Short Papers

Green Metric Optimization in Cooperative Cognitive Radio Networks With Statistical Interference Parameters

Ashok Karmokar, Muhammad Naeem, and Alagan Anpalagan

***Abstract*—We study an energy efficiency (EE)-optimized power allocation technique for a source and a relay in a cooperative cognitive radio network. We formulate the optimization problem with the constraint on probabilistic interference parameters and throughput as a fractional programming problem. The problem is quasi-convex, for which a local optimal solution may not be guaranteed as a global optimal solution. Hence, we transform the problem into an equivalent convex programming problem using the Charnes–Cooper transformation technique to obtain an optimal solution. We analyze the channel access probability, EE, and total power performance of the cooperative cognitive green radio network via simulation.**

***Index Terms*—Cognitive radio, convex optimization, cooperative, green communication, relay communication.**

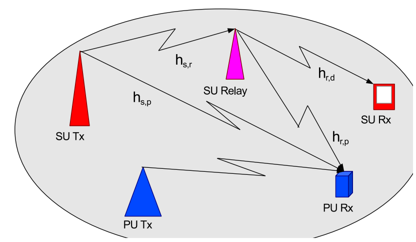

Fig. 1. Typical scenario of SU communications in PU bands in a geographic area, where SUs communicate via a virtual multiantenna system using cooperative relay stations.

I. Introduction

In addition to randomly varying channels, the power and the bandwidth are the two important parameters that are directly linked to the transmission capacity of wireless communications systems. Due to the static allocation of a natural bandwidth resource, cellular bands become extremely crowded due to the exponential demand and growth of wireless data services. The transmission power is important in optimizing the transmitters both in user devices and in a base station in order to reduce interference and CO_2 gas emissions. The idea of a cognitive radio, where a secondary user (SU) can opportunistically access the underutilized spectrum of a primary user (PU) without incurring excessive interference, is envisioned as a potential technology to cope with the scarcity of bandwidth in the cellular paradigm. The energy efficiency (EE) sensing in a cognitive radio network was studied in [1] and [2] as it is an important performance metric in cognitive radio networks.

In order to reduce interference, improve coverage via diversity, and enhance the rate of cell-edge users and the overall capacity, cooperative communication using a relay station has been studied in literature and is included in wireless standards, such as the Third Generation Partnership Project (3GPP) Long Term Evolution-Advanced [3]. Cooperative communication allows to realize a new form of space diversity to combat the detrimental effects of fading channels [4]. Therefore, an energy-efficient cooperative cognitive radio has the potential to increase the system capacity and to reduce the energy consumption. In [5], an energy-efficient relay selection method was studied. The EE and throughput tradeoff in a cooperative underlay network was studied in [6] from the perspective of high-priority PUs, where a low-priority SU serves as a relay for a PU. For a cognitive radio, it is of prime importance to maintain the SU-to-PU interference level under a prescribed limit. Although hard interference constraints are very common in literature, Bansal *et al.* [7] studied an adaptive power loading technique for cognitive radio networks to maximize the rate using statistical constraints on the interference. Previous studies mainly focused on the maximization of data rates, energy-efficient sensing, the minimization of power, etc.

Manuscript received November 3, 2014; revised March 4, 2015; accepted March 22, 2015. Date of publication July 22, 2015; date of current version March 23, 2018.

A. Karmokar and A. Anpalagan are with the Department of Electrical and Computer Engineering, Faculty of Engineering, Architecture, and Science, Ryerson University, Toronto, ON M5B 2K3, Canada (e-mail: alagan@ee.ryerson.ca).

M. Naeem is with the Department of Electrical Engineering, COMSATS Institute of Information Technology, Wah Cantt 47040, Pakistan.

Digital Object Identifier 10.1109/JSYST.2015.2451996

II. System Model

We consider a green cooperative cognitive radio network, as shown in Fig. 1, where a SU transmits to its receiver in a band licensed to PUs. The SUs communicate with each other via a relay.

