Energy-Efficient Power Adaptation for Cognitive Radio Systems under Imperfect Channel Sensing

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Abstract—In this paper, energy efficient power adaptation is considered in sensing-based spectrum sharing cognitive radio systems in which secondary users first perform channel sensing and then initiate data transmission with two power levels based on the sensing decisions (e.g., idle or busy). It is assumed that spectrum sensing is performed by the cognitive secondary users, albeit with possible errors. In this setting, the optimization problem of maximizing the energy efficiency (EE) subject to peak/average transmission power constraints and average interference constraints is considered. The circuit power is taken into account for total power consumption. By exploiting the quasiconcave property of the EE maximization problem, the original problem is transformed into an equivalent parameterized concave problem and Dinkelbach’s method-based iterative power adaptation algorithm is proposed. The impact of sensing performance, peak/average transmit power constraints and average interference constraint on the energy efficiency of cognitive radio systems is analyzed.

Index Terms—Channel sensing, energy efficiency, interference power constraints, power adaptation, probability of detection, probability of false alarm, transmit power constraints.

I. INTRODUCTION

The significant surge in demand for high data rate wireless applications and the unprecedented growth in the number of wireless users have led to larger amount of bandwidth being required for wireless transmissions and increased the energy consumption levels. On the other hand, high energy prices, limited battery power, increasing greenhouse gas emissions have led to the emerging trend of addressing the optimal and intelligent usage of energy resources. Hence, energy-efficient operation is a major consideration in wireless systems. In addition, bandwidth is generally a scarce resource in wireless communications. Although the available radio-frequency (RF) spectrum has already been allocated/licensed to various applications and services, the allocated spectrum is underutilized most of the time according to the Federal Communication Commission (FCC)’s report [1]. This inefficiency in the spectrum usage has led to the consideration of the new communication paradigm of cognitive radio [2, 3]. In cognitive radio systems, the unlicensed users (cognitive or secondary users) are able to opportunistically access the frequency bands allocated to the licensed users (primary users) as long as the interference inflicted on the primary users’ transmissions is limited. In this regard, cognitive radio enables better and more efficient utilization of the spectrum.

The energy efficiency (EE) of cognitive radio systems has been recently studied. For instance, the authors in [4] highlight the benefits of cognitive radio systems for green wireless communications. The authors in [5] design energy efficient optimal sensing strategy and optimal sequential sensing order in multichannel cognitive radio networks. In addition, the sensing time and transmission duration are jointly optimized in [6]. In the EE analysis of the aforementioned works, secondary users are assumed to transmit only when the channel is sensed as idle. The recent work in [7] mainly focuses on optimal power allocation to achieve the maximum energy efficiency in OFDM-based cognitive radio networks. Also, energy efficient optimal power allocation in cognitive MIMO broadcast channels is studied in [8]. In these works, secondary users always share the spectrum with primary users without performing channel sensing.

In order to further increase secondary users’ transmission opportunities, unlike above works, in this study we consider the transmission strategy of sensing-based spectrum sharing and assume that the secondary users can coexist with the primary users in the presence of both idle and busy sensing decisions while adapting their transmission power according to the sensing result. For such a model, we first formulate EE maximization problem subject to peak/average transmit power constraints and average interference constraints in the presence of imperfect sensing results. We explicitly consider circuit power consumption in the total power expenditure. In addition, due to imperfect sensing results, we model the additive disturbance as Gaussian mixture distributed and formulate the achievable rates of the cognitive radio systems accordingly. The EE maximization problem is transformed into an equivalent concave form and Dinkelbach’s method-based power allocation algorithm is proposed. We provide numerical results to illustrate the effects of imperfect sensing decisions and transmit/interference power constraints on the energy efficiency.

II. SYSTEM MODEL

We assume that the secondary users initially perform channel sensing in the first $\tau$ symbols of the frame duration of $T$ symbols. Hence, data transmission is performed in the remaining $T - \tau$ symbols.

