Energy Efficient Techniques for Resource Allocation in Cognitive Networks

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Abstract

The Cognitive Radio paradigm is aimed to optimize the utilization of licensed spectrum bands thanks to coexistence within the same network of licensed (primary) and cognitive (secondary) users. In this context, one of the most important key aspects is represented by an efficient resource allocation between secondary and primary users. Modeling it as an optimization problem, this paper provides a modified version of the well-known Iterated Water-Filling algorithm and a novel approach based on a game theory framework to solve this issue in a distributed and fair way. In particular, the proposed game is formulated as an S-Modular Game, since it provides useful tools for the definition of multi objective distributed algorithms in the context of radio communications. This paper provides also a performance comparison among the proposed solutions and the Simulated Annealing algorithm, that represents one of the most frequently used technique in this context.

Keywords: cognitive radio, resource allocation, game theory, energy efficiency.

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1 Introduction

The radio spectrum efficiency represents nowadays a significant problem, due to the fast development of a large number of radio technologies in the last decade. Recent spectrum analysis points out that a large number of assigned spectrum bands are underutilized in either time domain or spatial domain [1]. In this context, Cognitive Radio (CR) [2] offers a smart paradigm aimed to optimize the utilization of the radio resource, allowing cognitive users to share the spectrum bands with licensed users. One of the most relevant open issues is represented by the identification of efficient methods to distribute and manage radio resources. In particular, taking into account the power consumption problem, the definition of energy efficient power allocation strategies could represent a key feature in designing cognitive networks.

In order to increase frequency utilization efficiency, in a cognitive radio network a dynamic spectrum access (DSA) [3] has been used. In particular, the term DSA covers several approaches to spectrum access that can be distinguished in three different models, on the basis of the categorization made by DYSPAN group in [4]: dynamic exclusive use model, open sharing model, hierarchical access model. In our approach we adopt a hierarchical spectrum access structure, identifying two kind of users: primary and secondary users. The licensed spectrum is assigned to the primary users (owners of the spectrum rights), while secondary (unlicensed) users can access spectrum following the *underlay approach*, transmitting below the noise floor of primary users. Thus, a transmitting secondary user represent an interference source both for primary and the other secondary users.

On the basis of the underlay approach, we refer to a cognitive radio network wherein secondary users are cognitive users, since they are intelligent and interact with selfish network users. Contrary to secondary users, primary users may be unaware of the presence of secondary users, even though they coexist within the same network and sharing the same frequency bands. Due to the necessity of frequent spectrum sensing and transmissions, secondary users may have strictly energy constraints, especially if they are battery powered in order to satisfy mobility requirements. A feasible strategy to reduce energy consumption is represented by the implementation of energy efficient techniques of power allocation.

In this scenario, a game theoretic framework allows us to study, model and analyze cognitive radio networks in a distributed way. Such an attractive feature allows us to achieve the flexibility and the efficient adaptation to the operative environment that were previously mentioned.

The paper is organized as follows: in Section 2 an overview on the application of game-theoretic approaches to spectrum sharing scenarios is illustrated, while in Section 3 the proposed system model and applicative scenario are presented. The game description and the Nash Equilibrium existence and uniqueness is discussed in Section 5, while in Section 4 the Water-Filling algorithm and a energy efficient modified version is reported. In Section 6 the results from computer simulation are commented. Finally some conclusions are expressed in Section 7.

2 Game Theory for Cognitive Radio

Due to the players' behavior, non-cooperative game theory is closely connected to mini/max optimization and typically results in the study of various equilibria, most notably the Nash equilibrium [5]. Developed cognitive radio strategy has been formulated according the mathematical discipline of Game Theory, with particular reference to S-Modular Games [6].

Non-cooperative games have been proposed for spectrum sharing in [7], which reports a detailed survey on game theoretic approaches for dynamic spectrum sharing in cognitive radio networks, by in-depth theoretic analysis and an overview of the most recent practical implementations. In [8], the authors investigate the issue about the spectrum sharing between a decentralized cognitive network and a primary system, comparing a suboptimal distributed non-cooperative game with the optimal solution power control algorithm and the method proposed in [9]. Apart from in the above-mentioned papers, the power control problem in spectrum sharing model is also discussed in [10, 11].

