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Energy-Efficient Resource Allocation for OFDM-Based Cognitive Radio Networks with Imperfect Spectrum Sensing

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Abstract

In this study, energy-efficient (EE) resource allocation in orthogonal frequency division multiplexing-based cognitive radio networks with imperfect spectrum sensing is investigated. We present a new EE model by considering the sensing errors. Optimizing such an EE expression saves valuable resources, such as battery life, by selectively allocating power to underutilized subcarriers, and also achieves EE gain compared with general EE expression. Given that the primary user's interference tolerance can be defined as either the Peak Interference Power (PIP) constraint or Average Interference Power (AIP) constraint for all subchannels, we compare the EE performance for the two interference power constraints. Finally, we propose an optimal EE resource allocation scheme based on the quasiconcave relation between the EE and transmit power. Simulations show that the new EE design improves EE compared with the conventional EE design, and the EE is higher with AIP constraint than that with PIP constrain under certain interference power.

Keywords*: energy efficiency, OFDM, cognitive radio, imperfect spectrum sensing*

1. Introduction

With the growth of wireless multimedia and high data rate requirements, wireless spectrum resources are becoming increasingly crowded. By contrast, spectrum efficiency in the traditional wireless management scheme is extremely low [1]. Faced with the situation mentioned above, cognitive radio (CR) technology has been proposed to improve spectrum utility by exploiting the secondary user (SU) to access the spectrum hole that is not occupied by the primary user (PU). Orthogonal frequency division multiplexing (OFDM) has become a potential access technology in future CR systems because of its flexibility in radio resource allocation [2].

In recent years, the resource allocation problem in the OFDM-based CR system has been studied in the literature [3–8]. To improve SU's capacity, optimal and suboptimal power allocation schemes for OFDM-based CR systems are presented [3]. In [4], the authors proved that PU can achieve a larger throughput using Average Interference Power (AIP) constraint instead of Peak Interference Power (PIP) constraint. Adaptive power loading for OFDM-based CR systems with statistical interference constraint has been studied in [5-6]. Considering the PU activity, the authors presented a risk-return capacity model and improved the spectral efficiency (SE) in [7-8], although a reduction in the attainable throughput was obtained.

Meanwhile, with the explosive growth of high data rate wireless services and requirement of ubiquitous availability, energy consumption is also growing, leading to large amounts of greenhouse gas emissions and high operation expenditures. Green radio, which emphasizes energy efficiency (EE), is becoming a new research hotspot for future wireless networks. In [9], the authors addressed the EE resource allocation problem, and

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proposed optimal and low-complexity suboptimal algorithms in both downlink and uplink orthogonal frequency division multiple access (OFDMA) networks. The relationship between EE and SE has been studied in the downlink OFDMA network [10]. To maximize the system's EE, authors have proposed an optimal iterative algorithm based on convex optimization theory and parametric programming [11]. An efficient barrier method has been developed to maximize EE in [12].

However, most previous studies on EE resource allocation in CR networks were confined to the perfect spectrum sensing (SS). [7-8] considered PU activity or imperfect SS, but they did not consider EE. [9–12] only addressed the EE resource allocation problems with perfect SS. In practice, inevitable sensing errors for the subcarrier exist because of inherent feedback delays, estimation errors, and quantization errors.

Thus, in this paper, we specifically deal with the problem of EE resource allocation for an OFDM-based CR system with imperfect SS. In consideration of account sensing errors or available subcarrier, we propose a new EE model by defining a rate loss function. The new EE design differs from the traditional EE design in such a way that we can model the randomness in link capacity as a product of the probability of sensing error and rate loss, which is a function of allocated power in the corresponding subcarriers. Optimizing this EE expression saves valuable resources, such as battery life, by selectively allocating less power to underutilized subcarriers. After introducing the AIP and PIP constraints for PUs, we formulate a quasiconcave optimization problem for this new EE model, and determine the optimal solution for subcarrier power allocation.

This paper is organized as follows: Section II describes the system and formulates the objection function; Section III presents the optimal solution approach for maximum EE; Section IV contains the numerical results; and Section V presents the conclusion of the study.