A. Channel Sensing

Spectrum sensing can be formulated as a hypothesis testing problem in which there are two hypotheses based on whether primary users are active or inactive over the channel, denoted by $\mathcal{H}_1$ and $\mathcal{H}_0$, respectively. Many spectrum sensing methods have been studied in the literature (see e.g., [9, 10] and references
Secondary users are assumed to transmit under both idle and data transmission. The channel is considered to be block flat-

Cognitive Radio Channel Model

The rest of the conditional probabilities of idle sensing decision given the true hypotheses can be obtained as follows:

\[ P_1 = \Pr(\hat{H}_i | H_1) \], \quad (1) \]

\[ P_1^* = \Pr(\hat{H}_i | H_0) \]. \quad (2) \]

The rest of the conditional probabilities of idle sensing decision given the true hypotheses can be obtained as

\[ \Pr(\hat{H}_0 | H_1) = 1 - P_1, \quad (3) \]

\[ \Pr(\hat{H}_0 | H_0) = 1 - P_1^*. \quad (4) \]

B. Cognitive Radio Channel Model

After performing channel sensing, the secondary users initiate data transmission. The channel is considered to be block flat-
fading in which the fading coefficients stay the same during a frame duration and vary independently in the following frame.

Circuit power represents the average power consumption of the transmitter circuitry (i.e., mixers, filters, and digital-to-analog converters, etc.), which is independent of the transmission power. Also, \( \Pr(\hat{H}_i) \) and \( \Pr(H_0) \) denote the probabilities of channel being detected as busy and idle, respectively, which can further be expressed as

\[ \Pr(\hat{H}_1) = \Pr(H_0)P_1 + \Pr(H_1)P_1, \]

\[ \Pr(\hat{H}_0) = \Pr(H_0)(1 - P_1) + \Pr(H_1)(1 - P_1). \]

The achievable EE expression in (7) can serve as a lower bound since the lower bound on achievable rate \( R(P_0, P_1) \) in (6) is employed. The usefulness of this EE expression is due to its being an explicit function of the sensing performance.

The energy efficiency (EE) metric we adopt is the ratio of the achievable rate to the total power consumption (in joules) defined more explicitly as follows:

\[ \eta_{EE}(P_0, P_1) = \frac{R(P_0, P_1)}{P_{\text{avg}}(P_0, P_1)} = \frac{R(P_0, P_1)}{P_0 + P_1} \quad (7) \]

where \( \log \{ . \} \) denotes expectation operation with respect to the fading coefficient \( h \).

Fig. 1: Achievable EE \( \eta_{EE}(P_0, P_1) \) vs. achievable rate \( R(P_0, P_1) \).

In Fig. 1 we plot the achievable EE expression in (7) (indicated as the lower bound) and the exact achievable EE as a function of the achievable rate for both perfect sensing (i.e., \( P_1 = 1 \) and \( P_0 = 0 \)) and imperfect sensing (i.e., \( P_0 = 0.8 \) and \( P_1 = 0.2 \)). In order to evaluate the exact achievable EE with Gaussian input, we performed Monte Carlo simulations with
\(2 \times 10^6\) samples. In the case of perfect sensing, the lower bound and simulation result perfectly match as expected since in this case additive disturbance has Gaussian distribution rather than a Gaussian mixture. In the case of imperfect sensing, the lower bound is tight when the difference between noise variance and variance of primary users’ is small, e.g., when \(N_0 = \sigma^2 = 1\) or \(N_0 = 0.5, \sigma^2 = 1\). When the difference in the variances is large, e.g., when \(N_0 = 0.2, \sigma^2 = 1\), the gap between the lower bound and the exact EE increases. However, it is seen that achievable EE expressions in (7) is still a good lower bound. Since circuit power is taken into consideration and we assume \(P_c = 0.1\), achievable EE vs. achievable rate curve has a bell shape and also is quisciconcave. It is further observed that the maximum EE is attained at nearly the same achievable rate for both lower bound and exact EE expressions.

In the following section, we derive the power adaptation schemes that maximize EE of cognitive radio systems in the presence of sensing errors subject to different combinations of transmit power and interference power constraints.

