Fair Power Control in Cooperative Systems Based on Evolutionary Techniques

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***Abstract*— Cognitive Radios have emerged as a promising paradigm for increasing spectrum utilization and alleviating the spectrum scarcity problem. However, the majority of works in the Cognitive Radio domain focus on the interaction between the primary and secondary users, while the efficiency and fairness of transmissions between secondary users are rarely explored. In this scope, we introduce an algorithm for fair transmissions in cooperative Cognitive Radio networks. The proposed scheme places particular emphasis on the QoS of underprivileged users, while maintaining a high overall network utility. Specifically, a Genetic Algorithm is designed and used to select transmission power values, under fairness constraints. The proposed algorithm is evaluated through extensive simulations. Results indicate significant improvement in the SINR of underprivileged users with minimal impact in the overall network utility.**

Keywords-component; cooperative power control; interference mitigation; fairness; genetic algorithm

I. INTRODUCTION

A plethora of novel communication technologies and wireless standards were developed during the last decade, in order to provide wireless users with enhanced Quality of Service (QoS). These novel telecommunication technologies coexist with legacy systems for extended periods of time. Furthermore, emerging wireless network environments are characterized by a growing need for spectrum, especially for high data rate applications. In this context, static frequency allocation schemes are considered too constrained for coping with the previous challenges. Actually, the paradox is that licensed spectrum use is not high, as mentioned by Defense Advanced Research Projects Agency (DARPA) in [1]. This leads to the observation that dynamic spectrum access techniques will play a catalytic role towards addressing the spectrum scarcity problem [2], [3]. A promising technology for efficient spectrum utilization is Opportunistic Spectrum Access (OSA) [4]. OSA introduces opportunistic reallocation of unused spectrum bands, also known as white spaces. Cognitive Radios (CRs) constitute a key enabler for OSA.

Cognitive Radios, first introduced by J. Mitola, are radio systems able to sense the unused spectrum and adapt their operating characteristics to the real-time environment [5]. In this direction, CRs should decide on the best spectrum band, over all available, in order to meet QoS requirements. A typical cognitive radio network comprises of secondary cognitive users trying to transmit in unused frequency bands. Their main objective is to communicate without causing interference to existing primary users. However, secondary users also compete with each other for resource allocation. In this scope, power control between secondary users is a particularly important aspect of the resource allocation problem, directly impacting the QoS, performance and energy efficiency of the wireless network.

In addition to high spectrum utilization, a key requirement for CR networks is that resource allocation should be fair and every cognitive user should have the opportunity to transmit. A comprehensive definition of “fairness” is difficult to be given, but it can be described intuitively as the ability to provide equal satisfaction to all users. Specifically for computer networks a formal performance parameter for fairness is given by the equation below [6]:

$$fairness = \frac{(throughput)^{\beta}}{\overline{delay}} \tag{1}$$

where β is a weight factor. The main obstacle in treating fairly each user is that fairness function is non-convex and may have several maxima. As a consequence, it is quite challenging to achieve the optimal throughput for every user in a network.

The throughput of each individual user, as well as various other aspects of the operation of a cognitive radio network [7] is largely dependent on the transmission power level (Tx). Therefore, a cognitive user is trying to choose an appropriately high transmission power value, targeting to keep the quality of the signal at the receiver at tolerable levels. However, if all cognitive users demonstrate selfish behavior and transmit using the maximum valid power, the outcome will be an increased interference among them and more importantly to the primary users. For these reasons, several cooperative algorithmic schemes were proposed for power control in cognitive wireless networks [8]. Such schemes mainly focus on optimizing the performance of the network as a whole, ignoring the characteristics and QoS requirements of each cognitive user. Under these assumptions, a typical phenomenon is that depending on their relative locations, a portion of cognitive users get high power values, in order to transmit, and the rest are assigned significantly lower ones, in order to mitigate interference and reach a steady state for the system. However, there is little point in maximizing overall network performance without taking into consideration the actual performance of each cognitive user. For this reason, there is a strong need for power control algorithms, which conform to the concept of fairness and provide increased opportunities for transmission to the underprivileged users.