2. System Description and Problem Formulation

We consider an OFDM-based CR system. In the spectral domain, the side-by-side CR radio access model is used, as depicted in Figure 1. We assume that the frequency bands B1, B2,..., BL are occupied by the PUs. N available subcarriers exist in the vicinity of these PUs bands, and the SU can opportunistically access those subcarriers using OFDM. We assume that the bandwidth of each CR subcarrier is W. Let L={1, 2, ..., L} and N={1, 2, ..., N} denote the sets of all PUs and all available subcarriers, respectively.

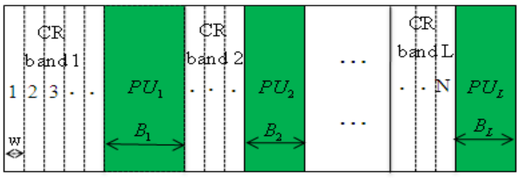


Figure 1. Spectrum in an OFDM-Based CR System

In this paper, we assume that the instantaneous channel gains are perfectly known at the transmitter, and denote the channel power gains from the base station to the CR and from the CR to the PU l, $l = 1, ..., L$, on subchannel n as h_n and $s_{l,n}$, respectively.

The power spectral density (PSD) of the SU signal on subchannel n can be written as follows [13]:

$$\varphi_n(f) = p_n T_s \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2 \tag{1}$$

Where p_n is the SU transmit power on the nth subchannel, and T_s is the symbol duration. Therefore, the interference power introduced by the SU signal on subchannel n into PU l's can be written as follows:

$$I_{n,l}(d_{n,l},p_n)=p_nT_s\left|s_{l,n}\right|^2\int_{d_{n,l}-B_l/2}^{d_{n,l}+B_l/2}\left(\frac{\sin\pi fT_s}{\pi fT_s}\right)^2\mathrm{df}=p_nK_n^{(l)} \tag{2}$$

Where $d_{n,l}$ is the spectrum distance between the nth subcarrier and lth PU band, and $K_n^{(l)}=T_s\left|s_{l,n}\right|^2\int_{d_{n,l}-B_l/2}^{d_{n,l}+B_l/2}\left(\frac{\sin\pi fT_s}{\pi fT_s}\right)^2\mathrm{df}$ denotes the interference factor of the nth subcarrier.

Similarly, the interference power introduced by the lth PU band into the nth subcarrier at the SU is as follows:

$$Q_{n,l}(d_{n,l},p_n)=\int_{d_{n,l}-W/2}^{d_{n,l}+W/2}\left|h_n\right|^2\varphi_{\mathrm{PU},l}(f)\mathrm{df} \tag{3}$$

Where $\varphi_{PU,l}(f)$ is the PSD of the lth PU signal.

Based on the Shannon capacity formula, the capacity on the nth subchannel is calculated as follows:

$$r_n=W\log_2\left(1+\frac{p_n\left|h_n\right|^2}{\Gamma(\delta_n^2+\sum_l^L Q_{n,l})}\right) \tag{4a}$$

Where δ_n^2 denotes the additive white Gaussian noise variance, and Γ is the signal-to-noise ratio gap parameter, which indicates how far the system is operating from capacity. We define $g_n=\frac{\left|h_n\right|^2}{\Gamma(\delta_n^2+\sum_{l=1}^L Q_{n,l})}$, so $r_n=W\log_2(1+p_ng_n)$.

A practical CR system has two types of sensing errors [14], namely, *misdetection* and *false alarm*. *Misdetection* occurs when a subchannel is sensed to be available for SU but is used by the PU, or a given channel fails to detect the presence of an arriving PU on the given channel. *False alarm* means that a subchannel is identified to be used but is actually vacant. In this study, we only consider *misdetection* events. Given the occurrence of *misdetection*, power investment in that subchannel is wasted. To reduce power waste, we define a rate loss $\chi(p)$ that is a function of the power invested by the cognitive network. We assume that α_n is the error detection probability (EDP) on subchannel n, namely, the *misdetection* probability, and the expected rate loss is expressed as follows: $\Delta r_n=\alpha_n\chi(p_n)$. Thus, the expected rate of the nth subchannel is expressed as follows:

$$\ddot{r}_n=W\log_2(1+p_ng_n)-\alpha_n\chi(p_n) \tag{4b}$$

Which is also known as the risk-return model [8]. Although many types of rate loss function exist [15], to simplify the analysis, we use a linear rate loss function: $\chi(p_n)=Cp_n$, where C is the normalized average cost per unit power for the SU to utilize the resource.

