The third metric is the interference in PU communications which is caused by the latency or non-detected PUs. In general, depending on the size of the sensing period, two cases of interference are possible. The first occurs during the transition from OFF to ON, when the channel sensing only occurs instants after the return of the PU to the channel, as depicted in Figure 8.a.

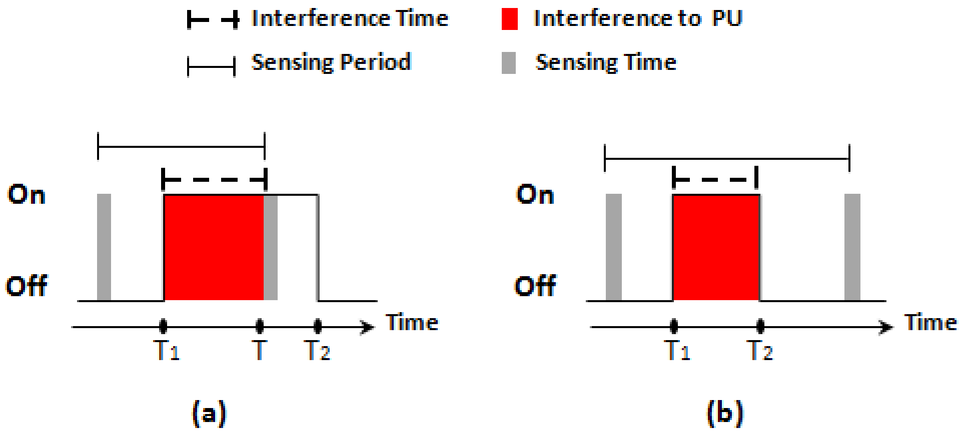

Figure 8. Interference time: (a) first case; (b) second case

Hence, the interference time (IT) can be given by Equation (8).

$$IT = T - T_1 \tag{8}$$

The second case is depicted in Figure 8.b. As can be seen, the time duration of the ON state is shorter than that of the sensing period. Thus, the SU does not perceive the interference that it caused to the PU.

Thus, for the second case, the interference time is given by the Eq. (9).

$$IT = T_2 - T_1 \tag{9}$$

4.2. Simulation Scenarios

We adopted three simulation instances that differ in terms of the number of channels (3, 6, and 9) in the evaluation. We analyzed the effectiveness of our scheme by comparing with the method based on fixed and unique sensing period for all channels [10], as well as with the adaptive method proposed in [9], namely Kim. The sensing and simulation time were set to 20ms and 100s, respectively. The mean duration of the ON and OFF states were uniformly distributed in [0.5 5.5], as in [9]. Table 3 summarizes the averages $1/\lambda_{TOFF}^{i}$ and $1/\lambda_{TON}^{i}$

Table 3. Channel Averages for the ON and OFF Times

	Ch1	Ch2	Ch3	Ch4	Ch5	Ch6	Ch7	Ch8	Ch9
$\frac{1}{\lambda_{TOFF}^{i}}$	2.61	4.94	2.4	0.93	1.96	0.23	1.03	3.48	2.62
$\frac{1}{\lambda_{TON}^{i}}$	1.77	0.79	3.12	1.04	0.94	3.22	2.11	2.66	1.8

Our GA scheme presents versions with different values of upper limit for the user-defined tolerable sensing overhead. Thus, the versions denoted as GA10, GA20 and GA40, aim at maximizing the number of discovered transmission opportunities conditioned to sensing overheads lower than or equal to 10%, 20%, and 40%, respectively. The sensing periods in the two instances of the fixed method, Fixed 1 and Fixed 2, are set to 0.5s and 1.0s, respectively. All results are presented with 95% confidence level.

4.3. Convergence evaluation

We examined the convergence of our scheme with regard to the metrics previously described, as well as the average value of the best fitness and the sensing period obtained during the evolutionary process of the GA.

Figure 9 shows the average evolution of the fitness of the best individual across generations for the GA10, GA20, and GA40, by considering a simulation instance with 3 channels. All the schemes show an evolutionary pattern towards fitness for the best individual along generations, and thus find better sensing periods, which give to the SU a greater number of opportunities, while ensuring that they do not surpass the stipulated sensing overhead rate. The average of the best fitness for the simulation instances with 6 and 9 channels had a similar pattern to that shown in Figure 9.