A widely used resource allocation scheme in wireless networks is max-min fairness [9]. In this approach, wireless nodes try to achieve enhanced resource allocation starting from a minimum valid level, until all nodes are assigned

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resources fairly. An important drawback of max-min fairness scheme is the need for extensive message exchange among wireless nodes in order to be fully synchronized. Additionally, such schemes typically require a full knowledge model, which implies perfect message exchange, an assumption that is often not a realistic especially for cognitive radios operating under high uncertainty.

In this paper, a novel technique is proposed in order to enhance fairness properties in cooperative power control. The introduced approach is based on the distributed and cooperative power allocation scheme of [10] that is known to perform well under uncertainties. However, the original algorithm lacks fairness, as the power level of each cognitive user is not examined over time in order to reject consistently low level power values. The key contributions in the current paper are:

- The extension of the algorithm proposed in [10] with a fairness module that caters for underprivileged users. Specifically, a fairness check point is executed every time cognitive users calculate their power values to transmit. In this case, each cognitive user is examined i.e., if he was treated in an unfair way for a certain chronicle window in the past. If so, enhanced power values are generated by the evolutionary execution of Genetic Algorithm.
- The evaluation of the algorithm's behavior in cases of an incomplete knowledge model (i.e., some of the users may not know all the information). This is particularly important for real systems, since a full knowledge model is typically an unrealistic assumption.

The rest of the paper is organized as follows: Section II describes the baseline algorithm for cooperative power control. In Section III, fairness issues are discussed and a brief description of Genetic Algorithms is provided. Additionally, assumptions are formulated for the proposed fairness scheme. Furthermore, Section IV evaluates the performance of the proposed fairness scheme, comparing the Genetic Algorithm execution with a simplified fairness policy. Finally, in Section V, the key points of the proposed technique are summarized.

II. COOPERATIVE POWER CONTROL ALGORITHM

In this section, a description of the algorithm in [10] is provided, in order to set the basis for the proposed fairness scheme. The main scope of the algorithm is to mitigate interference among cognitive users in licensed exempt spectrum bands. For this reason, each transmitter computes its power by taking into consideration both its Signal to Interference plus Noise Ratio (SINR) and the interference it causes to the other users. This formula prevents users from always setting their power to the maximum valid power level.

Initially, a set of L pair nodes is considered operating at the same frequency band, where K channels are available. The SINR of the i-th transmitter ($i \in \{1, 2,.., L\}$) in k-th channel ($k \in \{1, 2, ..., K\}$) is calculated by the equation given below:

$$\gamma_i(p_i^k) = \frac{p_i^k \cdot h_{ii}}{n_o + \sum_{j \neq i} p_j^k \cdot h_{ji}} \quad (2)$$

where,

- p_i^k is the power of i-th transmitter on channel k
- h_{ii} is the link gain between i-th receiver and i-th transmitter
- n_0 is the ambient noise level (equals 10^{-2}) [11]
- p_j^k is the power for all other users on channel k, assuming that $j \in \{1,2,\ldots,L\}$ and $j \neq i$
- h_{ji} is the link gain between i-th transmitter and j-th receiver

A flat faded channel without shadowing effects is considered (this assumption is only required for proving that the algorithm will converge in a limited number of steps [10], [11]). Since the channel is static, the only identified attenuation is the path loss h (channel attenuation or channel gain). Given that indoor urban environments are considered, the channel gain is $h_{ji} = d_{ji}^{-3}$, where d is the distance between the j-th transmitter and the i-th receiver.