Let us assume that the total number of PUs in that geographical area whose specified bands/channels may be used by the SUs is M. Therefore, the SU must maintain the individual interference limit set by the PUs when simultaneously transmitting with the specific PU in an underlay mode. Our objective is to select the best source and relay transmission power values under some criteria defined later. In each time slot, the SU senses the channel via out-of-band or in-band sensing, depending on whether the interference from the current acquired channel becomes manageable or not. If the interference from the PU to the SU receiver is too strong (measured via in-band sensing) for successful communications, the SU must conduct out-of-band sensing in order to pick another better channel; otherwise, it may continue to conduct in-band sensing for interference measurements. The energy for sensing channels depends on M. It is a design parameter and depends on the employed sensing scheme. Our study can incorporate any channel sensing scheme previously studied in literature. Wang *et al.* [8] and Shokri-Ghadikolaei and Fischione [9] surveyed some channel selection mechanisms and selection orders. The sensing time and the corresponding energy consumption depend on the sensing success. If a channel is sensed at the first try, the sensing energy is small. However,

1937-9234 © 2015 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

it can be large otherwise. We assume that the SU transmitter employs energy-efficient channel sensing and a sensing ordering technique. We assume that the channel between the secondary transmitter and the relay, and that between the relay and the secondary receiver can be estimated via a pilot signal. These channel gains are estimated at the relay and the receiver. They are fed back to the source during a power allocation decision. Given the channel information and the QoS requirements, the SU decides the source and relay power values so that the EE of the transmission over the selected channel is maximized.

Let $h_{s,r}$, $h_{s,d}$, and $h_{r,d}$ denote the channel fading gains between the source and the relay, between the source and the destination, and between the relay and the destination, respectively. Let us assume that the channel gains follow the Rayleigh distribution. Then, the probability density functions (pdfs) of channel power gains $\gamma_{s,r} = |h_{s,r}|^2$, $\gamma_{s,d} = |h_{s,d}|^2$, and $\gamma_{r,d} = |h_{r,d}|^2$ are exponentially distributed, respectively. For $\gamma_{s,r}$ (similarly for others), the pdf can be expressed as

$$f(\gamma_{s,r}) = \frac{1}{\bar{\gamma}_{s,r}} \exp\left(-\frac{\gamma_{s,r}}{\bar{\gamma}_{s,r}}\right) \tag{1}$$

where $\bar{\gamma}_{s,r}$ is the average channel power gain. Without loss of generality, let us consider a two-step half-duplex cooperative decode-and-forward (DF) relaying system [10]. In this scheme, the SU's source transmits (broadcasts) its information data to both the destination and the relay in the first time slot (phase 1). In the second time slot, the relay helps the source by decoding the received signal, reencodes it, and then retransmits it to the SU's receiver.

Let us assume that the source and the relay transmit with power p_s and power p_r, respectively, and $\mathbf{p} = \{p_s, p_r\}$ denotes the power vector. In phase 1, received signals $y_{s,d}$ and $y_{s,r}$ at the destination and the relay can be written as $y_{s,d} = \sqrt{p_s} h_{s,d} x + n_{s,d}$ and $y_{s,r} = \sqrt{p_s} h_{s,r} x + n_{s,r}$, respectively, where x is the transmitted information symbol, and $n_{s,d}$ and $n_{s,r}$ are the additive noise values that are modeled as zero-mean complex Gaussian random variables with variance N_0. If the decoded signal at the relay is denoted by $\hat{x}$, the transmitted signal from the relay can be denoted by $\sqrt{p_r}\hat{x}$, given that $\hat{x}$ has a unit variance. The received signal from the relay to the destination can be written as $y_{r,d} = \sqrt{p_r} h_{r,d} \hat{x} + n_{r,d}$, where $n_{r,d}$ is the additive noise that is modeled as a zero-mean complex Gaussian random variable with variance N_0.

The mutual information between the source and the destination for the DF relay system is determined by the mutual information of the weaker link between the source–relay and the combined channel from the source to the destination and from the relay to the destination. We can write it as follows [10]:

$$I_{\mathrm{DF}} = \frac{1}{2} \min\left\{\log\left(1 + \frac{\gamma_{s,r} p_s}{N_0}\right), \log\left(1 + \frac{\gamma_{s,d} p_s}{N_0} + \frac{\gamma_{r,d} p_r}{N_0}\right)\right\} \tag{2}$$

where the min operator takes into account the fact that the relay only transmits if decoded correctly; hence, the performance is limited by the weakest link between the source–destination and the source–relay.