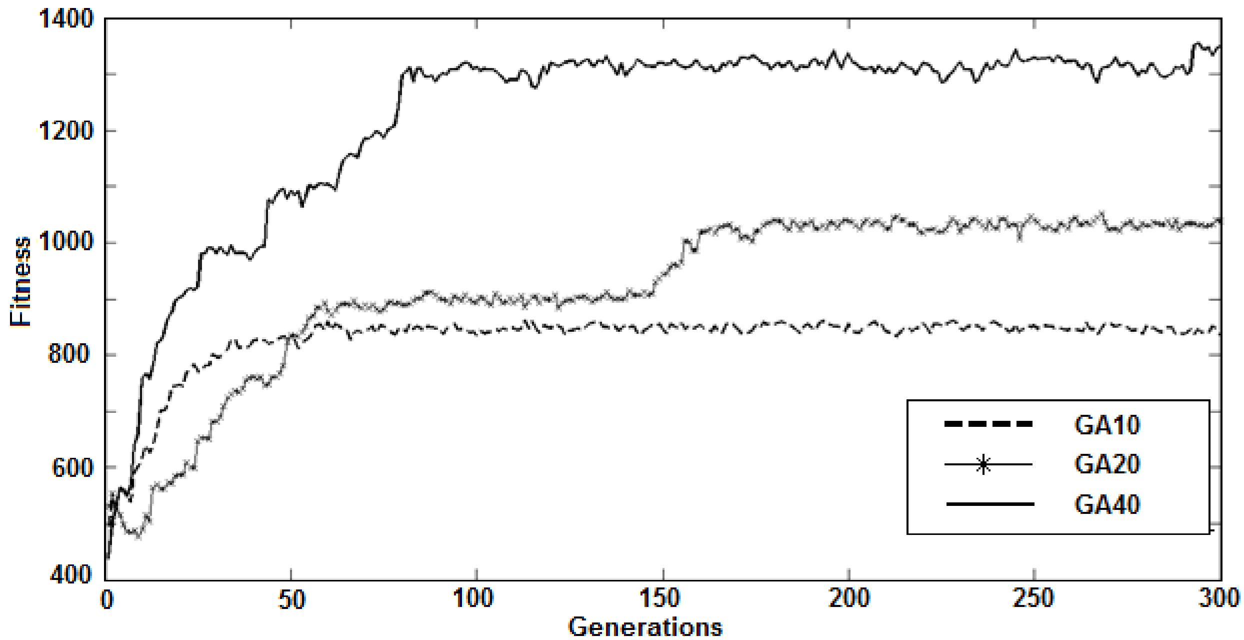

Figure 9. Average evolution of the best fitness

Fig. 10 illustrates the evolution of the sensing period for channel 1 through different generations. Note that all versions present a rapid convergence, and the sensing period is changed in each generation with the aim of finding a good value that is in accordance with both the usage pattern of the licensed channel and the stipulated sensing overhead. The convergence rate was similar for all the channels employed in the evaluation process.

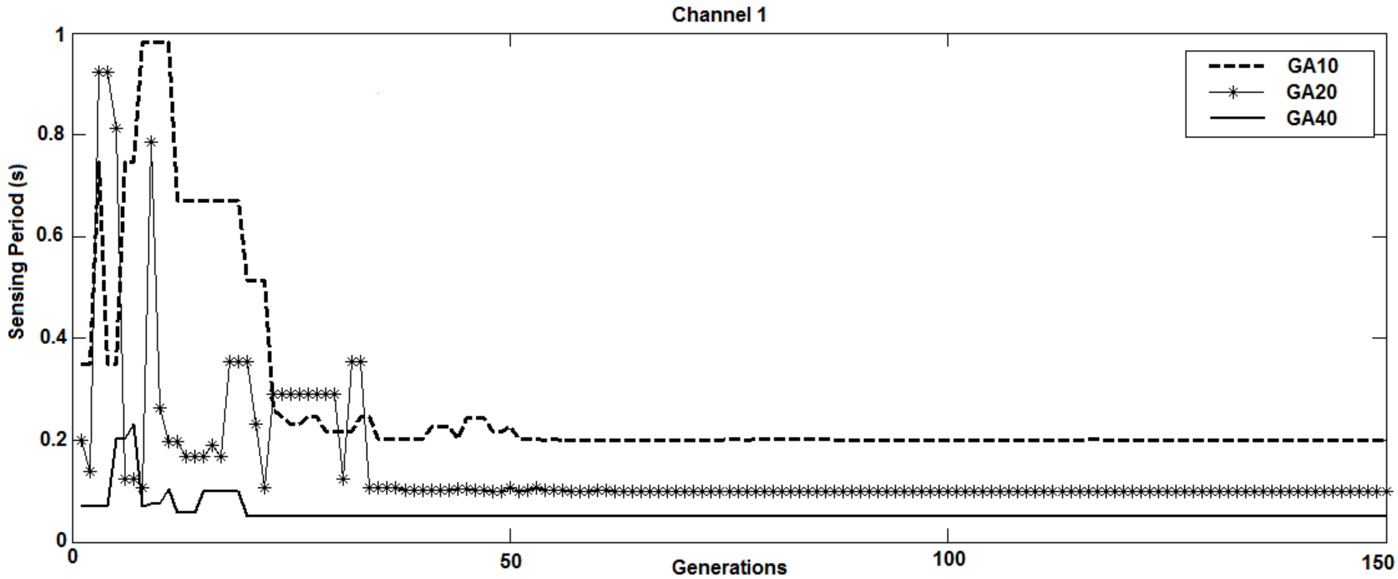

Figure 10. Evolution of the Sensing Period for the Channel 1

Figure 11 illustrates the evolution of the sensing overhead for Channel 1 over the generations. It can be observed that the best individual of a generation tends to evolve toward the value of the previous user-defined sensing overhead. Furthermore, there is a rapid convergence of the algorithms to obtain values of the overhead that are below that defined by the user. A similar performance is also found with all channels.