In [12, 13] the authors proposed different game-theoretic approaches to maximize energy efficiency of the users within wireless networks, making the utility functions being inversely proportional to the transmit power. Extending the above described results, this paper provides a distributed game-theoretic approach to obtain an energy efficient power allocation method that maximize the Signal to Interference-plus-Noise Ratio (SINR) level received by each user, taking into account throughput fairness among secondary users.

3 System Model

The proposed power allocation techniques refer to a cognitive radio context where a primary system (owner of the spectrum rights) coexisting with one

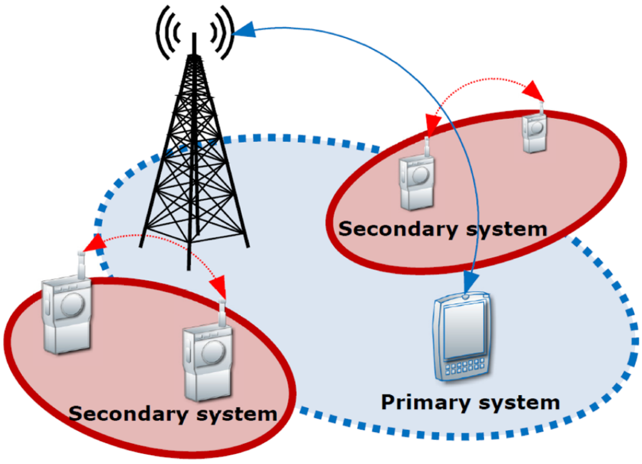

Figure 1 Example of coexistence between primary and secondary users.

or more secondary systems and sharing the same frequency band, as shown in Figure 1. Note that, considering a primary system in the network, the proposed scheme includes the possibility of existence of more than one primary user. Each secondary user is characterized by a dedicated sender and receiver, since each communicating couple consists of a transmitter site TX_i and a receiver site RX_i. Within each secondary transmission couple, we denote a *transmitter* and a *receiver* in order to identify the transmission course, however both the transmitter and receiver are assumed having a complete radio-frequency front-end and, therefore, both transmitter and receiver are able to transmit and receive data.

The system model uses a discrete-time model, based on iterations (which we ahead refer as t). Indeed, for every single iteration, all users act only once and until the next iteration they cannot do anything else. Each iteration represents a status update of the system; the real-time span modeled by each iteration will depend on the definition of the MAC layer.

By definition, primary users should not undergo a degradation of the required Quality of Service (QoS) due to the sharing of the same frequency band with secondary users. For this reason, a constraint on maximum transmission power level for secondary users must exist. This limitation can be obtained introducing the “Interference Cap” [14]; this parameter represents the total interference that the primary system willing to tolerate in order to not undergo a degradation of the required QoS. In case of cooperation existence between primary and secondary users, the Interference Cap can be send directly from primary users to secondary users on a shared channel. Otherwise, when primary users may be unaware of the presence of secondary users, in the proposed system there cannot be a cooperation among primary and secondary users; thus the Interference Cap will be fixed a priori, i.e. equal to noise floor of primary user. The presence of a chosen interference cap represents an upper bound of the total transmit power of the secondary users on the shared channel.

Each secondary user will choose the more suitable transmission power in order to achieve the best transmission quality, ensuring low interference to other secondary users. For simplicity of exposition, we will consider a fixed primary interference cap and therefore a fixed maximum transmission power for the secondary users; this assumption can be made without altering the validity of the system, since variations of this value are relatively slow compared with the time of convergence of the algorithm. In case of wireless networks with high primary mobility and/or more strict delay needs, a delay efficient approach should be followed, see [15].

4 Energy Efficient Iterative Water-Filling Algorithm

Among power allocation methods, actually Water-Filling [16] is one of the most frequently used algorithm. This algorithm bases on the idea that a vase can be filled by a quantity of water equal to the empty volume of the vase. It is well-known in the literature that a channel can be filled by an amount of power depending on the existing noise level. In order to maximize data-rate, power allocation in a multiuser scenario can follow the water filling principle. Due to the frequency band sharing, the increase of number of secondary users in the network equals to an increase of interference. Indeed for increasing number of users, secondary users experience higher levels of interference.