Although studies exist for source and relay power selection based on other criteria, no study has been done on relay selection based on an EE metric in cooperative cognitive radio networks. The performance of future green radio systems needs to be measured in terms of an EE metric. The EE can be defined as the total achievable rate throughput per unit total transmitter power (source plus relay). Let $\Gamma(\mathbf{p})$ denote the EE in information bits per joule; then, it can be written as

$$\Gamma(\mathbf{p}) = \frac{\min\{C_{s,r}, C_{s,d}\}}{p_c + p_s + p_r} \tag{3}$$

where p_c is the static circuit power of the source and the relay in the transmit mode. Rates $C_{s,r}$ and $C_{s,d}$ represent the maximum rates at which the relay and the destination can reliably decode the source message, respectively. They can be expressed as follows:

$$C_{s,r} = \frac{1}{2} \log\left(1 + \frac{p_s \gamma_{s,r}}{N_0}\right) \tag{4}$$

$$C_{s,d} = \frac{1}{2} \log\left(1 + \frac{p_s \gamma_{s,d}}{N_0} + \frac{p_r \gamma_{r,d}}{N_0}\right). \tag{5}$$

Since both the source and the relay are transmitting, they both cause interference to the PU. We also assume that the fading channel between the SU transmitter (or the SU relay) and PU_i can be described by a Rayleigh distribution with a fading gain denoted as $h_{s,p}^{(i)}$ (or $h_{r,p}^{(i)}$). The pdf of channel power gain $\gamma_{s,p}^{(i)} = |h_{s,p}^{(i)}|^2$ or $\gamma_{r,p}^{(i)} = |h_{r,p}^{(i)}|^2$ is also exponentially distributed. The interference power $I_{s,p}^{(i)}$ to PU_i due to the source transmission can be expressed as a function of p_s and channel gain $\gamma_{s,p}^{(i)}$ as follows:

$$I_{s,p}^{(i)} = \gamma_{s,p}^{(i)} p_s. \tag{6}$$

Similarly, the interference power $I_{r,p}^{(i)}$ to the ith PU due to the relay transmission can be expressed as a function of p_r and channel gain $\gamma_{r,p}^{(i)}$ as $I_{r,p}^{(i)} = \gamma_{r,p}^{(i)} p_r$. Note that the PU also causes interference to the SU. The interference from the PU to the SU can be directly measured by the SU receiver with a sensing technique [11]. Depending on the distance between the PU transmitter and the SU receiver (and hence the interference level), it can be either treated as noise (no particular interference cancelation technique is needed), or SU users can employ different interference suppression/cancelation techniques to reduce the interference from the PU [11], [12].

III. EE Optimization Problem

In this paper, our goal is to select power levels so that the overall EE of the communication is maximized with the statistical constraints on the PU interference caused by both the source transmitter and the relay transmitter, and the minimum rate of the link. It can be written as follows:

$$\max_{\mathbf{p}} \quad \Gamma(\mathbf{p}) \tag{7}$$

subject to:

$$C_1 : \Pr\left(I_{s,p}^{(i)} \le I_{\mathrm{th}}^{(i)}\right) \ge I_P^{(i)} \qquad \forall\, i \in \{1, 2, \ldots, M\}$$

$$C_2 : \Pr\left(I_{r,p}^{(i)} \le I_{\mathrm{th}}^{(i)}\right) \ge I_P^{(i)} \qquad \forall\, i \in \{1, 2, \ldots, M\}$$