III. OPTIMAL POWER ADAPTATION

A. Average Transmit Power Constraint and Average Interference Power Constraint

The maximum EE under both average transmit power and interference power constraints can be found by solving the following optimization problem

\[
\max_{P_0(g,h), P_1(g,h)} \ 
\eta_{EE}(P_0, P_1) = \frac{R(P_o(g,h), P_1(g,h))}{\mathbb{E}\{\Pr\mathcal{H}_0\} P_0(g,h) + \Pr\mathcal{H}_1 P_1(g,h) + P_c}\ 
\]  
\[
\text{subject to} \ 
\mathbb{E}\{\Pr\mathcal{H}_0\} P_0(g,h) + \Pr\mathcal{H}_1 P_1(g,h) \leq P_{avg}\ 
\]
\[
\mathbb{E}\{(1 - P_0) P_0(g,h)\} |g|^2 + P_0 \Pr\mathcal{H}_1 P_1(g,h) |g|^2 \leq Q_{avg}\ 
\]
\[
P_0(g,h) \geq 0, P_1(g,h) \geq 0\ 
\]  

where \(P_{avg}\) denotes the maximum average transmission power of the secondary transmitter and \(Q_{avg}\) represents the maximum average interference power at the primary receiver. Also, \(g\) denotes the channel fading coefficient between the secondary transmitter and the primary receiver and the expectations above are taken with respect to both \(g\) and \(h\).

The above optimization problem is quisciconcave since the achievable rate \(R(P_0, P_1)\) is concave in transmission powers, and the total power consumption \(P_{tot}(P_0, P_1)\) is both affine and positive. Then, the level sets \(S_\alpha = \{P_0, P_1 : \eta_{EE}(P_0, P_1) \geq \alpha\} = \{\alpha P_{tot}(P_0, P_1) - R(P_0, P_1) \leq 0\}\) are convex for any \(\alpha \in \mathbb{R}\). We employ an iterative power adaptation algorithm based on Dinkelbach’s method\(^\ref{12}\) to solve the quisciconcave EE maximization problem by considering the equivalent parameterized concave problem as follows:

\[
\max_{P_0(g,h), P_1(g,h)} \ 
\{R(P_o(g,h), P_1(g,h)) - \alpha(\mathbb{E}\{\Pr\mathcal{H}_0\} P_0(g,h) + \Pr\mathcal{H}_1 P_1(g,h) + P_c)\} \ 
\]  
\[
\text{subject to} \ 
\mathbb{E}\{\Pr\mathcal{H}_0\} P_0(g,h) + \Pr\mathcal{H}_1 P_1(g,h) \leq P_{avg}\ 
\]
\[
\mathbb{E}\{(1 - P_0) P_0(g,h)\} |g|^2 + P_0 \Pr\mathcal{H}_1 P_1(g,h) |g|^2 \leq Q_{avg}\ 
\]
\[
P_0(g,h) \geq 0, P_1(g,h) \geq 0\ 
\]  

where \(\alpha\) is a nonnegative parameter. At the optimal value of \(\alpha^*\), solving the EE maximization problem in (9) is equivalent to solving the above parametrized concave problem if and only if the following condition is satisfied

\[
F(\alpha^*) = R(P_0(g,h), P_1(g,h)) - \alpha^*(\mathbb{E}\{\Pr\mathcal{H}_0\} P_0(g,h) + \Pr\mathcal{H}_1 P_1(g,h) + P_c) = 0\ 
\]  

The detailed proof of the above condition is available in\(^\ref{12}\). Since the problem in (13) is concave, the optimal power values are obtained by forming the Lagrangian function as follows

\[
L(P_0, P_1, \lambda, \nu, \alpha) = R(P_0(g,h), P_1(g,h)) - \alpha(\mathbb{E}\{\Pr\mathcal{H}_0\} P_0(g,h) + \Pr\mathcal{H}_1 P_1(g,h) + P_c) - \nu(\mathbb{E}\{(1 - P_0) P_0(g,h)\} |g|^2 + P_0 \Pr\mathcal{H}_1 P_1(g,h) |g|^2 - Q_{avg})\ 
\]