The Iterative Water Filling (IWF) algorithm is obtained basing on the above previous considerations; iteratively, each user calculates its transmission power level P_i^t following the water-filling principle until an equilibrium is reached. The equilibrium state is reached when the algorithm returns the same power allocation set for n consecutive times. The transmission power level is calculated as follows:

$$P_i{}^{(t)} = \max\left\{0, \left(P_{\max}{}^{(t)} - \frac{P_i^{(t)} g_{ii}}{\gamma_i^{(t)}}\right)\right\}, \quad i = 1, \ldots, N \tag{1}$$

where $P_i^{(t)}$ is the power level assigned at the user i in the iteration t, $P_{\max}$ is maximum power that can be transmitted in the channel (the *water level*) and g_{ii} is the channel gain between transmitter TX_i and receiver RX_i. The factors $\gamma_i^{(t)}$ is the SINR at the receiver side at step t and it is calculated as follows:

$$\gamma_i^{(t)} = \frac{g_{ii} P_i^{(t)}}{\sum_{k \neq i} g_{ik} P_k^{(t-1)} + \sigma^2} \tag{2}$$

where σ^2 is the power level of noise. If

$$\frac{P_i^{(t)} g_{ii}}{\gamma_i(t)} > P_{\max}$$

the interference plus noise value is higher than maximum power that can be transmitted in the channel, then $P_i^{(t)} = 0$ is assigned to the user i.

Running IWF algorithm for low interference environments and/or limited number of users, we obtain good performance in terms of SINR received by secondary users. However for increasing values of interference, the algorithm get worst; indeed, users experiencing the best channel conditions will transmit at high power levels, while users experiencing bad channel conditions will receive high interference values and then they will be inactivated (i.e. when a receiver is close to another transmitter). For this reason, IWF can be considered to be unfair.

As it is, IWF is an energy inefficient algorithm, since it bases on the maximization of the total transmission power of each user in order to obtain the best SINR level. However, for a fixed target data-rate, we can identify a minimum target value for the SINR. In Figure 2 the SINR trends are reported for increasing values of the maximum transmission power for a different number of users. Taking into account such SINR trends, we propose the following energy efficient modified version of the algorithm, called Energy Efficient Iterative Water-Filling (EEIWF). It allows us to maintain the fixed data-rate, using the lowest total transmission power level. Each user updates $P_{\max}$ every iteration as follows:

$$P_{\max}^{(t)} = \begin{cases} \frac{P_{\max}^{(t-1)}}{k}, & \gamma^{(t)} \geq \gamma^{(t-1)} \\ P_{\max}^{(t-1)}, & \gamma^{(t)} < \gamma^{(t-1)} \end{cases} \tag{3}$$

where $k > 1$ represents the reduction factor and it controls the convergence speed of the algorithm. Note that for $k = 2$ the algorithm becomes the bisection method.

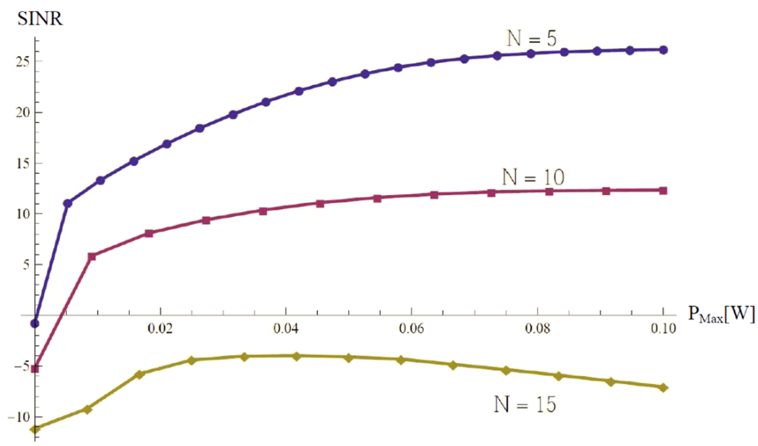

Figure 2 SINR trends for increasing values of maximum transmission power for different number of users.

The criterion expressed in (3) is enforced by observing that, running IWF, the SINR trend for increasing values of $P_{\max}$ is in the best case a monotonous increasing function and in the worst case a function with a maximum. The case of a monotonous decreasing function is not admitted by IWF. A continuous decreasing SINR when $P_{\max}$ increases means that an user experiments bad channel conditions: in this case user is inactivated.

EEIWF achieves the same SINR levels of IWF algorithm, allocating to secondary users an average transmission power level that is half of the one allocated by IWF; in Figure 3 are reported the average transmission power levels per user allocated by the two algorithm.