To ensure the quality of service of the PU, the interference power introduced by all subchannels to the PUs must be lower than a certain threshold. PU's interference tolerance can be defined as either the PIP constraint or AIP constraint. Therefore, we define probability Pr as the probability that the AIP to the lth PU is lower than the threshold $I_{\mathrm{th}}^{(l)}$

$$\sum_{n=1}^N p_nK_n^{(l)}\le I_{\mathrm{th}}^{(l)},\, l\in\{1,2,\cdots,L\} \tag{5a}$$

$$\Pr\left(\sum_{n=1}^N p_nK_n^{(l)}\le I_{\mathrm{th}}^{(l)}\right)\ge a,\, l\in\{1,2,\cdots,L\} \tag{5b}$$

Where a denotes the probability. We assume that s_l is the Rayleigh distribution with a known parameter θ_l, so the distribution of $|s_l|^2$ is an exponential distribution with parameter θ_l^2. Hence, Eq. (5b) can be written as follows:

$$1-e^{-\frac{I_{th}^{l}}{2\theta_l^2\sum_{n=1}^{N}p_nK_n^l}} \geq a, l \in \{1,2,\cdots L\} \tag{6}$$

After some mathematical manipulation, Eq. (6) can be rewritten as

$$\sum_{n=1}^{N} p_n K_n^{(l)} \leq \frac{I_{\text{th}}^{(l)}}{2\theta_l^2[-\ln(1-a)]}, l \in \{1,2,\cdots,l\} \tag{7}$$

Practically, energy consumption includes transmit power and circuit energy consumption, so all power consumption at the base station is [17]

$$P_{\text{sum}} = \xi P + P_{\text{c}} \tag{8}$$

Where P is the total transmit power, $P=\sum_{n=1}^{N} p_n$, ξ is the reciprocal of the drain efficiency of power amplifier, and P_{c} is the circuit power.

Considering the introduction of the EDP in this study, we propose a new EE model using Eq. (4b) as capacity. The general EE model (using EQ. (4a) as capacity) can also be considered. Thus, we aim to maximize EE under different cases (such as AIP constraint or PIP constraint for the PUs). In practice, a minimal rate requirement $R_{\min}$ is used to ensure the SU's reliable communication. Hence, the EE optimization problem can be written as follows:

$$\max \ \frac{R}{\xi P + P_c} \tag{9}$$

Subject to:

$$R = \sum_{n=1}^{N} r_n \ or \ R = \sum_{n=1}^{N} \tilde{r}_n \tag{10}$$

$$\sum_{n=1}^{N} p_n \leq P_{total} \tag{11}$$

$$R \geq R_{\min} \tag{12}$$

$$(5a) \ or \ (5b) \tag{13}$$

$$p_n \geq 0, \forall n \tag{14}$$

Where P_{total} is the total transmit power constraint to the SU.

3. Optimal Power Allocation

The EE optimization problem includes four cases. Given the limited space, we only conduct a detailed analysis on the new EE problem with AIP constraint.

Based on [9], we summarize the following theorem, which has been proved in the Appendix.

We redefine the optimization problem as follows:

$$\begin{aligned} \eta(P) &@ \frac{R(P)}{\xi P + P_c} \\ &@ \frac{\max R(\mathbf{P})}{\xi P + P} \\ &@ \max \frac{\sum_{n=1}^{N}(W\log_2(1+p_ng_n)-\varphi_nCp_n)}{\xi\sum_{n=1}^{N}p_n + P_c} \end{aligned} \tag{15}$$

subject to

$$\sum_{n=1}^{N} r_n \geq R_{\min} \quad (16)$$

$$\sum_{n=1}^{N} p_n K_n^{(l)} \leq \frac{I_{th}^{(l)}}{2\theta_l^2[-\ln(1-a)]}, l \in \{1,2,\cdots,L\} \quad (17)$$

$$\sum_{n=1}^{N} p_n = P \quad (18)$$

$$p_n \geq 0, n \in \{1,2,\cdots,N\} \quad (19)$$

Theorem 1: For a certain total transmit power P, the maximum EE, namely, $\eta(P)$, is continuously and strictly quasiconcave in P.