We adopt from the literature [11] the notion of interference price, which expresses the marginal loss of utility for receiver i if all the other users marginally increase their transmission power. The equation below computes the interference price for user i:

$$\pi_i^k = \frac{\partial u_i(\gamma_i(p_i^k))}{\partial(\sum_{i \neq i} p_j^k \cdot h_{ji})} \quad (3)$$

where,

- $u_i(\gamma_i(p_i^k)) = \theta_i \log(\gamma_i(p_i^k))$ is a logarithmic utility function
- θ_i is a user dependent parameter

As mentioned before, cognitive users select their transmission power value by taking into consideration their own utility and the degradation in utility of the other users. They compute the appropriate power value to transmit by maximizing the formula given below:

$$u_i(\gamma_i(p_i^k)) - \alpha \cdot p_i^k \sum_{j \neq i} \pi_j^k \cdot h_{ji} \quad (4)$$

The first part of the equation is closely related to the Shannon capacity of the channel, while the second part expresses the utility loss to other users if user i increases its power level. It should be noted that factor α is included as a weight in order to prevent underestimation of interference that user i will cause to the others. Underestimation is caused due to uncertainties in message exchange (i.e., message loss), large delays in the message exchange between users and users' mobility. The value of α ranges from 1 to 2. As a consequence, factor α compensates for the underestimation of interference, as the second part of the equation is increased.

The algorithm consists of three steps. The first is the initialization, where each user sets its power to a valid value (usually a minimum one) and calculates its interference price. The second step is the power update, where each user computes the appropriate power value in order to maximize the equation (4). The third step is the interference price update, where each user computes its interference price based on the updated power value from the second step. Finally, it announces its interference price to the other users. The second and the third step take place asynchronously for all users until a final steady state is reached. As a steady state, we define a state where no further enhancement in utility of any node pair can be achieved without negatively affecting the total network utility.

III. FAIRNESS POLICY BASED ON GENETIC ALGORITHMS

It is clear from the previous section and particularly from equation (4) that the original algorithm does not impose any lower bounds for the minimum power value a user chooses to transmit. Each user only attempts to balance the trade-off between utility optimization and interference mitigation. Furthermore, recalculating appropriate power values for L users is a multi-dimensional problem. In order to find the optimal power values, a search space of L-dimensions needs to be investigated. A simplified scheme would be to assign higher power values to underprivileged cognitive users, (for example the maximum allowed). However, this would lead to increased interference to other users and sharp degradation to the utility of the network. As a consequence, a trade-off between enhanced power value assignment and increased interference exists and the system can be tuned towards the desirable behavior using appropriate policies. Specifically, fairness policies are introduced to the cooperative power control algorithm, targeting to benefit cognitive users that are considered as underprivileged, without disregarding the needs of the other cognitive users. For example, choosing the maximum permitted power value for the underprivileged users is not an attractive option, as the rest of the users will face a significant increment of interference that will lead to QoS degradation.

In general, policies can be used to formalize the concept of decision making, especially when closed loop optimization is concerned. Typically, policies are comprised by constraint rules, which represent the set of limitations (i.e., memory size or battery level) and action rules, which specify procedures to be executed when certain conditions are met (e.g., [12], [13]). Such rules can be incorporated in machine learning schemes (such as Genetic Algorithms, Neural Networks, etc.) in order to enhance the flexibility and performance of the system. In this work, Genetic Algorithms (GAs) are utilized as a function optimization technique since they are known to perform well in problems with multidimensional and large search space.

Genetic Algorithms (GAs), first introduced by John Holland in [14], belong to the overall category of Evolutionary Computing techniques (EC). Typically, a candidate solution is structured as a string and is referred to as chromosome. A chromosome consists of a series of genes, in accordance to the dimensions of the search problem. It is usual to represent chromosomes as binary strings, but other encodings are also permissible. GAs use the principles of evolution and natural selection to optimize an initial set of chromosomes in order to reach a final optimal solution.

The execution of GAs starts from a set of chromosomes, constituting the initial population. A series of crossovers and mutations on the initial population produces offsprings that are incorporated to the population. Afterwards, based on a fitness function each chromosome of the population is being evaluated. Finally, a subset of the population will proceed to next generation based on a selection scheme. The procedures of mutation, crossover and selection are repeated iteratively until a termination criterion is satisfied. Terminal condition of a GA could be a fixed number of generations, an optimal threshold value for the fitness function, or a minimum deviation between the best chromosomes of two consecutive generations. Figure 1 depicts the steps of a GA.