5 The Energy Efficient Fair Game

5.1 Game description

In this paper we propose a non-cooperative game with N secondary users, namely the players of the game, operating on one radio resource. This game can be easily extended considering a larger number of radio resources M (i.e. subcarriers of the same multi-carrier channel or different channels) following the approach proposed in [17], where subcarrier allocation is based on the normalized channel gain. Formally, the proposed non-cooperative game can be modeled as follows:

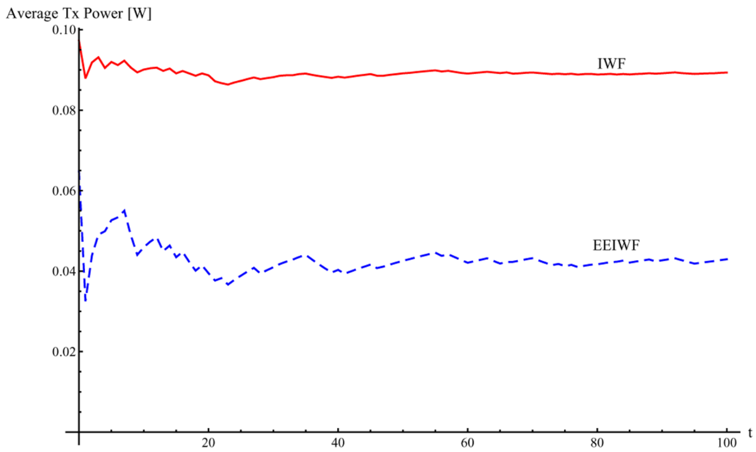

Figure 3 Average transmission power per user (Montecarlo simulation)

- Players: $\mathbf{N} = \{1, 2, 3, \ldots, N\}$ where $i \in \mathbf{N}$ is the i-th secondary user.
- Strategies: $\mathbf{S} = \{P_{\min}, \ldots, P_{\max}\}$.
- Utility Function: $u_i\ (p)$ where $i \in \mathbf{N}$ is the i-th secondary user and $p \in \mathbf{S}$ is the complete set of strategies.

We take into account the energy efficiency problem at the physical layer, considering an utility function expressed in bit/Joule as performance measure of the model [12, 18]. During the game each player tries to maximize the following utility function:

$$u_i\ (p(t), p(t-1)) = W \frac{R_i f(\gamma_i)}{p_i(t)} - \Omega_i(p(t), p(t-1))p_i(t) \tag{4}$$

where p is the complete set of strategies of all secondary users, W is the ratio between the number of information bits per packet and the number of bits per packet, R_i is the transmission rate of the ith user in bits/s, $f(\gamma_i)$ is the efficiency function (depending on the considered modulation), that represents a stochastic modeling of the number of bits that are successfully received for each unit of energy drained from the battery for the transmission, γ_i is the instantaneous SINR. Since the SINR depends on the path gains, each secondary user need to know them. In order to solve this problem that could have a strong impact on the signaling process, we assume that each receiver periodically send out a beacon, thanks to which transmitters can measure path gains. This procedure is feasible since both the transmitter and receiver are able to transmit and receive data, as presented before in Section 3. The period

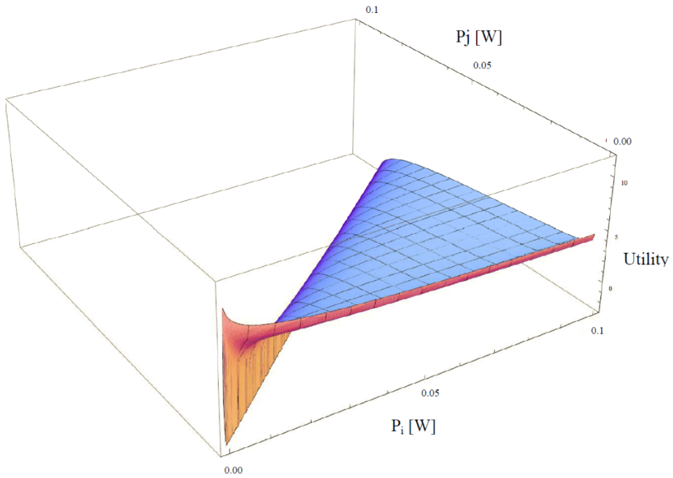

Figure 4 Trend of utility function (on z-axis) depending on transmission power levels (on x and y axes) for a two-player game; for each user in every single iteration the utility function have a maximum.

of beacon transmission should be chosen on the base of the coherence time of the channel.