We assume $P_{\min}$ is the minimum transmit power when $R(P)$ is under constraint (16), and P_{th} denotes the maximum transmit power when $R(P)$ is under constraint (17). $P_{\min}$ and P_{th} can be calculated using the following equations:

$$P_{\min} = \sum_{n}^{N} p_n \text{, } p_n = \left(\frac{W}{(1/\mu + \alpha_n C)\ln 2} - \frac{1}{g_n} \right)^+ \quad (20)$$

$$P_{\text{th}} = \sum_{n}^{N} \hat{p}_n \text{, } \hat{p}_n = \left(\frac{W}{(\sum_{l=1}^{L} \lambda_l K_n^{(l)} + \alpha_n C)\ln 2} - \frac{1}{g_n} \right)^+ \quad (21)$$

Where μ and λ_l are the non-negative dual variables associated with the non-equality constraints (16) and (17), and the notation $(\cdot)^+$ is defined as $(\cdot)^+ = \max\{\cdot,0\}$. The solution can be obtained based on Theorem 2.

For a certain transmit power P ($P \in [P_{\min} \min (P_{\text{th}} P_{\text{total}})]$), R(P) under the constraints (17), (18), and (19) is difficult to solve. We then propose Theorem 2 to solve this problem.

Theorem 2: The total transmission capacity $R(P)$ is maximized by

$$p_n^* = \left(\frac{W}{(\sum_{n=1}^{N} \lambda_l K_l^n + \mu + \varphi_n C)\ln 2} - \frac{1}{g_n} \right)^+ . \quad (22)$$

Proof: Considering that maximization of a concave function is equivalent to minimization of its negative value, we can rewrite the optimization problem as follows:

$$\min \sum_{n=1}^{N} (\varphi_n C p_n - W \log_2(1+p_n g_n)) \quad (23)$$

Subject to

$$(17),(18),(19) \quad (24)$$

Introducing the so-called Lagrange parameters υ_l, β, and μ_n to the constraints in Eqs. (17), (18), and (19), respectively, the Karush–Kuhn–Tucker conditions can be written as follows [17]:

$$\upsilon_l \geq 0, \forall l \in \{1,2,\cdots L\} \quad (25)$$

$$\mu_n \geq 0, \forall n \in \{1,2,\cdots N\} \quad (26)$$

$$\mu_n p_n^* = 0, \forall n \in \{1,2,\cdots N\} \quad (27)$$

$$\upsilon_l (\sum_{n=1}^{N} K_n^{(l)} p_n^* - \frac{I_{th}^l}{2\theta^2[-\ln(1-a)]}) = 0, \forall l \in \{1,2,\cdots L\} \quad (28)$$

$$\beta (\sum_{n=1}^{N} p_n^* - P) = 0 \quad (29)$$

$$-\frac{Wg_n}{(1+p_n^* g_n)\ln 2}+\varphi_n C-\mu_n+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta=0,\forall n\in\{1,2,\cdots N\} \tag{30}$$

We can rewrite Eq. (30) as follows:

$$\mu_n=-\frac{Wg_n}{(1+p_n^* g_n)\ln 2}+\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta \tag{31}$$

We then substitute Eq. (31) into Eqs. (26) and (27), and eliminate μ_n.

$$\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta\geq\frac{Wg_n}{(1+p_n^* g_n)\ln 2},\forall n\in(1,2,\cdots N) \tag{32}$$

$$(-\frac{Wg_n}{(1+p_n^* g_n)\ln 2}+\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta)p_n^*=0,\forall n\in(1,2,\cdots N) \tag{33}$$

When $\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta<\frac{Wg_n}{\ln 2}$, then Eq. (32) can only be true if $p_n^*>0$, according to Eq. (33).

