Energy-Efficient Link Adaptation for Cognitive Radios with Heterogeneous QoS requirements

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***Abstract*—Energy efficiency is crucial in wireless communication systems, especially in cognitive radio (CR) systems in which the exclusive functionality of spectrum sensing inevitably incurs additional energy consumption. In this paper, we study energy-efficient link adaptation for the secondary users (SUs) with heterogeneous quality of service (QoS) requirements in an interference-limited CR system. Two classes of SUs with different QoS are considered: delay-sensitive SUs (DS-SUs) and delay-tolerant SUs (DT-SUs). We focus on energy efficiency (EE) maximization taking into account the SUs' heterogeneous QoS and PU interference constraint. The problem of EE maximization is formulated as a nonlinear fractional programming problem, which is transformed into an equivalent parametric programming problem. Moreover, optimal solution to joint subcarrier assignment and power allocation is derived with the bisection method and dual decomposition method (DDM) in convex optimization theory. Simulation results illustrate the significant performance improvement of our scheme over an existing one which aims at maximizing system throughput rather than EE.**

I. Introduction

Cognitive radio (CR) technology, which is regarded as an effective way to combat the shortage of spectrum resource, has drawn increasing attention in recent years [1], [2]. In a CR system, secondary users (SUs) are able to sense the licensed channels of primary users (PUs) and opportunistically utilize the idle channels unused by PUs, which significantly improves the efficiency of spectrum utilization.

As an efficient modulation technique, orthogonal frequency division multiplexing (OFDM) has aroused great interests with extensive applications of high speed multimedia services due to its strong anti-multipath fading and high spectrum efficiency. In a OFDM-based CR system, the inevitable out-of-band (OOB) emission causes side-lobe interference (SLI) while PUs and SUs are operating in adjacent subcarriers, which degrades performance of the whole network. In addition, imperfect channel sensing which incurs miss detection and false alarm of active PUs' transmission also degrades the performance. In [3] and [4], SUs' channel is divided into a number of frequency-flat subcarriers, and system throughput based on the sensing information is maximized taking into account SLI. In [5], throughput of a CR system is maximized by jointly optimizing both power allocation and detection operation considering the influence of miss detection and false alarm. The author of [6] studied the cross-layer design for the SUs system with heterogeneous QoS requirements in interference-limited CR systems.

With the proliferation of intelligent devices (e.g. smart phones) with more powerful capabilities, energy consumption becomes a critical issue, which makes energy-efficient transmission in wireless communication system an eye-catching topic [7]. In [8], an energy-efficient power allocation scheme for OFDM-based CR network is investigated, and the energy efficiency (EE) is maximized taking into account the total transmit power and interference constraints. The problem of EE in heterogeneous CR networks with femtocells is studied in [9], where the energy-efficient resource allocation is formulated as a Stackelberg game and the Stackelberg equilibrium solution is obtained by a gradient-based iteration algorithm. In [10], the non-cooperative spectrum sharing problems are considered in cognitive wireless mesh networks formed by a number of clusters, where the stochastic learning process is employed to model the competition behaviors of SUs in a dynamic environment and the average amount of bits received correctly per unit of energy consumption is considered as the reward function.

There have been volumes of existing literatures on CR networks with heterogeneous QoS requirements or energy-efficient link adaptation, however, most of previous works are separately focus on either throughput maximization for CR networks considering the heterogeneous QoS requirements or EE maximization for CR networks without heterogeneous QoS requirements. In other words, few of existing works jointly considered both heterogeneous QoS requirements and energy-efficient link adaptation in CR networks.

In this paper, we study the energy-efficient link adaptation for an OFDM-based CR system with heterogeneous QoS requirements. The contribution of our work is summarized as follows.

- We investigate link adaptation aiming at EE maximization in a CR network with heterogeneous QoS requirements (e.g. transmission delay).
- By transforming a nonlinear fractional programming problem into an equivalent parametric programming, we maximize the EE of a CR network constrained by total power consumption, interference and heterogeneous QoS requirements of delay-sensitive SUs (DT-SUs).

The rest of this paper is organized as follows. In Section

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II, the system model and problem formulation are presented, where the SLI and the DS-SUs' delay requirements are described. Mathematical analysis is given in section III. The DDM and bisection method are then elaborated to solve the energy-efficient link adaptation problem in section IV. Section V presents the numerical results and we conclude the whole paper in section VI.