In order to make the Nash Equilibrium of the game as efficient as possible (moving it closer to the Pareto Optimum), we consider the adaptive pricing function $\Omega_i(p_{i,-i})$ that generates pricing values basing on the interference generated by network users. Thus, the greater is the interference generated by a user transmitting at high power level, the greater will the value of pricing it will be pay, due to the fact that $\Omega(p)$ is strictly increasing with p.

The pricing function is written as follows [18]:

$$\Omega_i(p(t-1)) = \beta - \delta \exp\left(-\mu \frac{p_i(t-1)\sum_{i=1,k\neq i}^{N} g_{k,i}}{I_i^r(p_{-i}(t-1), P)}\right) \tag{5}$$

where p is the complete set of strategies of all secondary users, P is the power transmitted by the primary user and g_{ii} is the channel gain between transmitter TX_i and receiver RX_i. The term $I_i^r(p_{-i}(t-1), P)$ represents the total interference received by the ith user and it can be wrote as

$$I_i^r(p_{-i}(t-1), P) = \sum_{k\neq i} g_{k,i}\, p_k(t-1) + \sigma^2 + g_{12,i} P \tag{6}$$

Moreover, the pricing function bases on:

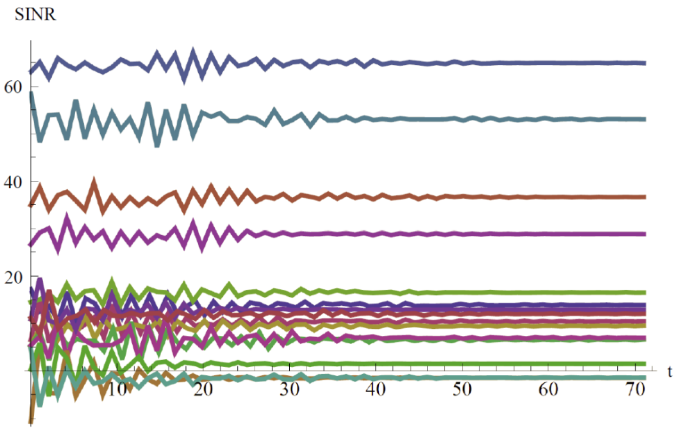

Figure 5 SINR convergence in a 15-user simulation with $\delta = 10^4$.

- $\beta > 1$ is the maximum pricing value,
- $\delta > 1$ is the price weight of the generated interference,
- $\mu > 0$ is the sensitivity of the users to interference.

These three parameters represent an useful tool to adapt the pricing function to the considered wireless network requirements, i.e. decreasing the value of δ the algorithm converges faster; we can force all secondary users to transmit at lower power levels increasing their sensitivity to the interference [18].

Thanks to the definition of the utility function as given in (4) and taking into account the pricing function given in (5), for each user in every single iteration the utility function have a maximum, depending on the transmission power levels of all the players in the game, as shown in Figure 4 for a two-player simulated game.

Simulation results show that the proposed algorithm has a fast convergence, also for large numbers of secondary users in the networks, as shown in Figure 5, where the SINR levels measured by each of the 15 users of the simulation are reported.

5.2 Existence and Uniqueness of the Nash Equilibrium

Under certain conditions, a Nash Equilibrium [19] offers a stable outcome and it can be guaranteed to exist, but does not necessarily mean the best payoff for all the players involved, especially in presence of pricing techniques. In the literature there are lots of mathematical methods to demonstrate the existence and uniqueness of Nash Equilibrium, like graphical [18, 20], quasi-concavity curve [21] and super-modularity [12].

Supermodular Games represent an interesting class of games since there are several compelling reasons like existence of pure strategy Nash Equilibrium, dominance resolvability, identical bounds on joint strategy space etc. that make them a strong candidate for resource allocation modeling. Supermodular games are based on the "supermodularity" concept, which is used in the social sciences to analyze how one agent's decision affects the incentives of others.

S-Games are normal form games $\Gamma = \langle N, S, \{f_i\}\rangle$ where N is the set of users, S the strategy space, f_i the set of utility functions and $\forall i \in N$ these conditions are satisfied:

1. the strategy space S_i of user i is a complete lattice.
2. f_i is supermodular in s_i.
3. f_i presents increasing differences in s.