$$C_3 : C_{s,j} \ge C_{\mathrm{th}} \qquad \forall\, j \in \{d, r\}$$

$$C_4 : p_j \ge 0 \qquad \forall\, j \in \{s, r\}$$

where $I_{\mathrm{th}}^{(i)}$ is the interference threshold (the upper limit of the permissible interference) for PU_i, $I_P^{(i)}, \forall \mathrm{PU}_i \in \mathcal{M}$ are the interference probability thresholds (the lower limit of the interference threshold maintaining the probability), and C_{th} is the rate threshold (the lower limit of the received rate as determined by the QoS requirement). Constraints C_1 and C_2 ensure that the total interference to a PU is below a specified threshold by a specified probability margin, and C_3 ensures the rate constraints; C_4 ensures nonnegative power values in the optimization process. For a Rayleigh fading channel, after some mathematical manipulation of constraint C_1 in (7), it can be shown that

$$p_s \le \frac{I_{\mathrm{th}}^{(i)}}{\bar{\gamma}_{s,p}^{(i)} \left(-\ln\left(1 - I_P^{(i)}\right)\right)} \qquad \forall\, i \in \mathcal{M}. \tag{8}$$

The relay power can be similarly found by replacing $\bar{\gamma}_{s,p}^{(i)}$ with $\bar{\gamma}_{r,p}^{(i)}$. Note that the statistical constraints are transformed into linear constraints for Rayleigh fading channels. The power values are dependent on the average gain, which is easier to obtain than the instantaneous channel gain between the PU and the SU.

Problem (7) is a max-min problem; thus, let us introduce a new variable $z = \min\{C_{s,r}, C_{s,d}\}$. Then the max-min problem can be written as a maximization problem with additional constraints on $C_{s,r}$ and $C_{s,d}$ as follows:

$$\max_{\mathbf{p},z} \quad \frac{z}{p_c + p_s + p_r} \tag{9}$$

subject to:

$$C_1: p_s \le \frac{I_{\text{th}}^{(i)}}{\bar{\gamma}_{s,p}^{(i)}\left(-\ln\left(1 - I_P^{(i)}\right)\right)} \qquad \forall i \in \mathcal{M}$$

$$C_2: p_r \le \frac{I_{\text{th}}^{(i)}}{\bar{\gamma}_{r,p}^{(i)}\left(-\ln\left(1 - I_P^{(i)}\right)\right)} \qquad \forall i \in \mathcal{M}$$

$$C_3: \frac{1}{2}\log_2\left\{1 + \frac{p_s\gamma_{s,r}}{N_0}\right\} \ge C_{\text{th}}$$

$$\frac{1}{2}\log_2\left\{1 + \frac{p_s\gamma_{s,d}}{N_0} + \frac{p_r\gamma_{r,d}}{N_0}\right\} \ge C_{\text{th}}$$

$$C_4: z \ge 0, p_j \ge 0 \qquad \forall j \in \{s, r\}$$

$$C_5: \frac{1}{2}\log_2\left\{1 + \frac{p_s\gamma_{s,r}}{N_0}\right\} \ge z$$

$$\frac{1}{2}\log_2\left\{1 + \frac{p_s\gamma_{s,d}}{N_0} + \frac{p_r\gamma_{r,d}}{N_0}\right\} \ge z.$$

IV. Convex Problem via CCT

Let the numerator and the denominator of (9) be defined as $f(\mathbf{p}, z) = z$ and $g(\mathbf{p}, z) = p_c + p_s + p_r$, respectively. In addition, let functions $h_i(\mathbf{p}, z), i = 1, \ldots, 2M + 5$ represent all the constraints of (9). Then, we can write (9) as the following fractional programming problem:

$$\min_{\mathbf{p},z} \quad \frac{f(\mathbf{p}, z)}{g(\mathbf{p}, z)} \tag{10}$$

$$\text{subject to:} \quad h_i(\mathbf{p}, z) \le 0, \quad i = 1, \ldots, 2M + 5.$$

Functions $f(\mathbf{p}, z)$, $g(\mathbf{p}, z)$, and $h_i(\mathbf{p}, z)$ are all real valued. It can be noted that functions $f(\mathbf{p}, z)$ and $g(\mathbf{p}, z)$ are convex and affine, respectively. Since all the constraints are also convex, fractional programming problem (10) is a convex fractional programming (CFP) problem. The objective function of the CFP problem is quasi-convex, and a local optimal solution in a quasi-convex problem cannot be guaranteed as a global minimum [13]. Only in a special case, the CFP problem has one minimum solution point when $f(\mathbf{p}, z)$ is strictly convex or $g(\mathbf{p}, z)$ is strictly concave [14].