II. System Model And Problem Formulation

Consider an OFDM-based CR system, where there are K CR transmitter-receiver pairs and N subcarriers that are available for SUs. In order for PU protection, we assume that the SUs will access the licensed band only if the PUs are detected to be absent on that channel, which is referred to as the listen-before-talk (LBT) scheme [11]. It is also assumed that the channel state information (CSI) at the CR base station is accurate and no false alarm and miss detection are incurred.

In downlink transmission scenario shown in Fig. 1, generally, there are three types of channel power gain with respect to SUs: (1) the one between the transmitter and receiver of SU k on subcarrier n, denoted by $g_{k,n}$; (2) the one between the transmitter of SU k and PU's receiver on subcarrier n, denoted by $h_{k,n}$; (3) the one between the PU's transmitter and the receiver of SU k on subcarrier n, denoted by $h^{'}_{k,n}$. We assume that $g_{k,n}$, $h_{k,n}$ and $h^{'}_{k,n}$ can be known beforehand through SU's channel estimation.

We consider a side-by-side CR radio access model similar with that in [15], with B denoting the PUs' bandwidth. The unoccupied channels available for SUs' transmission are located aside the PUs' band, as shown in Fig. 2. The available bandwidth for SUs' transmission is divided into N subcarriers (also referred to as channel in this paper) with spacing Δf Hz.

According to the Shannon's channel capacity, in the case of

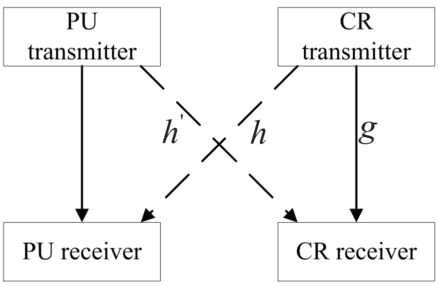

Fig. 1. Spectrum Sharing between PUs and SUs

perfect channel sensing, the transmission rate at the subcarrier n on the SU k, denoted by $R_{k,n}$, is given by

$$R_{k,n} = \Delta f \, log_2(1 + \frac{g_{k,n}Pk,n}{\sigma^2}) \tag{1}$$

where $P_{k,n}$ and $g_{k,n}$ denote the transmit power and channel power gain of SU k on subcarrier n, σ^2 denotes the variance of additive white Gaussian noise (AWGN) on the link between a CR transmitter-receiver pair. Notice that the interferences to SUs caused by PUs are ignored.

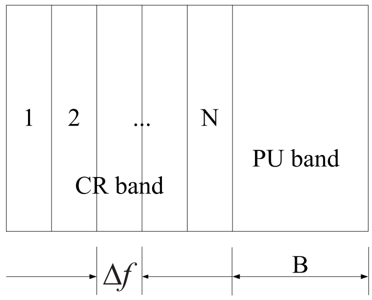

Fig. 2. Distribution of PUs and SUs in the frequency domain

As is mentioned in [12], due to the coexistence of PUs and SUs on side-by-side bands, the inherent SLI of OFDM-based CR system is inevitably incurred. In what follows, we provide brief description and mathematical models for the SLI mentioned above. We have neglected the interference that the PU may cause to the SU, as well as the effect of inter-carrier interference (ICI) by assuming that the primary system and CR system perform transmission synchronously.

A. Side-lobe Interference (SLI)

The SLI is caused by OOB emissions of OFDM technique, which makes PUs and SUs interfere with each other. In this paper, the OOB emissions of SUs on aggregate interference to PUs are considered. The power density spectrum (PSD) of the SU k on subcarrier n is denoted by $\phi_{k,n}(f) = P_{k,n}T_s(\sin \pi f T_s / \pi f T_s)$ [13], where $P_{k,n}$ is the transmit power of SU k on subcarrier n. T_s is the OFDM symbol duration and f denotes the center frequency of the subcarrier n. Let $I_{SPSk,n}$ denote the SLI power caused by SU k to the PUs' band on subcarrier n. According to [14], $I_{SPSk,n}$ can be mathematically expressed as the integration of the PSD of SU k on subcarrier n across the PUs' band, which is:

$$\begin{aligned} I_{SPSk,n} &= \int_{dn-\frac{B_{PU}}{2}}^{dn+\frac{B_{PU}}{2}} h_{k,n}P_{k,n}T_s(\frac{\sin \pi f T_s}{\pi f T_s})\, df \\ &= P_{k,n}\varphi_{k,n} \end{aligned} \tag{2}$$

where d_n is the spectral distance between the subcarrier n and the center of PUs' spectrum with bandwidth B_{PU}. $\varphi_{k,n}$ is named the interference factor of SU k on subcarrier n for expression simplicity.