The proposed utility function in (4) can be easily demonstrated to be supermodular, since:

1. the strategy space P is a complete lattice;
2. $$\frac{\partial^2 u_i(p)}{\partial p_i \partial p_j} \geq 0 \tag{7}$$
   for all $p \in P$ and $i \neq j$.
3. the utility function has the increasing difference property.

For details of the proofs we refer to [12], under the proposed conditions. Uniqueness of the Nash Equilibrium can be also demonstrated following the same approach, since we use a Best Response rule. Even if our proposed pricing function is more complicated, in comparison with the above-cited work, the demonstration procedure does not change. Indeed, the pricing function $\Omega\,(p(t-1))$ can be considered linear in $p(t-1)$, since the coefficient of $p(t-1)$ at time t is a constant.

6 Simulation Results and Performance Comparison

In order to evaluate the performance of a cognitive network based on the our proposed methods, we run Montecarlo simulations; in this paragraph we show the obtained results. The operating context is a terrain square area of 1 km edge, with a suburban path-loss profile. Primary transmitter and receiver positions are fixed; secondary transmitters are independently located in the area, while the secondary receivers positions are placed randomly in a 200 m diameter circle around the respective transmitters. Each secondary user transmits isotropically with $p_i \leq P_{\max}$, where $P_{\max} = 20$ dBm on the base of a fixed interference cap. Moreover, we consider a noise power $\sigma^2 = -100$ dBm, frequency $f = 1GHz$, $W = 4/5$, a common rate $R_i = 10$ kbit/s, $\beta = 10^4$, $\delta = 10^4$ and $\mu = 10^{-2}$; the values of the pricing parameters are chosen in order to obtain a fast convergence of the algorithm (depending on $\beta - \delta$) and to set a low sensitivity of the users toward interference (depending on μ). In order to obtain a qualitative evaluation of the proposed power allocation methods, we decide to compare their performance with an optimal centralized heuristic power allocation system, like Simulated Annealing (SA) [22]. The mean value of the SINR received by secondary users has been chosen as the performance index for the three optimization methods. We run Montecarlo simulations for increasing number of secondary users, while all the other parameters of the system remain the same of the previous mentioned operating context.

Simulation results illustrated in Figure 6 show clearly that the SA and the proposed game have similar performance: the curves have the same trend, but the game's one is on average 1.5 dB below. On the other hand, Water-Filling obtains lower mean SINR levels and performance worsens for increasing number of users in the network, as highlighted previously.

In addition to the SINR, the energy efficiency of the three considered methods is an another important key feature that we need to investigate. If the SINR performance are quite the same for the proposed game and the SA, on the contrary we can observe a great difference in terms of power allocations. Indeed, Figure 7 shows an example of mean transmission power levels allocated by the three investigated methods at the end of a simulation with 15 users; in this figure we can observe that SA allocation uses more power than game allocation to obtain similar SINR performance, as shown in Figure 6. For what concern the EEIWF, while some users are switched off, the others transmit at highest levels, compared with the other two proposed allocations. In Figure 7 the power allocation of the proposed game is shown in purple, in yellow is reported the additional power allocated by SA (with respect to game) and in blue the excess additional power allocated by EEIWF (with respect to SA).

Looking at the results from a general network view, we can easily observe that the power allocation obtained by the proposed game is the most fair, since all the users are able to transmit, even if they are experiencing very bad

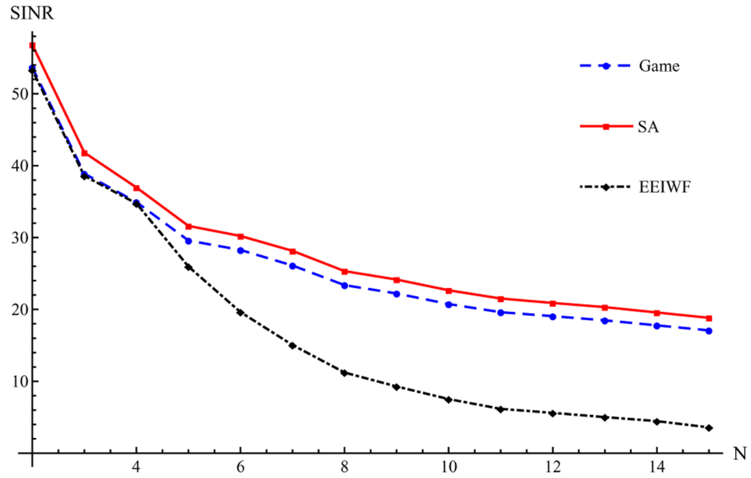

Figure 6 Trends of SINR mean values for increasing number of secondary users in the network.