However, using the Charnes–Cooper transformation (CCT), the CFP problem can be transformed into a convex program (CP) problem, and for the CP, we can guarantee any local minimum point as a global minimum point. Now, let us consider the following CCT that will permit us to convert the CFP problem into an equivalent CP problem (also known as the parameter-free CP problem): $\mathbf{y} = t\mathbf{p}$ and $t = (1/g(\mathbf{p}, z))$, where variable t is positive, and $\mathbf{y} = \{y_1, y_2, y_3\} = \{zt, p_s t, p_r t\}$. Using the CCT, we can write the equivalent CP problem of (10) [14] as

$$\min_{\mathbf{y},t} \quad -y_1 \tag{11}$$

subject to:

$$C_1: y_2 - t\frac{I_{\text{th}}^{(i)}}{\bar{\gamma}_{s,p}^{(i)}\left(-\ln\left(1 - I_P^{(i)}\right)\right)} \le 0 \qquad \forall i \in \mathcal{M}$$

$$C_2: y_3 - t\frac{I_{\text{th}}^{(i)}}{\bar{\gamma}_{r,p}^{(i)}\left(-\ln\left(1 - I_P^{(i)}\right)\right)} \le 0 \qquad \forall i \in \mathcal{M}$$

$$C_3: C_{\text{th}} - \frac{1}{2}\log_2\left\{1 + \frac{y_2\gamma_{s,r}}{tN_0}\right\} \le 0$$

$$C_{\text{th}} - \frac{1}{2}\log_2\left\{1 + \frac{y_2\gamma_{s,d}}{tN_0} + \frac{y_3\gamma_{r,d}}{tN_0}\right\} \le 0$$

$$C_4: -t < 0, -y_k \le 0 \qquad \forall k \in \{1, 2, 3\}$$

$$C_5: y_1 - \frac{1}{2}t\log_2\left\{1 + \frac{y_2\gamma_{s,r}}{tN_0}\right\} \le 0$$

$$y_1 - \frac{1}{2}t\log_2\left\{1 + \frac{y_2\gamma_{s,d}}{tN_0} + \frac{y_3\gamma_{r,d}}{tN_0}\right\} \le 0$$

$$C_6: tp_c + y_2 + y_3 = 1.$$

Note that maximizing a concave objective is equivalent to minimizing its negative. The last constraint represents the relationship between the new variables. Problem (11) is a convex optimization problem and can be easily solved using any standard optimization algorithm.

V. Numerical Results

We present the performance results using a Monte Carlo simulation averaged over 10^4 samples using MATLAB. We assume that the channel sensing is perfect and energy efficient. Therefore, we put our attention on an energy-efficient transmission technique. Unless specified otherwise, the data for the simulations are as follows: the number of PUs $M = 2$; noise power variance $N_0 = 10^{-6}$ W; the average channel gain between the source (or relay) transmitter and the PU is $\bar{\gamma}_{s,p}^{(i)} = \bar{\gamma}_{r,p}^{(i)} = -10$ dB, $\forall i \in \mathcal{M}$; the average channel gain between the SUs is $\bar{\gamma}_{s,r} = \bar{\gamma}_{s,d} = \bar{\gamma}_{r,d} = 1$ dB; interference threshold $I_{\text{th}}^{(i)} = 10^{-3}$ W; rate threshold $C_{\text{th}} = 5$ bit/s/Hz; and static circuit power $p_c = 10^{-9}$ W.

It can be seen in (9) that the transmission power values are upper bounded by statistical interference constraints C_1 and C_2. Furthermore, they are lower bounded by rate constraint C_3. Therefore, for a particular channel condition, both constraints together may not give a feasible region. In this situation, the channel is not accessible for that particular rate and interference constraints. We define the channel access probability as the probability of satisfying all the constraints. Moreover, the SU measures the interference from the PU via in-band sensing. When the interference from the primary transmission is strong, the SU looks for another channel via out-of-band sensing.