B. SU Traffic Model

Two types of SU are considered, in this paper, namely, DT-SUs and DS-SUs, respectively. The former is non-delay-sensitive, e.g. emails, while the latter have stringent demands on the transmission delay, e.g. video streaming or voice services. We assumed that the data buffers of DT-SUs are extremely large in CR base station where the data packets are always waiting to transmit while data buffers of DS-SUs are limited and the arrival process of packets can be modeled as a Poisson process. To guarantee the QoS of DS-SUs, a constraint condition for average transmission delay should be satisfied.

C. Problem Formulation

In this part, we present the basic idea of energy-efficient link adaptation for CRs with heterogeneous QoS requirements and formulate this problem as an optimization problem. To formulate the energy-efficient resource allocation problem, some system constraints should be considered: (1) Total power constraint: where P_{tot}, $P_{k,n}$ denote the maximum transmission power of CR base station, and the transmit power on subcarrier n for SU k. (2) Interference threshold constraint of PUs introduced by SLI, denoted by I_{th}. (3) Average delay constraint for each DS-SU, denoted by T_k ($k \in K_{DS}$ and K_{DS} denotes the set of the DS-SUs).

For energy-efficient transmission, our objective is to maximize the throughput per Joule, calculated as the ratio of sum-rate of the SUs to total power consumption while satisfy constraints aforementioned. Mathematically, the resource allocation for the CR system can be formulated as the following optimization problem:

$$\begin{aligned} \max_{\{P_{k,n},S_k\}} \quad & \frac{\sum_{k=1}^{K}\sum_{n\in S_k} R_{k,n}}{\varepsilon\sum_{k=1}^{K}\sum_{n\in S_k} P_{k,n}+P_C} \\ s.t. \quad & \sum_{k=1}^{K}\sum_{n\in S_k} P_{k,n} \leqslant P_{tot} \\ & \sum_{k=1}^{K}\sum_{n\in S_k} P_{k,n}\varphi_{k,n} \leqslant I_{th} \\ & E[W_k] \leqslant T_k, \forall k \in K_{DS} \\ & S_i \cap S_j = \phi, \forall i \neq j \\ & \bigcup_{k=1}^{K} S_k \subseteq \{1,2,\cdots,N\} \\ & P_{k,n} \geqslant 0, \forall\, k \,\text{and}\, \forall\, n \end{aligned} \tag{3}$$

where S_i denotes the set of subcarriers assigned to SU i ($i \in \{1,2,\cdots,N\}$), and W_k denotes the time that the packets of the SU k ($k \in K_{DS}$) wait in the queue plus the service time whose expectation can be denoted by $E[W_k]$. ε is ratio of the peak-to-average ratio (PAR) of the power amplifier (PA) to the drain efficiency of the PA, and P_C is the power consumed by other transceiving circuits. T_k denotes the delay constraint in terms of time. Since the delay constraint condition is intractable, we transform the delay constraint into a transmission rate constraint of the SU k ($k \in K_{DS}$) [6] by modeling the data buffer of SU as an M/G/1 queue [15], which is given by [6]:

$$R_k \geqslant \psi(T_k, \upsilon_k, Z) \tag{4}$$

where R_k denotes the transmission rate of the SU k ($k \in K_{DS}$) and $\psi(T_k, \upsilon_k, Z)$ is given by:

$$\begin{aligned} & \psi(T_k, \upsilon_k, Z) \\ = & \frac{(T_k\upsilon_k+1)+\sqrt{(T_k\upsilon_k+1)^2-2T_k\upsilon_k}}{2T_k} E[Z] \end{aligned} \tag{5}$$

where υ_k denotes the independent packet arrival rate of the delay-sensitive services, which can be modeled as a Poisson process, and Z represents the packet size [6] which is a random variable.

III. Mathematical Analysis

In this part, we present the basic idea to solve the problem of energy-efficient link adaptation. Considering the problem is a nonlinear fractional programming problem, thus it is extremely difficult to solve directly. However, refer to a prior work [16], this nonlinear fractional programming problem can be solved by transforming it into an equivalent parametric programming problem, and the mathematical representation of the theory can be written as follows.