where \(\lambda\) and \(\nu\) are nonnegative Lagrangian multipliers. According to the Karush-Kuhn-Tucker (KKT) conditions, the optimal values of \(P_0^*(g,h)\) and \(P_1^*(g,h)\) satisfy the following equations

\[
\frac{-T}{\log_2 e} \Pr\mathcal{H}_0 |g|^2 \sigma_\alpha^2 \leq -\lambda + \alpha \Pr\mathcal{H}_0 - \nu |g|^2 (1 - P_d) = 0\ 
\]
\[
\frac{-T}{\log_2 e} \Pr\mathcal{H}_1 |g|^2 \sigma_\alpha^2 \leq -\lambda + \alpha \Pr\mathcal{H}_1 - \nu |g|^2 P_d = 0\ 
\]
\[
\lambda(\mathbb{E}\{\Pr\mathcal{H}_0\} P_0^*(g,h) + \Pr\mathcal{H}_1 P_1^*(g,h) - P_{avg}) = 0\ 
\]
\[
\nu(\mathbb{E}\{(1 - P_0) P_0^*(g,h)\} |g|^2 + P_0 \Pr\mathcal{H}_1 P_1^*(g,h) |g|^2 - Q_{avg}) = 0\ 
\]
\[
\lambda \geq 0, \nu \geq 0\ 
\]

Hence, the optimal power values \(P_0^*(g,h)\) and \(P_1^*(g,h)\) can be found, respectively as in (24) and (25) given at the top of the next page, where \(|x|^+\) denotes \(\max(x, 0)\). The Lagrange multipliers \(\lambda\) and \(\nu\) can be jointly obtained by inserting the optimal power adaptation formulations in (24) and (25) into the constraints given in (14) and (15). However, solving these equations does not result in closed form expressions for \(\lambda\) and \(\nu\). Therefore, subgradient method is employed, i.e., \(\lambda\) and \(\nu\) are updated iteratively according to the subgradient direction until convergence as follows

\[
\lambda^{(n+1)} = \left[\lambda^{(n)} - t(\mathbb{E}\{\Pr\mathcal{H}_0\} P_0^{(n)}(g,h) + \Pr\mathcal{H}_1 P_1^{(n)}(g,h))\right]^+\ 
\]
\[
\nu^{(n+1)} = \left[\nu^{(n)} - t(\mathbb{E}\{(1 - P_d) P_0^{(n)}(g,h) + P_0 P_1^{(n)}(g,h)\} |g|^2)\right]^+\ 
\]  

where \(n\) denotes the iteration index and \(t\) denotes the step size. When the step size is chosen to be constant, it was shown that
the subgradient method is guaranteed to converge to the optimal value within a small range [13]. For a given value of \( \alpha \), the optimal power adaptations in (24) and (25) are found in [14]. In the case of \( F(\alpha) = 0 \) in [13], the solution is optimal. Otherwise, an \( \epsilon \)-optimal solution is obtained. In the following table, Dinkelbach’s method-based iterative power adaptation algorithm for energy efficiency maximization under imperfect sensing is summarized.

**Algorithm 1** Dinkelbach’s method-based power adaptation that maximizes the EE of cognitive radio systems under both average transmit power and interference constraints

1: Initialization: \( P_0 = P_{0,\text{init}}, P_1 = P_{1,\text{init}}, \epsilon > 0, t > 0, \alpha^{(0)} = \alpha_{\text{init}}, \lambda^{(0)} = \lambda_{\text{init}}, \nu^{(0)} = \nu_{\text{init}} \)

2: \( n \leftarrow 0 \)

3: repeat

4: calculate \( P_0^*, (g, h) \) and \( P_1^* (g, h) \) using (24) and (25), respectively;

5: update \( \lambda \) and \( \nu \) using subgradient method as follows;

6: \( k \leftarrow 0 \)

7: repeat

8: \( \lambda^{(k+1)} = \left[ \lambda^{(k)} - t (P_{\text{avg}} - \mathbb{E}\{\Pr\{H_0\} P_0^R (g, h) + \Pr\{H_1\} P_1^R (g, h)\}) \right]^+ \)