Fig. 2 shows the channel access probability for different rate thresholds. It is seen that the channel access probability decreases with the increase in the interference probability threshold. Furthermore, the rate of decrease is more for the higher rate threshold. This is because as the interference probability threshold increases, it puts tighter bounds; hence, the feasible region decreases. This fact, as a result, decreases the channel access probability. In addition, the rate of decrease for the same rate threshold increases with the increase in the interference probability threshold. When the rate decreases, the probability of channel access increases. For example, when the rate threshold is 1 bit/s/Hz, the channel is accessible for almost all channel conditions (in almost all the time slots). As the rate threshold is relaxed, the feasible region gets bigger, and the channel access probability increases. Moreover,

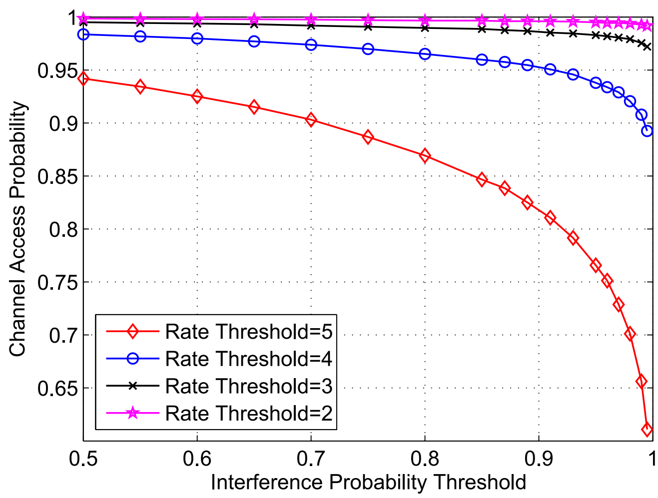

Fig. 2. Channel access probability versus the interference probability threshold for different rate thresholds.

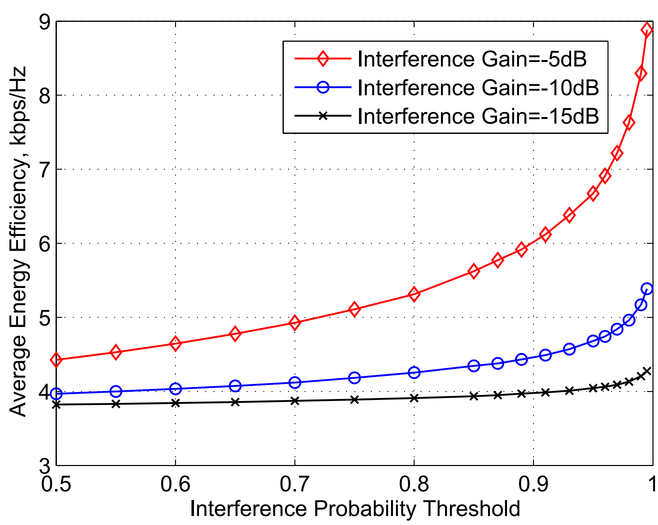

Fig. 3. EE versus the interference probability threshold for different interference gains between the SU and the PU.

when the interference probability threshold is relaxed for the same rate, the channel access probability is increased.

The effect of the interference gains and the interference probability thresholds on the EE is shown in Fig. 3. When the interference probability threshold increases, the EE also increases. In addition, the EE is more for a higher interference gain. The source and the relay need to use lower power to maintain the interference threshold in both cases. The capacity also decreases with the power. However, the capacity logarithmically decreases, and the decrease in the power is dominant here. Thus, while in the lower interference probability region, higher rates are supported, the EE is lower there, and vice versa. The channel gain between the SUs also affect the total power, as shown in Fig. 4. As the channel gain increases, the SUs can use lower power even in lower channel states to continue transmission with a particular rate threshold. Since lower power values are required, the total power decreases with better channel conditions.