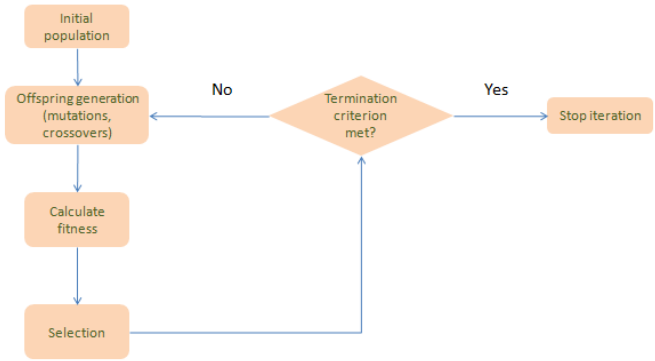

Figure 1. Flowchart of genetic algorithm

The main advantage of a GA is its capability to perform global search and, thus, converge efficiently to a near optimal solution [15]. This is due to the deviant nature of the candidate solutions that start from different points in the search space, in contrast to other heuristic methods that follow single candidate solution approach. Mutations and crossovers ensure production of different chromosomes (i.e., different candidate solutions to the search problem) during the generation process. Also, the ability of manipulating different chromosomes simultaneously makes GAs quick and robust. The main disadvantage of GAs is that for a high dimensional search space, it is complex to model the problem; however, this is not a major concern for the considered case, because the number of unprivileged users is a small percentage of the total number of users and therefore, exploring the search space is computationally feasible in an acceptable timeframe.

In our approach, a gene is a power value of a secondary cognitive user. Thus, a chromosome includes the power values of all the secondary cognitive users. The key point in GA execution is the evolutionary modification of the power values of the underprivileged users to more fair ones. Thus, appropriate assumptions and modifications were conducted for the phases of mutation, crossover and selection. In case of mutations, only genes, which correspond to underprivileged power values are mutated (i.e., increased). This modification is inline with the requirement for keeping cognitive users, which are not considered underprivileged, unaffected. Furthermore, the crossover procedure is designed to be simple. Thus, a single crossover point is selected randomly (the selection scheme followed in our approach is roulette wheel mechanism). Based on this scheme, the chromosome with the best fitness value passes to the next generation and following that, fitness values of the remaining chromosomes correspond to bounds between [0,1]. A random number on the same

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bounds determines which chromosome will follow the best chromosome to the next generation. The fitness function captures the trade-off between the increment of underprivileged users' Tx power and the increment of interference that will cause to the rest users and is computed for every chromosome. The proposed fitness function is given by the following equation:

$$\frac{\dfrac{\overline{Power_u}}{\overline{Interference}} - \dfrac{\overline{Power_u^0}}{\overline{Interference^0}}}{P_{max} - P_{min}} \quad (5)$$

where,

- $\overline{Power_u}$ is the mean power of underprivileged users
- $\overline{Power_u^0}$ is the initial mean power of underprivileged users
- $\overline{Interference}$ is the current mean interference price
- $\overline{Interference^0}$ is the initial mean interference price
- P_{max} and P_{min} are the boundaries of users' Tx power

Finally, as mentioned before, GA is iterative and stops when a terminal criterion is met. In our approach termination criterion is considered to be the state where no significant enhancement is achieved between two consecutive generations.

IV. PERFORMANCE EVALUTATION

The performance of the proposed algorithm is evaluated through extensive MATLAB simulations. Towards this direction, our GA approach is compared to a scheme of fixed power value assignment (maximum valid power level). The main objective is to give "fairer" power values to the underprivileged cognitive users. This concludes to a more "fair" treatment, but incurs loss in system performance, as principles of the power control algorithm are violated. The major difference between the two proposed techniques is that in case of GA, underprivileged users get better power values, but not the maximum ones due to the negative impact of interference in the fitness function.