9: \( \nu^{(k+1)} = \left[ \nu^{(k)} - t (Q_{\text{avg}} - \mathbb{E}\{(1 - P_d) P_0^R (g, h) | g|^2 + P_d P_1^R (g, h) | g|^2\}) \right]^+ \)

10: \( k \leftarrow k + 1 \)

11: until \( |\nu^{(k)} (Q_{\text{avg}} - \mathbb{E}\{(1 - P_d) P_0^R (g, h) | g|^2 + P_d P_1^R (g, h) | g|^2\})| \leq \epsilon \) and \( |\lambda^{(k)} (P_{\text{avg}} - \mathbb{E}\{\Pr\{H_0\} P_0^R (g, h) + \Pr\{H_1\} P_1^R (g, h)\})| \leq \epsilon \)

12: \( \alpha^{(n+1)} = \frac{R(P_0^*, (g, h), P_1^* (g, h))}{\mathbb{E}\{\Pr\{H_0\} P_0^R (g, h) + \Pr\{H_1\} P_1^R (g, h)\} + P_c} \)

13: \( n \leftarrow n + 1 \)

14: until \( |F(\alpha^{(n)})| \leq \epsilon \)

Note that in the case of \( \alpha = 0 \), EE maximization problem is equivalent to spectral efficiency (SE) maximization.

**Remark 1:** The power adaptation schemes in (24) and (25) depend on the channel quality between the secondary transmitter and secondary receiver, denoted by \( |h|^2 \), the interference channel quality between the secondary transmitter and the primary receiver, \( |g|^2 \), and the sensing performance through detection and false alarm probabilities, \( P_d \) and \( P_t \), respectively. When both perfect sensing, i.e., \( P_d = 1 \) and \( P_t = 0 \), and SE maximization are considered, i.e., \( \alpha \) is set to 0, the power adaptation schemes become similar to that given in [15]. However, the secondary users have two power adaptation schemes depending on the presence or absence of the primary users.

**B. Peak Transmit Power Constraint and Average Interference Power Constraint**

Next, we consider peak transmit power constraint and average interference constraint for EE maximization in cognitive radio systems. In this case, energy-efficient power adaptation can be obtained by solving the following problem:

\[
\max_{P_0 (g, h), P_1 (g, h)} \eta_{EE} (P_0, P_1) = \frac{R(P_0 (g, h), P_1 (g, h))}{\mathbb{E}\{\Pr\{H_0\} P_0 (g, h) + \Pr\{H_1\} P_1 (g, h)\} + P_c} \leq 1
\]

subject to \( P_0 (g, h) \leq P_{0,\text{pk},0} \), \( P_1 (g, h) \leq P_{1,\text{pk},1} \), \( \mathbb{E}\{(1 - P_d) P_0 (g, h) | g|^2 + P_d P_1 (g, h) | g|^2\} \leq Q_{\text{avg}} \), \( P_0 (g, h) \geq 0, P_1 (g, h) \geq 0 \)

where \( P_{0,\text{pk},0} \) and \( P_{1,\text{pk},1} \) denote the peak transmit power limits when the channel is detected as idle or busy, respectively.

By transforming the above optimization problem into an equivalent parametrized concave form and following the same steps as in Section III-A, the power adaptation schemes are obtained as in (33) and (34), respectively, given at the top of the next page.

**Remark 2:** The power adaptation schemes in (33) and (34) have the same structure as those in [15] in the case of perfect sensing and \( \alpha = 0 \).

Algorithm 1 can be modified to maximize the EE subject to peak power constraint and average interference constraint in such a way that \( P_0^*(g, h) \) and \( P_1^*(g, h) \) are calculated using (33) and (34), respectively, and only the Lagrange multiplier \( \nu \) is updated according to (27).