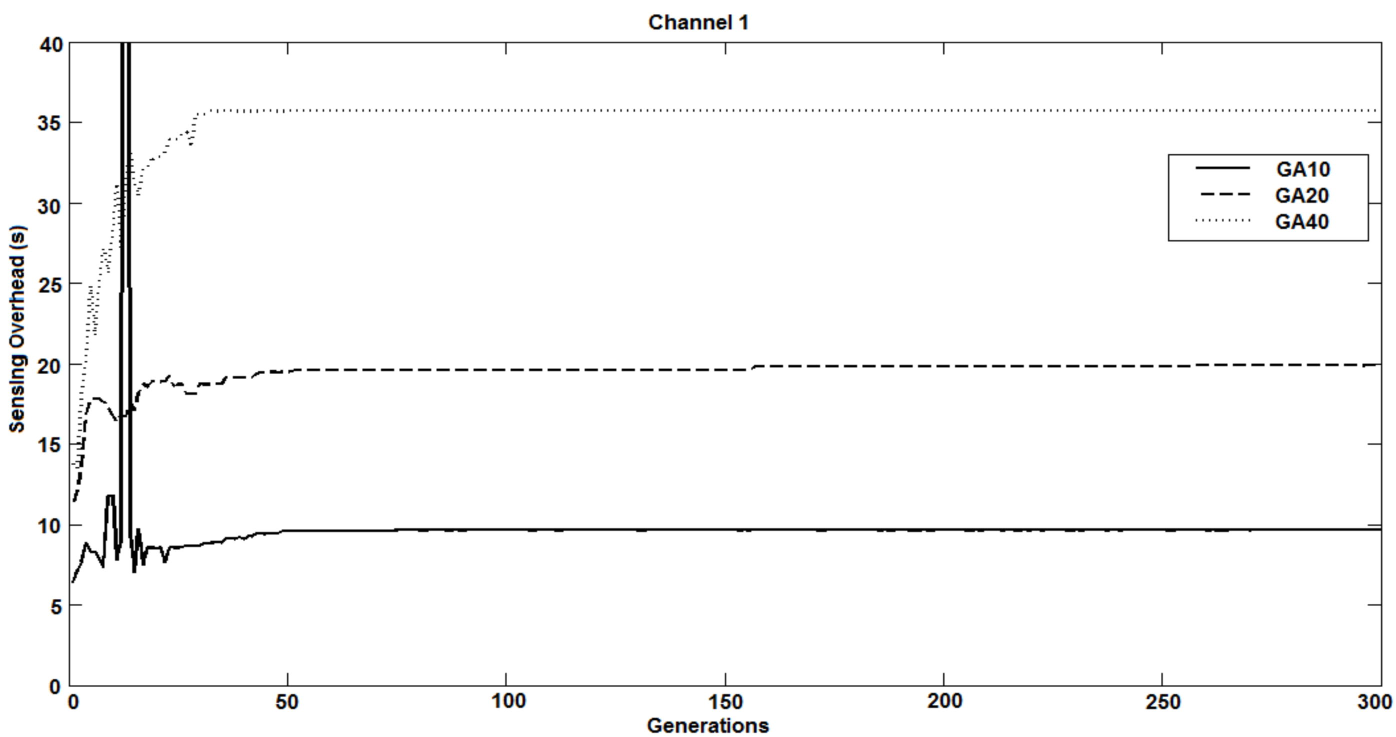

Figure 11. Sensing Overhead in the Channel 1

Figure 12 shows the evolution of the number of opportunities found with the best individual for each generation and channel 1. It can be noted that the number of opportunities increases with the generations. In addition, all versions present rapid convergence for an even smaller number of generations than what is defined in the stop criterion. With other channels, we obtained similar behavior for all GA versions.