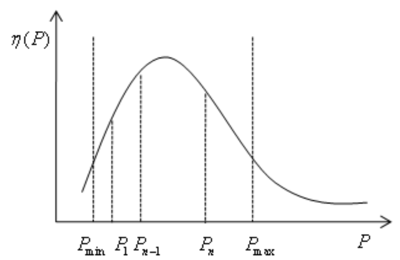
$$p_n^*=\frac{W}{(\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta)\ln 2}-\frac{1}{g_n} \tag{34}$$

However, if $\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta\geq\frac{Wg_n}{\ln 2}$, then $p_n^*>0$ is not possible because it would violate Eq. (33). Thus, $p_n^*=0$ is the only solution in this case. The optimal power can be rewritten as follows:

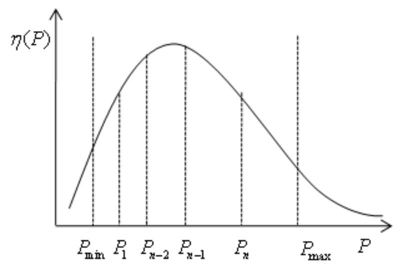
$$p_n^*=[\frac{W}{(\varphi_n C+\sum_{l=1}^{L}K_n^{(l)}\upsilon_l+\beta)\ln 2}-\frac{1}{g_n}]^+,\forall n\in\{1,2,\cdots N\} \tag{35}$$

This formula completes the proof of Theorem 2.

For any strictly quasiconcave function, a unique global maximum always exists. In this study, we need to determine the maximum of the quasiconcave function η(P) in [P_{min}, P_{max}] (P_{max} = min (P_{th}, P_{total}). To determine the maximum or minimum of a function in a certain range when the function is concave or quasiconcave, fully developed algorithms in [17] can be used. We then describe our scheme to determine the optimal power allocation that can maximize EE. This scheme is illustrated in Figure 3. First, P_{min} and P_{max} are calculated using Eqs. (20) and (21). P_{min} is used as the initial value, which is shown in Step 1. If $\eta(P)$ decreases at P_n after some iteration, we can roughly determine the scope of the optimal value. However, Figure 2 illustrates two possible cases. If we use [P_{n-1}, P_n] as the scope of the optimal value, such as Case 1, we will not find the optimal value if Case 2 occurs. Based on the above two cases, we can use [P_{n-2}, P_n] instead of [P_{n-1}, P_n], and the optimal value must be found in the range [P_{n-2}, P_n], which is shown in Step 2. Finally, we use the Golden Section Search to find the optimal value of $\eta(P)$ in [P_{n-2}, P_n], which is shown in Step 3.



Case 1



Case 2

Figure 2. EE–Power Relationship in OFDM-Based CR System

Power Allocation Algorithm

1. Initialization:

Calculate $\mathbf{P} = [p_1, p_2, \cdots, p_n]$ and $\hat{\mathbf{P}} = [\hat{p}_1, \hat{p}_2, \cdots, \hat{p}_n]$ using (20) and (21), and get $P_{\min}$ and $P_{\max}$,

$$P_1 \leftarrow P_{\min}, \eta_1 \leftarrow \frac{\sum_{n=1}^{N}(W\log_2(1+p_n g_n)-\varphi_n C p_n)}{\xi P_1 + P_c};$$

2. One-dimensional search:

2.1) $P_0 \leftarrow P_1, P_2 \leftarrow \min(kP_1, P_{\max})$, where $k > 1$,

Calculate $\mathbf{P}_2 = [p_1^2, p_2^2, \cdots, p_n^2]$ using (22),

$$\eta_2 \leftarrow \frac{\sum_{n=1}^{N}(W\log_2(1+p_n g_n)-\varphi_n C p_n)}{\xi P_2 + P_c};$$

If $\eta_2 \le \eta_1 \mid P_2 == P_{\max}$, go to step 3; othewise continue.

2.2) $P_0 \leftarrow P_1, P_1 \leftarrow P_2, \eta_1 \leftarrow \eta_2, P_2 \leftarrow \min(kP_1, P_{\max})$,

Calculate $\mathbf{P}_2 = [p_1^2, p_2^2, \cdots, p_n^2]$ using (22),

$$\eta_2 \leftarrow \frac{\sum_{n=1}^{N}(W\log_2(1+p_n g_n)-\varphi_n C p_n)}{\xi P_2 + P_c};$$

If $\eta_2 \le \eta_1 \mid P_2 == P_{\max}$, go to step 3;
othewise go to step 2.2).