The proposed implementation examines a commonly used environment of 10 LTE mobile cognitive users (CUs) (e.g., [16], [17]) cooperating in order to transmit with an acceptable power value. The power range is between 10 and 23 dBm and the distances between the cognitive users is a random number in the [50, 550] meters range [18]. The users set their transmission power levels to maximize equation (4) until the algorithm converges to a steady state for a given topology. The whole procedure lasts for 10 topologies (i.e., steps) that reflect the mobility of the users in consecutive time frames. For every successive step, the fairness policy mechanism is called, in order to examine if underprivileged users exist. If so the GA algorithm is activated, so as to enforce fairness. In order to identify if a cognitive user is underprivileged, previous Tx powers are examined for a certain time window in the past. The size of the window is considered to be 3. Consequently, our fairness policy examines the current step and the previous 3 to detect underprivileged users.

Figure 2 illustrates 10 steps where each cognitive user (CU) chooses to transmit with a certain power value (in dBm) based on the original algorithm in [10]. On the first step, the average power value is 13.719 dBm, which is also the general upper bound for the "unfair" power values. For the simplified fixed power value schema (FX), maximum power values will be assigned to the underprivileged users. In such cases, an arbitrary increase in Tx power value of a CU usually results to a non cooperative state, where all CUs are negatively affected. Alternatively, fairness policy is called in every step and is enforced only in the fourth and eighth steps for the CUs 1, 9, 10 and CUs 9, 10 respectively. The initial power values for the fourth step will be re-calculated in case of GA. The same situation occurs in the eighth step as well. Both in case of GA or in case of fixed power values, the privileged users are not affected directly (i.e., by decreasing their transmission power).

	CU 1	CU 2	CU 3	CU 4	CU 5	CU 6	CU 7	CU 8	CU 9	CU 10
1.	13.055	14.765	14.700	14.095	14.069	14.700	14.674	14.102	13.029	10.007
2.	13.282	15.018	14.953	14.336	14.316	14.953	14.927	14.342	13.256	10.007
3.	12.802	14.472	14.407	13.816	13.796	14.407	14.387	13.822	12.776	10.007
4.	12.555	14.199	14.134	13.556	13.536	14.134	14.108	13.556	12.535	10.007
GA	**14.550**	14.199	14.134	13.556	13.536	14.134	14.108	13.556	**14.707**	**14.305**
FX	**23.000**	14.199	14.134	13.556	13.536	14.134	14.108	13.556	**23.000**	**23.000**
5.	12.795	14.465	14.401	13.809	13.790	14.401	14.374	13.816	12.769	10.007
6.	13.230	14.959	14.888	14.277	14.258	14.888	14.862	14.284	13.204	10.007
7.	13.471	15.226	15.161	14.537	14.518	15.161	15.135	14.544	13.438	10.007
8.	13.724	15.519	15.447	14.810	14.791	15.447	15.421	14.817	13.698	10.007
GA	13.724	15.519	15.447	14.810	14.791	15.447	15.421	14.817	**15.527**	**14.155**
FX	13.724	15.519	15.447	14.810	14.791	15.447	15.421	14.817	**23.000**	**23.000**
9.	13.484	15.239	15.174	14.550	14.531	15.174	15.148	14.557	13.451	10.007
10.	13.042	14.745	14.680	14.076	14.056	14.680	14.654	14.082	13.016	10.007

Figure 2. Converged power values for 10 cognitive users

Figure 3 illustrates the average Tx power values of the CUs for each of the 10 topologies. As can be seen again, the fairness policy is enforced in the fourth and eighth topology.

The purpose of a fairness scheme is to support the underprivileged users and minimize the negative impact to the network. Indeed, in the proposed scheme the underprivileged users get enhanced power values; however, this is done in a planned way, so that the impact in the overall performance of the network is limited (marginal reduction of the average network SINR by approximately 0.3 dB). This is a reasonable trade-off for enhancing the overall fairness, especially considering that the SINR of the underprivileged users and the related QoS is increased.