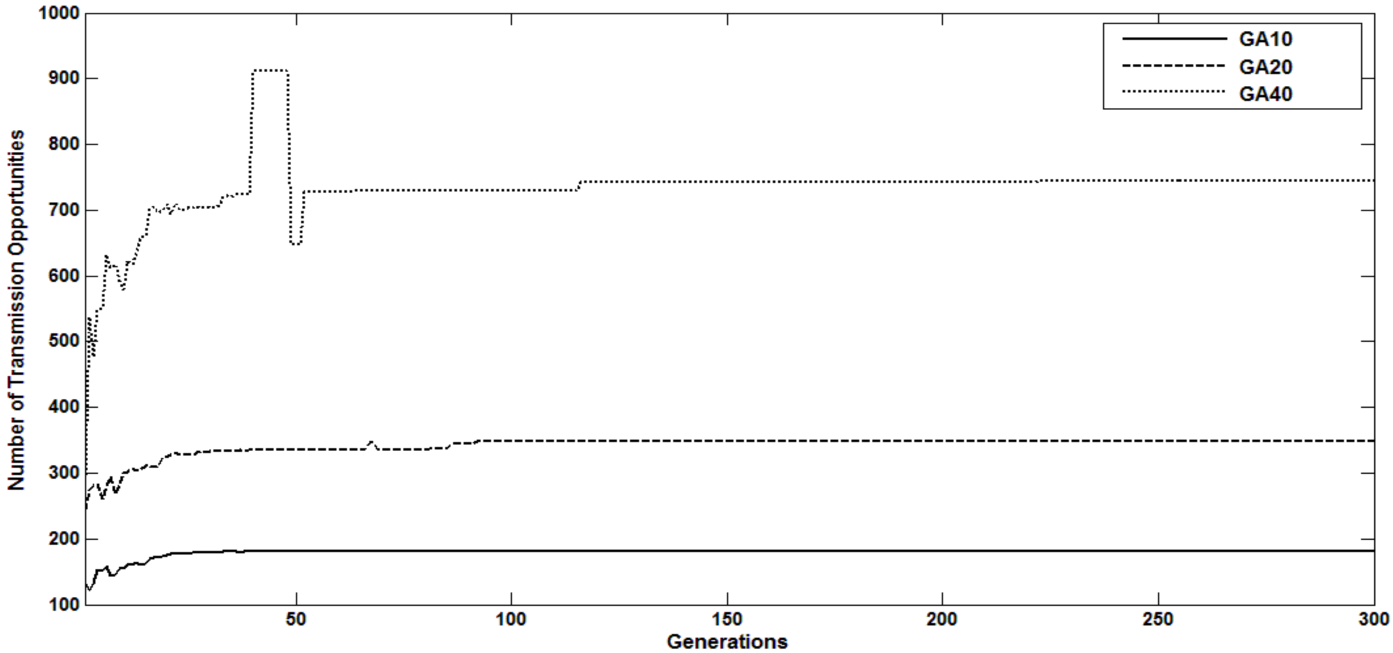

Figure 12. Evolution of the Number of Opportunities

Figure 13 shows the evolution of the interference time for the best individual of each generation for Channel 1. Note that there is a reduction of the interference time when the sensing overhead increases, as expected. For other channels, the GA versions behaved in a similar way as that shown for Channel 1.

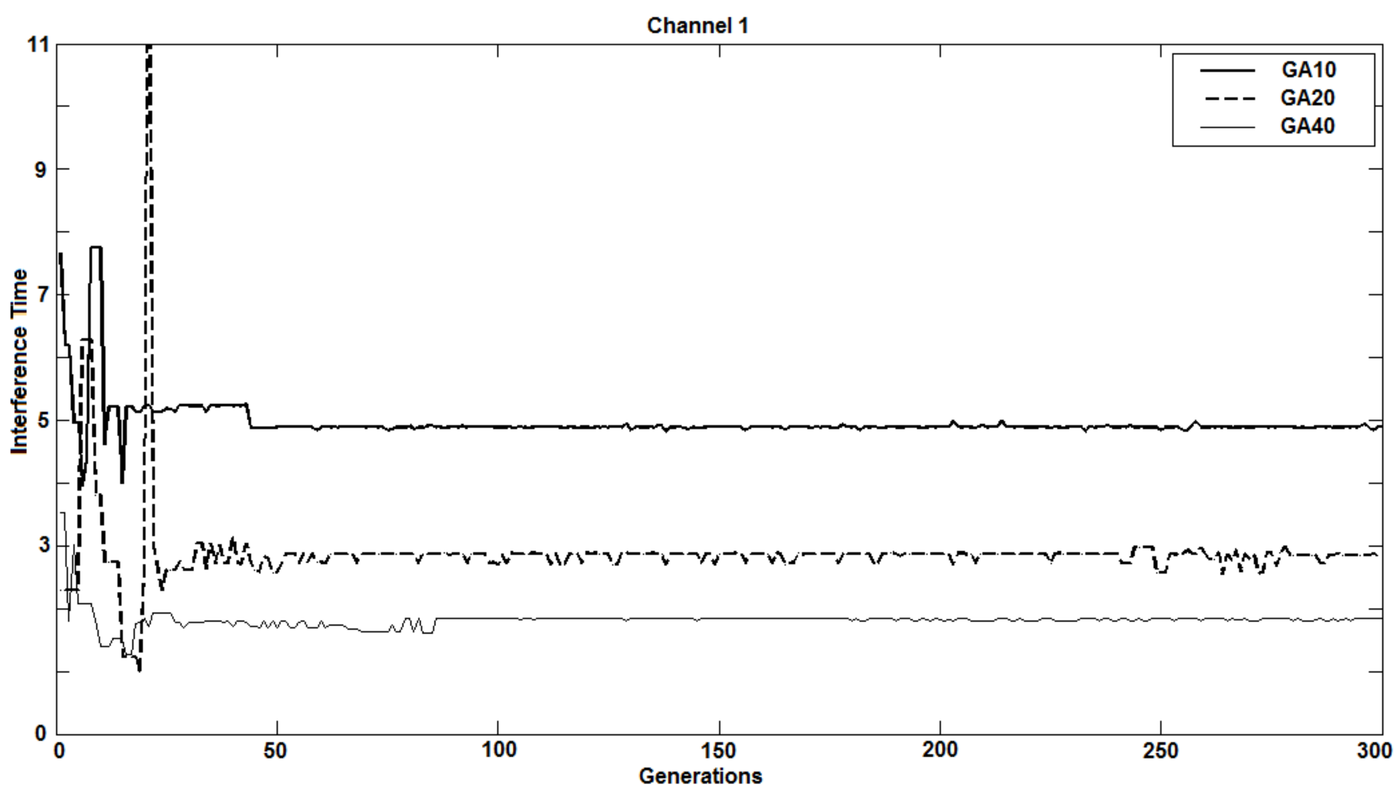

Figure 13. Evolution of the Interference Time

4.4. Evaluation of the schemes

This section draws a comparison between our GA scheme and those ones defined in Section 4.2.

Figure 14 shows the average number of discovered transmission opportunities achieved as a function of the number of channels. We note that the GA versions outperform both the fixed (Fixed 1 and Fixed 2) and Kim methods.