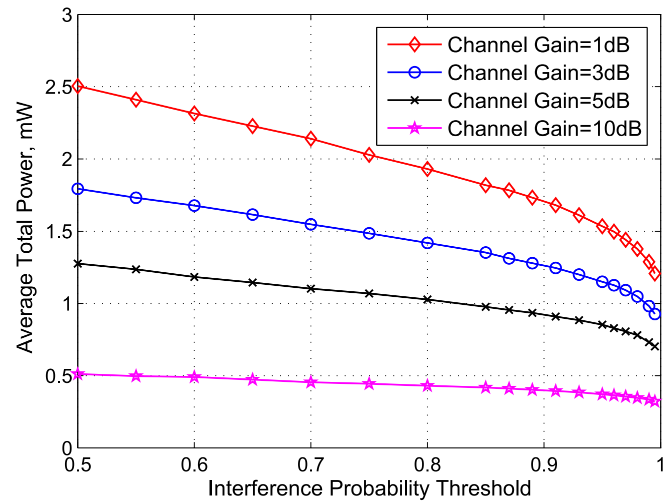

Fig. 4. Total power versus the interference probability threshold for different channel gains of the SUs.

VI. Conclusion

We have presented an energy-efficient technique for the optimal selection of transmitter power values at the source and the relay in a cooperative cognitive radio network. As opposed to static interference parameters, we have used a probabilistic model for the interference threshold. Since the formulated problem is a quasi-CFP problem, we have proposed an alternative solution technique using the CCT. We have analyzed the effect of the channel access probability, the EE, and the total power as a function of the interference probability threshold for different system parameters via simulation over Rayleigh fading channels.

References

[1] E. C. Y. Peh *et al.*, "Energy-efficient cooperative spectrum sensing in cognitive radio networks," in *Proc. IEEE Globecom*, 2011, pp. 1–5.

[2] S. Althunibat, M. D. Renzo, and F. Granelli, "Optimizing the K-out-of-N rule for cooperative spectrum sensing in cognitive radio networks," in *Proc. IEEE Globecom*, 2013, pp. 1607–1611.

[3] Y. Q. Qian Li, R. Q. Hu, and G. Wu, "Cooperative communications for wireless networks: Techniques and applications in LTE-advanced systems," *IEEE Wireless Commun. Lett.*, vol. 19, no. 2, pp. 22–29, Apr. 2012.

[4] K. B. Letaief and W. Zhang, "Cooperative communications for cognitive radio networks," *Proc. IEEE*, vol. 97, no. 5, pp. 878–893, May 2009.

[5] O. Amin and L. Lampe, "Opportunistic energy efficient cooperative communication," *IEEE Wireless Commun. Lett.*, vol. 1, no. 5, pp. 412–415, Oct. 2012.

[6] M. Costa and A. Ephremides, "Energy efficiency in cooperative cognitive wireless networks," in *Proc. Annu. CISS*, Mar. 2014, pp. 1–6.

[7] G. Bansal, M. J. Hossain, and V. Bhargava, "Adaptive power loading for OFDM-based cognitive radio systems with statistical interference constraint," *IEEE Trans. Wireless Commun.*, vol. 10, no. 9, pp. 2786–2791, Sep. 2011.

[8] S. Wang, Y. Wang, J. P. Coon, and A. Doufexi, "Energy-efficient spectrum sensing and access for cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 61, no. 2, pp. 906–912, Feb. 2012.

[9] H. Shokri-Ghadikolaei and C. Fischione, "Analysis and optimization of random sensing order in cognitive radio networks," , *IEEE J. Sel. Areas Commun.*, vol. 33, no. 5, pp. 803–819, May 2015.

[10] J. Laneman, D. Tse, and G. Wornell, "Cooperative diversity in wireless networks: Efficient protocols and outage behavior," *IEEE Trans. Inf. Theory*, vol. 50, no. 12, pp. 3062–3080, Dec. 2004.

[11] X. Hong *et al.*, "Cognitive radio networks: Interference cancelation and management techniques," *IEEE Veh. Technol. Mag.*, vol. 4, no. 4, pp. 76–84, Dec. 2009.

[12] P. Popovski *et al.*, "Opportunistic interference cancellation in cognitive radio systems," in *Proc. IEEE DySPAN*, 2007, pp. 472–475.

[13] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[14] S. Schaible and T. Ibaraki, "Fractional programming," *Eur. J. Oper. Res.*, vol. 12, no. 4, pp. 325–338, Apr. 1983.