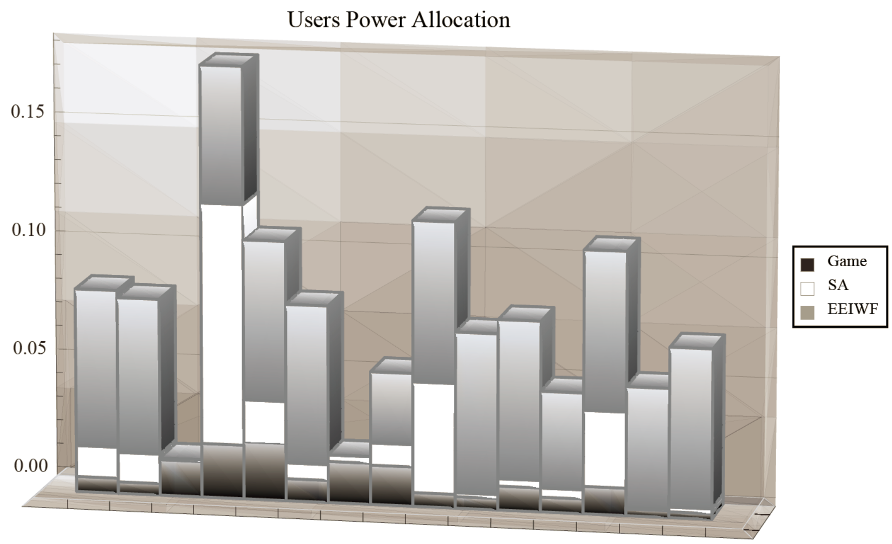

Figure 7 Example of mean values of power allocation for a 15 users network obtained thanks to Monte-Carlo method.

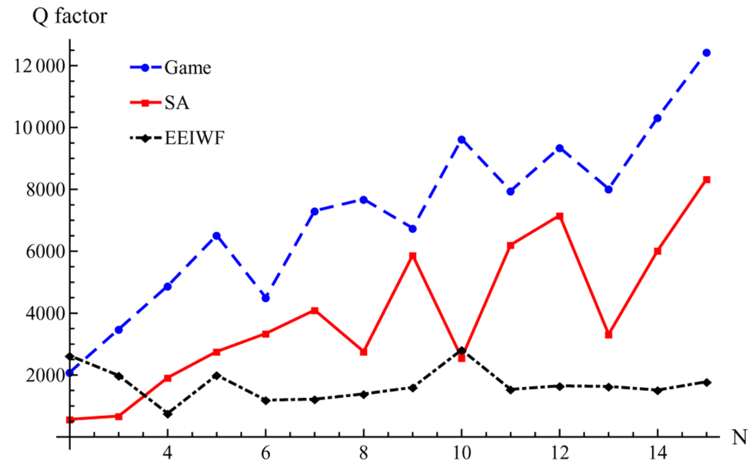

Figure 8 Trend of Q for increasing number of users.

channel condition. In order to obtain a qualitative estimation that takes into account at the same time SINR performance and energy efficiency of the three considered methods, in Figure 8 is reported the trend Q, that represents the mean value of the ratio between the SINR level received and allocated power of the transmitter, calculated for each user and obtained thanks to Monte-Carlo method.

7 Concluding Remarks

In this paper we provide two different power allocation methods, a modified version of the Iterated Water-Filling, called EEIWF, and a game theoretic framework based on S-Modular game. Both these methods take into account energy efficiency in a cognitive network, wherein primary and secondary users coexist. Transmission power of secondary users is limited by the presence of an interference cap, defined as the total interference that primary users willing to tolerate, without loosing their required QoS. Moreover, in the proposed game secondary users are discouraged to transmit at high power levels, since they are charged on the base of the interference they generate, thanks to the introduction of a pricing function inside of the utility function. Simulation results show a fast convergence of the proposed game also for a large number of users in the cognitive network. Moreover, the EEIWF is demonstrated to achieve the same SINR levels of IWF algorithm, allocating to secondary users an average transmission power level that is half of the one allocated by IWF.