GA10 improves the discovered transmission opportunities, on average, by 21.54% and 28.07% for 3 and 9 channels, respectively, and has a similar sensing overhead to the Kim method. It should be noted that as the number of channels increases, e.g. to 9 channels, the number of discovered transmission opportunities also increases for GA20, which achieves 64.68% and 79.88% more opportunities than the adaptive and Fixed 1 methods, respectively. The best performance was obtained by GA40, which significantly enhanced the number of opportunities by 82.5% and 94.98%, compared with the Kim and Fixed 2 methods, when 9 channels are considered.

In addition, it can be observed in Figure 14 that the feasibility of regulating the upper limit of the sensing overhead is directly related to ability to detect the presence of the PU in the licensed channel and to discover communication opportunities for the SU. This is explained by the fact that the greater the sensing overhead, the more frequent will be the number of times the SU will sense the channel. Thus, in scenarios where there must be a minimum amount of interference, our scheme can adapt to a greater or smaller sensing overhead percentage to improve the monitoring of the channel and, hence, reduce interference to the PU.

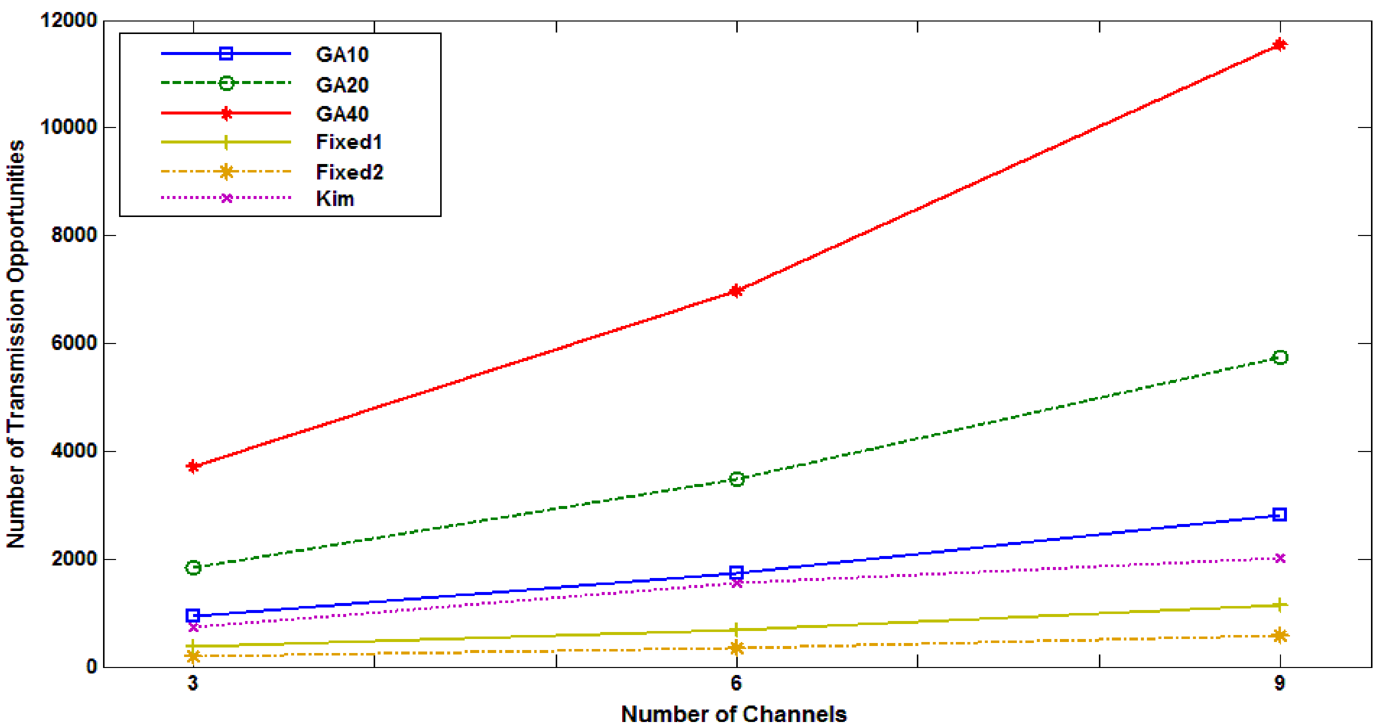

Figure 14. Average number of Discovered Opportunities

Figure 15 shows the results of the average sensing overhead obtained by the schemes. Note that the three GA versions (GA10, GA20 and GA40) attained the upper limit defined by the user. The GA10 obtained a similar sensing overhead to the Kim, with light increase when nine channels are considered. This increase in the sensing overhead led to an improvement of 28.07% in the number of found opportunities by GA 10.

The sensing overhead of GA20 scheme increased, when compared with both the Kim and Fixed1 ones, and achieved a growth rate of up to 52.07% and 74.2%, respectively, in simulation instances that use 9 channels. Hence, this behavior increased the number of opportunities to 64.68% and 79.88%, respectively.

GA40 obtained a greater sensing overhead (reaching 72.97% and 92.53%) for a simulation using 9 channels, than the Kim Method and Fixed2. However, it increased the number of discovered transmission opportunities by 82.5% and 94.98%.