3. Golden section search:

while $(P_2 - P_0 > \varepsilon, \varepsilon > 0, \lambda = 0.618)$

{

$P_0^* = P_0 + (1-\lambda)(P_2 - P_0)$;

$P_1^* = P_0 + \lambda(P_2 - P_0)$;

Calculate $\mathbf{P}_k^* = [p_1^k, p_2^k, \cdots, p_n^k]$ using (22), $k \in \{0,1\}$;

$$\eta_k \leftarrow \frac{\sum_{n=1}^{N}(W\log_2(1+p_n g_n)-\varphi_n C p_n)}{\xi P_k^* + P_c}, k \in \{0,1\};$$

If $\eta_1 > \eta_2$, $P_2 \leftarrow P_1^*$, othewise $P_0 \leftarrow P_0^*$.

}

4. Finish:

$P = \frac{1}{2}(P_2 + P_0)$, Calculate $\mathbf{P} = [p_1, p_1, \cdots, p_1]$ using (22);

$$\eta \leftarrow \frac{\sum_{n=1}^{N}(W\log_2(1+p_n g_n)-\varphi_n C p_n)}{\xi P + P_c}.$$

Figure 3. Proposed Research Algorithm

The above is our detailed analysis, and an optimal solution can be obtained by applying the research algorithm.

4. Simulation Results

In this Section, several numerical examples are presented to compare the EE under different cases. In the simulation, we consider a simple system consisting of two PU_s, PU_1 and PU_2, as shown in Figure 4. Three sub-bands consist of 16 subcarriers. In this paper, the values of Γ, T_s, W, and B are 1, 4 μs, 0.3125 MHz, and 1 MHz, respectively. The circuit power P_c is assumed to be 10^{-2} W. The total power budget is assumed to be P_{total} = 1 W. The noise power is assumed to be $N_0 = 10^{-12}$ W/Hz. We assume that the EDP or every subcarrier available is the same for all subchannels, and the linear loss function with normalized cost per unit power C = 3.125 × 104 bits/s/mW. The channel gain h_n and $s_{l,n}$ are assumed to be independent identically distributed Rayleigh random variables. The drain efficiency of the power amplifier is set to 78%.