A performance comparison among the proposed game, an optimal centralized resource allocation method (Simulated Annealing) and the EEIWF is also included. Simulation results show clearly that the proposed game converges to the same SINR values obtained from the heuristic optimization method and, in general, game theory obtains better performance than EEIWF. Moreover, the proposed game results to be the most energy efficient, also for a large number of considered users. Further investigations will be made in order to quantify and analyze the signaling process among secondary users.

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Biography

Enrico Del Re was born in Florence, Italy. He received the Dr. Ing. degree in electronics engineering from the University of Pisa, Pisa, Italy, in 1971. Until 1975 he was engaged in public administration and private firms, involved in the analysis and design of the telecommunication and air traffic control equipment and space systems. Since 1975 he has been with the Department of Electronics Engineering of the University of Florence, Florence, Italy, first as a Research Assistant, then as an Associate Professor, and since 1986 as Professor. During the academic year 1987-1988 he was on leave from the University of Florence for a nine-month period of research at the European Space Research and Technology Center of the European Space Agency, The Netherlands. His main research interest are digital signal processing, mobile and satellite communications, on which he has published more than 300 papers, in international journals and conferences. He is co-editor of the book *Satellite Integrated Communications Networks* (North-Holland, 1988), one of the authors of the book *Data Compression and Error Control Techniques with Applications* (Academic, 1985) and editor of the books *Mobile and Personal Communications* (Elsevier, 1995), *Software Radio Technologies and Services* (Springer, 2001), *Satellite Personal Communications for Future-Generation Systems* (Springer, 2002), *Mobile and Personal Satellite Communications 5-EMPS2002* (IIC, Italy, 2002) and *Satellite Communications and Navigation Systems* (Springer, 2008). He has been Chairman of the European Project COST 227 "Integrated Space/Terrestrial Mobile Networks" (1992–1995) and the EU COST Action 252 "Evolution of satellite personal communications from second to future generation systems" (1996–2000). He has been Chairman of the *Software Radio Technologies and Services Workshop* (2000), the *Fifth European Workshop on Mobile/Personal Satcoms* (2002) and the *Satellite Navigation and Communications Systems* (2006). He received the 1988/89 premium from the IEE (UK) for his paper entitled "Multicarrier demodulator for digital satellite communication systems". He is Head of the Signal Processing and Communications Laboratory of the Department of Electronics and Telecommunications of the University of Florence. Presently he is President of the Italian Interuniversity Consortium for Telecommunications (CNIT), having served before as Director. Professor Del Re is a Senior Member of the IEEE and a member of the European Association for Signal Processing (EURASIP).

Pierpaolo Piunti received the Degree in Telecommunications Engineering from University of Florence on April 2011. From June 2011 to December 2011 he worked as contractor ad Interuniversitary Italian Consortium for Telecommunications (CNIT). Actually he is a Ph.D. student of University of Florence. His research activity is focused on energy efficiency of communications networks and cognitive radio.

Renato Pucci received his degree in Telecommunication Engineer From the University of Florence in 2008, winning with his thesis the AICT & AEIT awards as *Best 2008 Italian Thesis on ICT scientific innovation* and as *Youngest researcher in ICT scientific innovation* and being one of the four finalists of the *Best italian Thesis of 2008* AICA award. In 2012 Renato received his Ph.D. from the University of Florence, collaborating with Thales Alenia

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Luca Simone Ronga [IEEE S89-M94-SM04] received his M.S. degree in electronic engineering in 1994 and his Ph.D. degree in telecommunications in 1998 from the University of Florence, Italy. In 1997 joined the International Computer Science Institute of Berkeley, California, as a visiting scientist. In 1998 obtained a post-doc position in the engineering faculty of the University of Florence. In 1999 he joined the Italian National Consortium for Telecommunications, where he is currently head of research. He conducts research activity and project management in various telecommunications areas, mainly in the satellite and terrestrial wireless fields. He has been leader of national and international research groups. He authored over 50 papers published in international journals and conference proceedings. He has been editor of *EURASIP Newsletter* for four years. His interests range from satellite communications to Software Defined Radio and Cognitive Radio techniques.