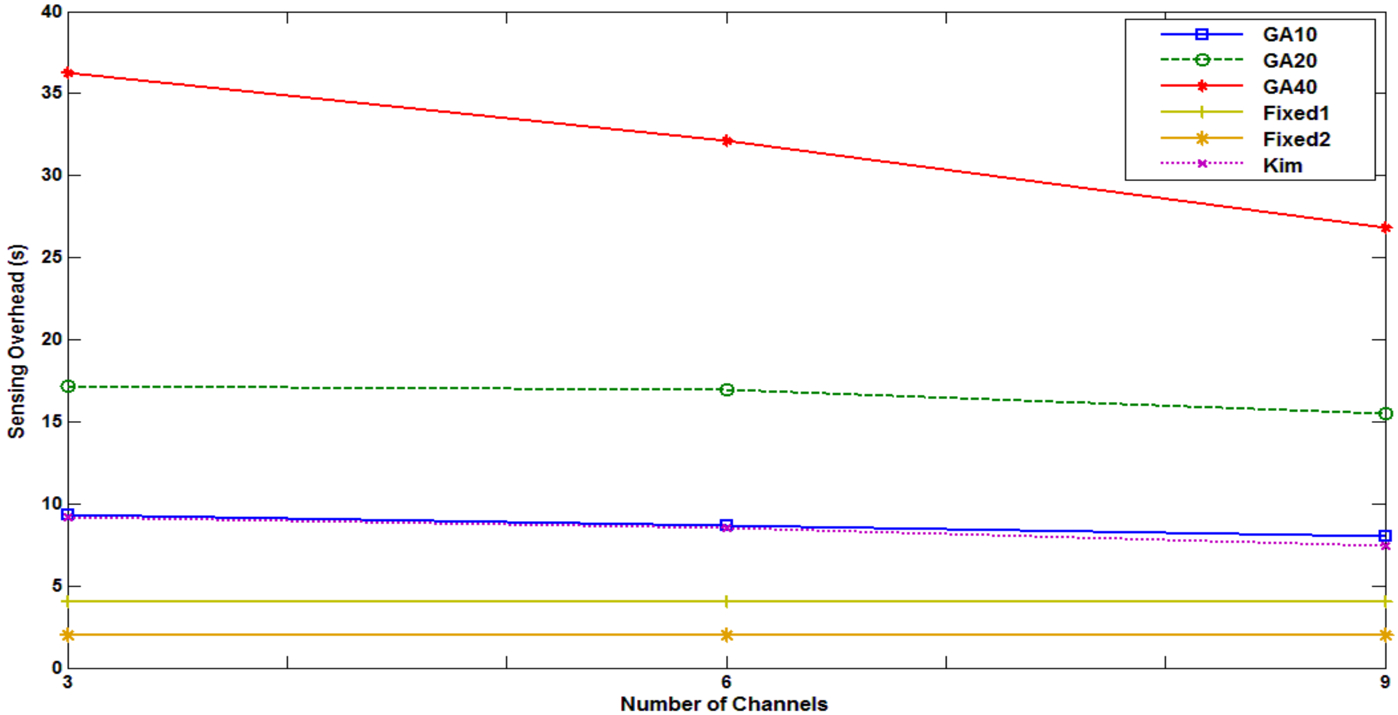

Figure 15. Average Sensing Overhead

Figure 16 shows the average values for the interference time obtained by all schemes. The GA versions achieved the best performance for all number of channels. The reduction of the interference time for GA10 was, on average, 8.34% and 26.9%, with respect to the Kim method in scenarios with 3 and 9 channels, respectively. By using the GA20 scheme, the reduction in the interference time was equal to 52.21% and 76.14%, when compared with the Kim and the Fixed1 scheme, respectively, in the instance of 9 channels. Finally, the GA40 achieved the smallest interference time of all the simulated cases. Particularly, with three channels, the GA40 made an improvement of approximately 64.49% and 66.83% in the interference time, when compared with the Kim method and Fixed2.

Moreover, the GA20 version was able to achieve a lower interference time than GA10 one, and the GA40 obtained a greater reduction than GA20. Thus, for all the channels the calculated interference time decreases with the increase of the sensing overhead. The flexibility in determination of the sensing overhead threshold enables that different protection levels to the PU can be adjusted according the interference level tolerable by PU communication