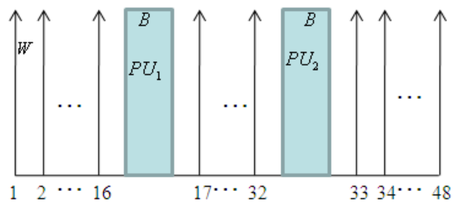


Figure 4. Example of a Simple OFDM-Based CR System

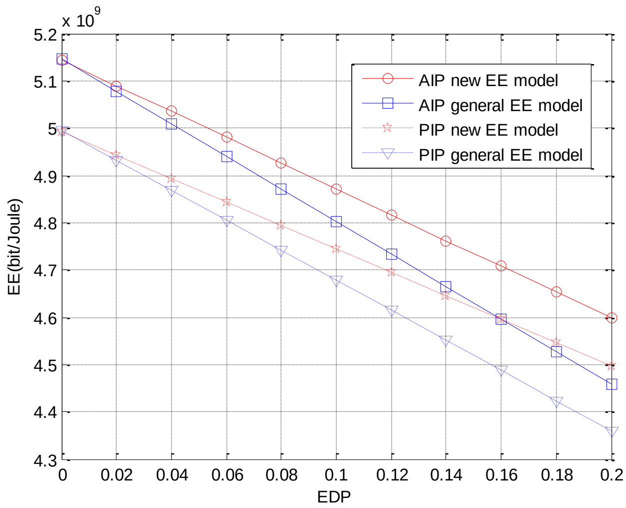


Figure 5. EE versus the EDP with $I_{th} = 10^{-6}$ W

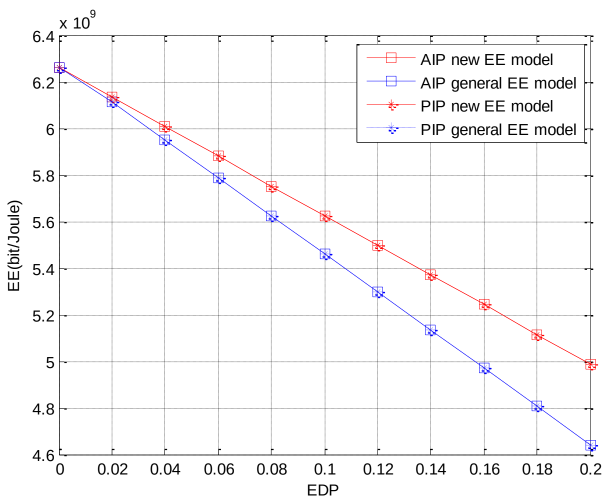


Figure 6. EE versus the EDP with $I_{th} = 10^{-4}$ W

Figures 5 and 6 show the EE versus EDP under different cases with a = 0.98. In Figure 5 ($I_{th} = 10^{-6}$ W), we observe that the EE decreases as the EDP increases, and the EE with AIP constraint is higher than that with PIP constraint. As the EDP increases, the waste of the power increases, thereby decreasing the EE. Previous analysis showed that the SU can transmit more power under AIP constraint before reaching the maximum EE, and a high EE results in a large transmit power. We can also find that the EE of the new model is higher than the EE of the general model, and the gap between them increases with rising EDP. When EDP is equal to 0, the EE for the new model and general model is the same because no error is detected when EDP = 0. However, as the EDP increases, the waste of power with the general EE model is higher than that with the new EE. We consider the power loss brought by the error detection in the new EE model, reducing the unnecessary waste of power. Unlike Figure 5, Figure 6 ($I_{th} = 10^{-4}$ W) shows that the EE under different constraints (AIP or PIP) is the same. We also find that the EE is higher than that in Figure 5. Given the increase in interference threshold, SU is allowed to transmit more power so that the EE improves. Similar EE under AIP constraint and PIP constraint can be explained by the fact that the EE has reached the maximum within the scope of the interference threshold to the PU.

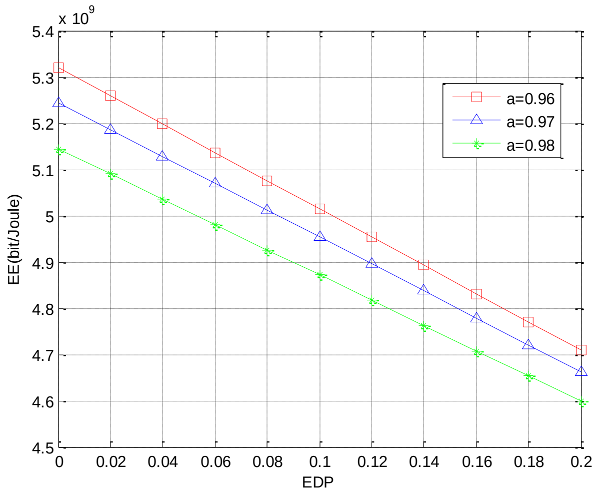


Figure 7. EE versus the EDP under Different *a*

We depict the EE of the new model versus the EDP in Figure 7. Figure 7 shows that the EE decreases as the EDP increases. Moreover, Figure 7 shows that the EE increases as a decrease. This phenomenon is very easy to understand. The interference threshold will increase when a decreases, so the SU can transmit more power, thereby improving the EE.

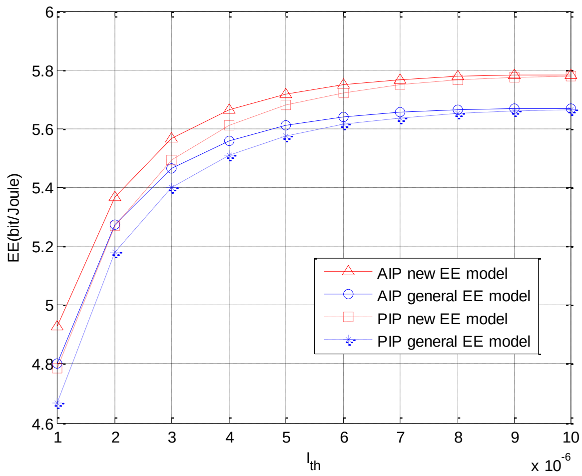


Figure 8. EE versus the Interference Threshold

In Figure 8, we plot the expected EE versus interference threshold I_{th}, where α_n and a are 0.1 and 0.98, respectively. We observe that as I_{th} increases, the EE initially increases and then saturates. Given that the EDP is not equal to 0, the EE of the proposed model is always higher than the EE of the general model for different interference thresholds. As Figure 8 shows, when the interference threshold is small, the EE with AIP constraint is higher than that with PIP constraint, but the EE with the two constraints is almost the same when the interference threshold is large. For a small interference threshold, the power transmitted by the SU is small, and the power does not maximize the EE. However, for a bigger interference threshold, the SU can transmit a larger power, and the EE may be maximized (Figure 2). By comparing Figures 5 and 6, we can also obtain a similar solution.