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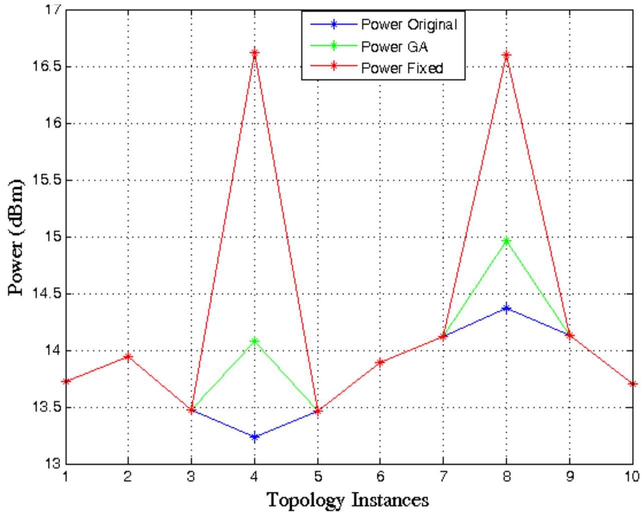

Figure 3. Average power values for 10 topologies

Figure 4 illustrates SINR values for the 10th CU in topologies where fairness was enforced. Specifically, concentrating on the underprivileged CUs 9 and 10, enhanced Tx power levels are calculated. This increase leads also to enhanced SINR at the receiver.

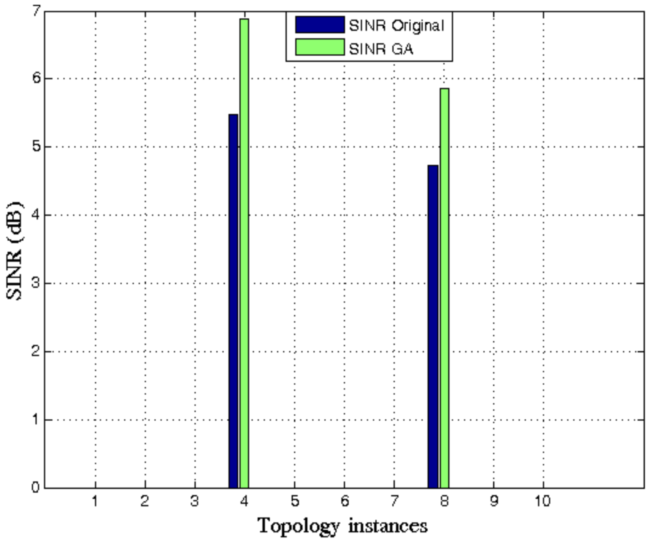

Figure 4. SINR improvement for underprivileged users

Since equation (4) strikes the optimal balance from a system utilization perspective between the selfish need for transmission at the highest level and the social conformance of reducing the interference to other neighboring users, altering the Tx Power to the constantly underprivileged users will also have a negative impact to the rest of the users in the environment. Figure 5 shows a comparative analysis of the average SINR gains of the underprivileged users against the average SINR degradation that the other users will experience.

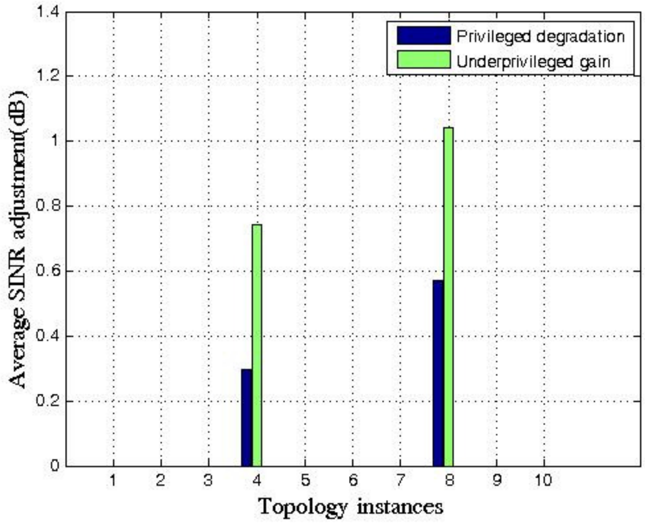

Figure 5. Fairness SINR gains against SINR degradation

As mentioned previously, many fairness schemes are challenging in their application to real world systems due to the full knowledge requirement and the stringent synchronization constraints among the wireless nodes that this requirement imposes. In our case the genetic algorithm can operate efficiently with a significantly relaxed knowledge model and synchronization scheme. For our evaluation of this highly desirable property we have conducted 1000 experiments assuming the same environment as before; the fundamental difference is that the system suffers a 10-20% message loss, thus leading to undesired effects for the nodes, as they will not have a complete knowledge of the environment. Figure 6 shows that in cases of an incomplete knowledge model the GA is triggered again exactly 2 times (as in the case with full knowledge) with probability equal to 42%. The results also show that cases of not triggering the GA when needed (false negatives) are not possible, but there are some false positive cases where the algorithm is triggered more times than actually needed.