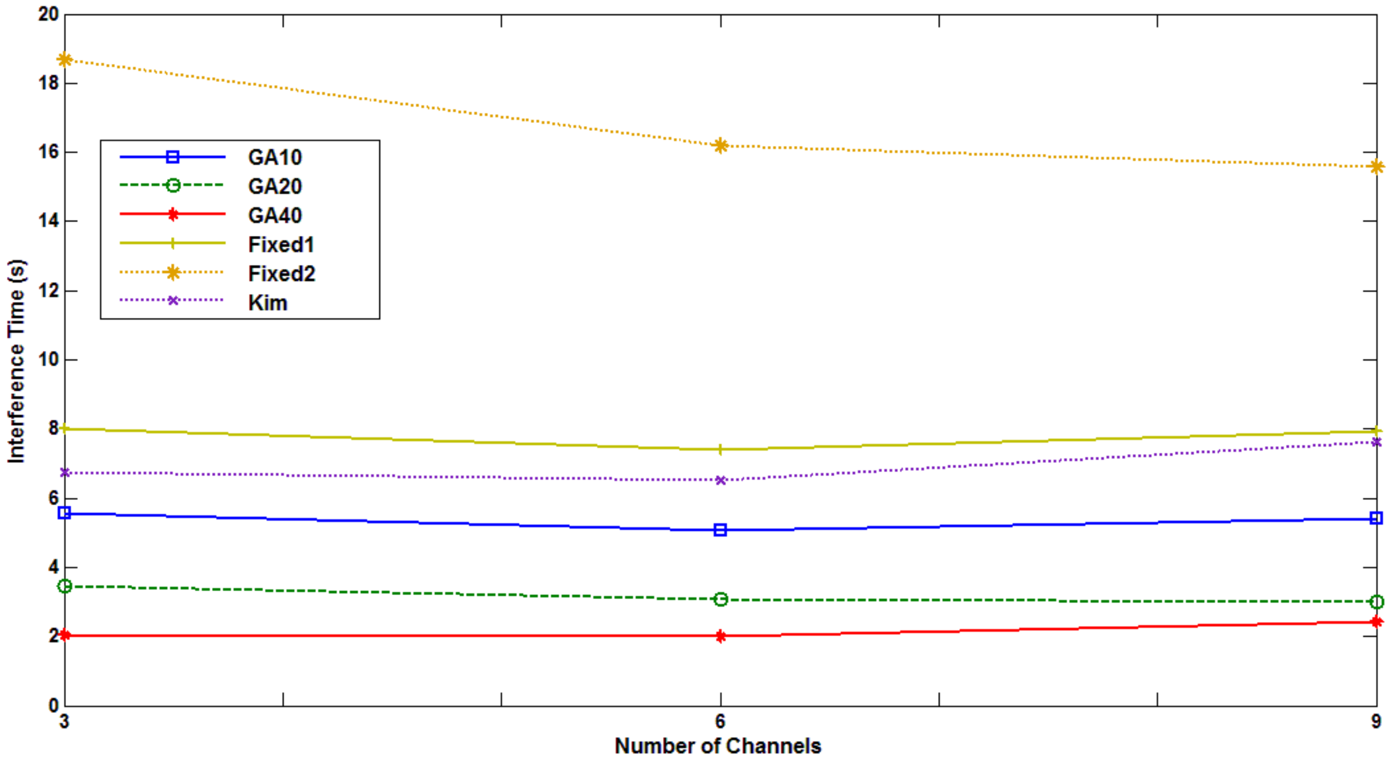

Figure 16 Interference Time

The superiority of our GA schemes when compared to the fixed ones is due to the sensing period to be adapted in accordance to the channel usage pattern. When compared to Kim approach, our strategy is based on an evolutionary process that uses sensing samples to obtain a good sensing period for the operation. At the same time, the Kim method adjusts the sensing period based on average channel behavior, which may not involve significant variations.

Furthermore, to determine the sensing periods, our scheme, through the overhead sensing threshold, indirectly considers the interference caused to the undetected PUs that resume an operation, which is overlooked in the related works. As our scheme enables the configuration of threshold for sensing overhead, it provides different levels of protection to PU communication and a good number of transmission opportunities for SU.

5. Discussion

From previous results, we note that our scheme outperformed the fixed and Kim ones in terms of number of discovered opportunities. Therefore, indirectly, the scheme based on GA can achieve better spectral utilization and provide higher throughput for SU. If we consider the use of channel aggregation techniques [19], these points become more evident, since if there are many discovered transmission opportunities(idle channels), they can be aggregated to support users high date rate services(e.g. video streaming).

In practical scenarios, there are various services using the licensed spectrum. These ones present different usage pattern (e.g. ON/OFF periods), time scales (e.g. hour, minutes and seconds), and signal characteristics (e.g. transmit power, bandwidth, transmit frequency). Then, they have different levels of tolerance to interference from other communications. Thus, this aspect must be considered to determine the sensing periods of the channels and to protect the PU communication. Our approach meets this requirement. It allows adjusting the sensing overhead threshold to reflect the level of protection desired. Moreover, despite the radio environment heterogeneity, our scheme is able to determine the sensing periods of the channels without any changes in its formulation, since it is not dependent of traffic models or stochastic assumptions.

In terms of deployment in network, our scheme can work both in centralized as decentralized architectures. In the first one, the base station (BS) or central server runs the optimization based on GA and sends the obtained sensing periods to the cognitive radio devices. In the second one, the processing overhead is distributed amongst the cognitive radio devices in a cooperative sensing way. Thus, each CR runs our scheme to obtain the sensing periods for a subset of channels and sends the results to the other cognitive radios.

6. Conclusions and Future Directions

We have shown that GA can significantly optimize the spectrum sensing period in CRNs. Our proposal outperforms non-optimized schemes by up to 90%. It also achieved similar or superior performance to Kim proposal, with the added advantage that it enables users to specify the permitted sensing overhead that can reflect the interference level tolerable by PU.

As our scheme enables users to specify the permitted sensing overhead, it can also be applicable in scenarios where there are different types of PUs with non-uniform levels of protection. It considers these different levels and finds the sensing period for each primary channel that meets the levels of protection required.

Moreover, different from previous studies, our work analyzed the amount of time that SU spends on spectrum sensing, which has significant impact on both number of discovered transmission opportunities and amount of interference caused to primary communication. Moreover, our scheme can be applied in scenarios with other traffic models, since it is not dependent of analytical or stochastic assumptions to its derivation, which is not true in others schemes in literature.