5. Conclusion

In this study, we considered the problem of EE resource allocation in an OFDM-based CR system with imperfect SS. To incorporate power waste during error detection, we introduced a new EE model by defining a rate loss function. AIP constraint and PIP constraint for all subchannels were considered. Finally, we formulated an optimization EE problem, and determined the optimal power allocation by the quasiconcave relation between the EE and transmit power. Simulation results show that the EE with the new model is higher than that with the general model, and the EE with AIP constraint also improves compared with that with PIP constraint. However, we must consider the influence of the interference threshold on EE.

6. Appendix

Proof: First, we prove that R(P) is strictly concave with constraints (11), (16), (17), and (19). We can easily prove that R(P) is concave. Eqs. (11), (17), and (19) are linear constraints, so we can easily prove them for concave constraints using the definition. For (16), it can be proven as follows: we assume $\mathbf{P}_1=[p_1^1, p_2^1, \text{L}, p_n^1]$ and $\mathbf{P}_2=[p_1^2, p_2^2, \text{L}, p_n^2]$ meet Eq. (16), and $\mathbf{P}_3=\theta\mathbf{P}_1+(1-\theta)\mathbf{P}_2$ ($\theta \in (0,1)$).

Then, we have

$$\begin{aligned}&\sum_{n=1}^{N}(W\log_2(1+p_n^3 g_n)-\varphi_n C p_n^3)\\&=\sum_{n=1}^{N}(W\log_2(1+(\theta p_n^1+(1-\theta)p_n^2)g_n)-\varphi_n C(\theta p_n^1+(1-\theta)p_n^2))\\&>\sum_{n=1}^{N}(\theta(W\log_2(1+p_n^1 g_n)-\varphi_n C p_n^1)+(1\text{-}\theta)(W\log_2(1+p_n^2 g_n)-\varphi_n C p_n^2))\\&\geq\theta R_{\min}+(1\text{-}\theta)R_{\min}\\&=R_{\min}\end{aligned}\qquad(36)$$

Hence, $R(\mathbf{P})$ is strictly concave in P_n.

Second, we prove that $R(P)$ is continuously and strictly concave with constraints (11), (16), (17), (18), and (19). Let $\boldsymbol{P}_i$ be the transmit power matrix corresponding to $R(P_i)$. We assume that $P_1<P_2<P_3$, and define $\mathbf{P}_2=\frac{P_3-P_2}{P_3-P_1}\mathbf{P}_1^*+\frac{P_2-P_1}{P_3-P_1}\mathbf{P}_3^*=\omega\mathbf{P}_1^*+(1-\omega)\mathbf{P}_3^*$, where $\omega=\frac{P_3-P_2}{P_3-P_1}$. $R(P_2)=R(\mathbf{P}_2^*)\geq R(\mathbf{P}_2)>\omega R(\mathbf{P}_1^*)+(1-\omega)R(\mathbf{P}_3^*)=\omega R(P_1)+(1-\omega)R(P_3)$. For every P, a unique and limit $R(P)$ always exists, so $R(P)$ is continuously and strictly concave in P.

Finally, we prove $\eta(P)$ is strictly quasiconcave in P. We then denote the super level sets of $\eta(P)$ as $S_\alpha=\{P\in[P_{min}, P_{max}]|\eta(P)\geq\alpha\}$. According to [16], $\eta(P)$ is strictly quasiconcave in P if S_α is strictly convex for any real number α. When $\alpha < 0$, no points exist on the counter $\eta(P)=\alpha$. When $\alpha\geq 0$, S_α is equivalent to $S_\alpha=\{P\in [P_{min}, P_{max}]|\alpha\xi P+\alpha P_C\text{-}R(P)\leq 0\}$.

Thus, we have proved that $R(P)$ is strictly concave in P, so S_α is strictly convex in P. This formula completes the proof of *Theorem* 1.

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