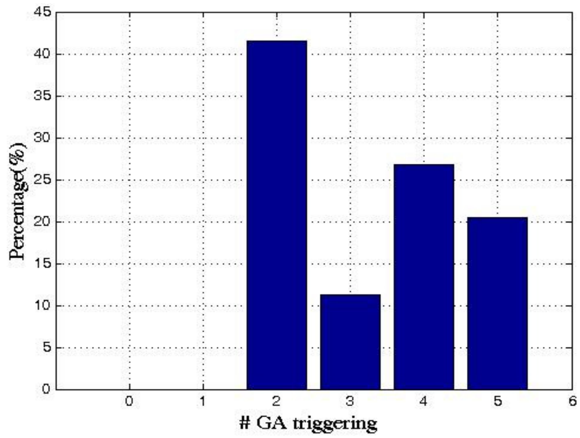

Figure 6. GA behavior in cases of an incomplete knowledge model

However, these false positives do not influence the efficiency of the algorithm as even in that cases the SINR of the users is only marginally affected. Figure 7 shows a characteristic example where the GA was triggered four times.

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As it is shown, only on topologies 4 and 8 the SINR of the underprivileged users was adjusted while on other cases the algorithm did not change the transmission power of the users.

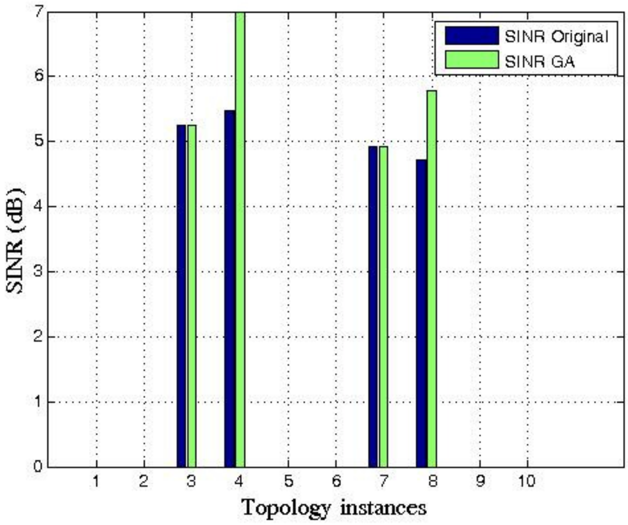

Figure 7. SINR improvement for underprivileged users in a false positive case

V. CONCLUSION

A novel technique for enforcing a fairness policy in cooperative power control for cognitive radio networks was presented. The proposed scheme extends the cooperative power control algorithm of [10] with a fairness check module. The power level values, which are assigned to the underprivileged cognitive users, are calculated through the evolutionary execution of a Genetic Algorithm. GAs were selected as a heuristic able to search multidimensional search spaces. The outcome of the GA algorithm was compared both with the original cooperative power control scheme and with a simplified fairness scheme. The results indicate that increased power values were assigned to the underprivileged users, considering also the negative impact in power gain of the network. Specifically, simulations show significantly improved SINR for the underprivileged users compared to the original algorithm with minimal impact in the SINR of the privileged users. Furthermore, in comparison to the case of a simplified fairness policy, which assigns underprivileged cognitive users with the maximum valid power level, the proposed scheme offers considerable power gains to the network. Finally, we have shown that the proposed algorithm can operate efficiently even in cases of partial knowledge models and imperfect message exchange/synchronization between the nodes, a property that is highly desirable for application in real world systems.

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