Future works include a study on the most adequate multi-objective GA approach to be used to optimize the scheduling of sensing periods. In this point, a comparative study of the main approaches presents in literature can be accomplished. In this study, both convergence metrics and cognitive radio metrics need to be take into account in the evaluation of the approaches.

In addition to the number of opportunities and overhead sensing, we intend to insert a new aspect in the sensing period problem, the energy consumption. As the cognitive radio is a device with limited battery, it is important to define sensing periods for channels that optimize energy consumption and provide a good performance in terms of throughput achieved by SU and protection to PU communication. Thus, as future work, we will formulate a new sensing period problem and we will seek energy efficient sensing periods to be used by SU.

Other future work involves energy efficient solution for sensing period and cooperative sensing in cognitive radio sensor networks. In the cooperative approach, the spectrum sensing is performed by various SUs, which exchange sensing information among themselves to determine the transmission opportunities, i.e. idle channels. Thus, the SU spends energy performing three main actions: spectrum sensing, exchanging sensing information and transmitting data. If all users perform spectrum sensing, the energy consumption is higher. As in in sensor networks, a great objective is maximizing the lifetime of the network. Therefore, it is important to define both an optimal sensing period for each channel as which channels will be sensed for which users in order to achieve a long network's lifetime, good throughput for SU and to provide protection to PU communication.

7. References

[1] A. Balieiro, P. Yoshioka, K. Dias, D. Cavalcanti, and C. Cordeiro, "Adaptive Spectrum Sensing for Cognitive Radio Based on Multi-Objective Genetic Optimisation,"IET Eletronics Letters, vol.49, nº.17, 2013

[2] Federal Communications Commission, "Spectrum policy task force report, FCC 02-155," Nov. 2002.

[3] I. F. Akyildiz, W. –Y. Lee, M. C. Vuran and S. Mohanty, “Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey”, Elsevier Computer Networks (50), 2006.

[4] T. Yucek. H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications”, IEEE Communications Surveys & Tutorials, vol. 11, no. 1, pp 116-130, 2009.

[5] Telcordia's TV Bands White Space Database. http://www.telcordia.com/services/interconnection/ white -spaces.html?sc_cid=whitespace_vanity

[6] Spectrum Bridge's White Space database. http://whitespaces.spectrumbridge.com/whitespaces/home.as px

[7] D.E. Goldberg. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, 1989.

[8] Si Chen et al. “Genetic algorithm-based optimization for cognitive radio networks,” IEEE Sarnoff Symposium, pp. 1-6, 2010.

[9] H. Kim and K. G. Shin, “Efficient Discovery of Spectrum Opportunities with MAC-Layer Sensing in Cognitive Radio Networks,” IEEE Transactions on mobile computing, vol . 7, no. 5, pp. 533-545, 2008.

[10] Yang L., Cao L., Zheng H. “Proactive channel access in dynamic spectrum networks”. Conference on Cognitive Radio Oriented Wireless Networks and Communications, 2007.

[11] K.K. Choi, “Adaptive sensing technique to maximize spectrum utilization in cognitive radio”, IEEE Transactions on Vehicular Technology, vol. 59, no. 2, pp. 992-998, 2010

[12] H. He, G. Y. Le and S. Li, “Adaptive Spectrum Sensing for Time-Varying Channels in Cognitive Radios”, IEEE Wireless Communications Letters, vol. 2, no. 2, 2013.

[13] J-K. Choi, S-J. Yoo, Optimal sensing interval considering per-primary transmission protection in cognitive radio networks”, International Conference on Ubiquitous and Future Networks, 2013.

[14] S. Li, P. Gong, Q. Yang, M. Li and L. Ma, “Optimal Spectrum Sensing Interval to Minimize the Transmission Delay for Cognitive Radio”, International Conference on Systems Engineering and Modeling, 2013.

[15] N. Baldo and M. Zorzi, “Learning and Adaptation in Cognitive Radio using Neural Networks”, 5th IEEE Consumer Communications a Networking Conference (CCNC 2008), pp. 998-1003, 2008.

[16] A. He, Kyung Kyoon Bae, T.R. Newman, J. Gaeddert, J.H.Reed, et. al., "A Survey of Artificial Intelligence for Cognitive Radios, IEEE Trans. on Vehicular Technology, vol.59, no.4, pp.1578-1592, May 2010.

[17] S. Chantaraskul and K. Moessner, “Implementation of a genetic algorithm-based decision making framework for opportunistic radio” IET Communications., 2010, Vol. 4, Iss. 5, pp. 495–506

[18] N. A. Saoucha, A. C. Lammari, K. Benatchba, “Real-Coded Genetic Algorithm Parameter Setting for Cognitive Radio Adaptation”, International Conference on Smart Communications in Network Technologies,2013.

[19] K. Arshad and K. Moessner. “Optimisation of Collaborative Spectrum Sensing with SIMO Cognitive Terminal using Genetic Algorithm”, 20th International Symposium on Personal, Indoor and Mobile Communications, 2009.

[20] J. Lee and J. So. “Analysis of Cognitive Radio Networks with Channel Aggregation”, IEEE Wireless Communications and Networking Conference, 2010.