**IV. NUMERICAL RESULTS**

In this section, we present numerical results to illustrate the performance of the proposed EE-maximizing power adaptation methods. Unless mentioned explicitly, it is assumed that noise variance is \( N_0 = 0.2 \), the variance of primary user signal is \( \sigma^2 = 1 \). Also, the prior probabilities \( \Pr\{H_0\} = 0.4 \) and \( \Pr\{H_1\} = 0.6 \). The frame duration \( T \) and sensing duration \( \tau \) are set to 100 and 10, respectively. The circuit power is \( P_c = 0.1 \). The step sizes \( \lambda \) and \( \nu \) are set to 0.1 and tolerance \( \epsilon \) is chosen as 0.0001.

In Fig. 2 we display achievable maximum EE as a function of the constraints on peak/average transmit power for perfect...
Fig. 3: (a) Maximum achievable EE, $\eta_{\text{EE}}(P_0, P_1)$ vs. probability of detection, $P_d$; (b) optimal achievable rate maximizing EE, $R(P_0, P_1)$ vs. $P_d$; (c) optimal total transmission power, $P_{\text{tot}}$ and $P_0$, $P_1$ vs. $P_d$. 

sensing (i.e., $P_d = 1$ and $P_1 = 0$) and imperfect sensing with $P_d = 0.8$ and $P_1 = 0.1$. $Q_{\text{avg}}$ is set to $-1$ dB. It is seen that higher energy efficiency is achieved with perfect sensing compared to that attained with imperfect sensing. In the case of perfect sensing, the probabilities $\Pr(\mathcal{H}_1|H_0)$ and $\Pr(H_0|H_1)$ are zero. Therefore, the secondary users in idle-sensed channels do not experience additive disturbance from the primary users, which results in higher achievable rates, hence higher achievable EE compared to that in the imperfect-sensing case. It is also observed that maximum achievable EE initially increases as the peak/average transmit power constraints relax. However, when the peak/average transmit power constraints become sufficiently loose compared to $Q_{\text{avg}}$, the maximum achievable EE becomes fixed since the transmission power is now determined by the average interference constraint, $Q_{\text{avg}}$ rather than the peak/average transmit power constraints. Moreover, higher achievable EE is achieved under the average transmit power constraint since the power allocation under the average transmit power constraint is more flexible than that under the peak transmit power constraint.

In Fig. 3, maximum achievable EE, optimal achievable rate, $R(P_0, P_1)$, and optimal powers, $P_{\text{tot}}$, $P_0$ and $P_1$, are plotted as a function of the detection probability, $P_d$. We consider different peak and average transmit power constraints, e.g., $P_{\text{pk,0}} = P_{\text{pk,1}} = P_{\text{avg}} = -4$ dB and $P_{\text{pk,0}} = P_{\text{pk,1}} = P_{\text{avg}} = -10$ dB. Average interference constraint, $Q_{\text{avg}}$ is set to $-8$ dB. It is assumed that probability of false alarm is $P_1 = 0.1$. We only display $R(P_0, P_1)$ and optimal powers, $P_{\text{tot}}$, $P_0$ and $P_1$, under the best performance, i.e., when $P_{\text{avg}} = -4$ dB since the same trends are observed for other transmit power constraints. As $P_{\text{d}}$ increases, secondary users have more reliable sensing performance. Hence, secondary users experience miss detection events less frequently, which results in increased achievable rates. The transmission power $P_{\text{d}}$ under idle sensing decision increases with increasing $P_{\text{d}}$ while transmission power $P_1$ under busy sensing decision decreases with increasing $P_{\text{d}}$. Since the achievable rate increases and the total transmission power decreases, maximum achievable EE increases as sensing performance improves.
In the presence of sensing errors, EE maximization problem power constraints and average interference power constraints. Performance through detection and false alarm probabilities. It is shown that power adaptation schemes depend on the sensing performance through detection and false alarm probabilities.

When the objective is to maximize EE, the total transmission power maximizing the EE increases with increasing $P_1$, which leads to lower achievable EE. For instance, it is shown that maximum achievable EE increases with increasing $P_1$, and decreases with increasing $P_1$. Moreover, under the same average interference constraint, secondary users operating subject to peak transmit constraints have smaller achievable EE than that attained under average transmit power constraints.

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