Let E^n be the Euclidean space of dimension n and S be a connected and compact subset of E^n. And let $N(x)$ and $D(x)$ be real-valued and continuous functions of x ($x \in S$). Furthermore, it is assumed that $D(x) > 0$ for all $x \in S$.

There are two types of problems mentioned above, and one of which is the nonlinear fractional programming problem:

$$\max_{x\in S} q = \frac{N(x)}{D(x)} \tag{6}$$

And the other is the parametric programming problem, which can be written as follows:

$$\max_{x\in S} N(x) - qD(x),\ q \in E^1 \tag{7}$$

Both the problems have solutions indeed, since S is compact, $N(x)$ and $D(x)$ are continuous, and the singular points defined by $D(x) = 0$ are excluded.

Let $F(q) = \max\{N(x) - qD(x)\}$ ($x \in S$), where q is treated as a parameter, thus $F(q)$ is a continuous, convex and strictly decreasing function of q.

And let x^* be the solution of (6), namely, $q^* = N(x^*)/D(x^*)$, the necessary and sufficient conditions $q = q^*$ is $F(q) = 0$. Thus searching the optimum of problem (6) is equal to find the solution of the nonlinear parametric equation $F(q) = 0$.

In our case, the nonlinear fractional programming problem is (3), and the corresponding transformed nonlinear parametric programming problem can be deduced as follows:

$$\begin{aligned} \max_{\{P_{k,n},S_k\}} \quad & \sum_{k=1}^{K}\sum_{n\in S_k} R_{k,n} - q(\varepsilon\sum_{k=1}^{K}\sum_{n\in S_k} P_{k,n}+P_C) \\ s.t. \quad & \sum_{k=1}^{K}\sum_{n\in S_k} P_{k,n} \leqslant P_{tot} \\ & \sum_{k=1}^{K}\sum_{n\in S_k} P_{k,n}\varphi_{k,n} \leqslant I_{th} \\ & R_k \geqslant \psi(T_k, \lambda_k, Z), \forall k \in K_{DS} \\ & S_i \cap S_j = \phi, \forall i \neq j \\ & \bigcup_{k=1}^{K} S_k \subseteq \{1,2,\cdots,N\} \\ & P_{k,n} \geqslant 0, \forall\, k \,\text{and}\, \forall\, n \end{aligned} \tag{8}$$

Then the optimum of problem (3) can be transformed to the zero root of problem (8).

IV. Energy-efficient Resource Allocation

In this part, we propose the method to solve the EE maximization problem in detail. According to the mathematical theory mentioned above, the nonlinear fractional programming problem transforms into a nonlinear parametric programming problem in the first place. Similar to [17] and [18], the duality gap of the optimization problem (8) is nearly zero when the number of subcarrier is large. Thus, using DDM, the primal optimization can be solved. The Lagrangian dual function corresponding to (8) can be formulated as:

$$\begin{aligned} g(\lambda,\mu,\vec{\nu}) &= \max_{\{P_{k,n}\}} \mathcal{L}(\{P_{k,n}\},\lambda,\mu,\vec{\nu}) \\ &= \max_{\{P_{k,n}\}} \{\sum_{k=1}^{K}\sum_{n=1}^{N} R_{k,n} - q(\varepsilon\sum_{k=1}^{K}\sum_{n=1}^{N} P_{k,n} + P_C) \\ &+ \lambda(P_{tot} - \sum_{k=1}^{K}\sum_{n=1}^{N} P_{k,n}) \\ &+ \mu(I_{th} - \sum_{k=1}^{K}\sum_{n=1}^{N} P_{k,n}\varphi_{k,n}) \\ &+ \sum_{k\in K_{DS}} \nu_k(\sum_{n=1}^{N} R_{k,n} - \psi_k)\} \end{aligned} \tag{9}$$

where λ, μ and $\vec{\nu}$ are introduced Lagrange Dual Multipliers (LDMs), and ν_k denotes the multiplier of SU k ($k \in K_{DS}$) in $\vec{\nu}$. Let ψ_k denotes $\psi_(T_k,\lambda_k,Z)$, in other words, $\psi_k = \psi_(T_k,\lambda_k,Z)$. Then the dual optimization problem can be formulated as:

$$\begin{aligned} &\min_{\lambda,\mu,\vec{\nu}} \quad g(\lambda,\mu,\vec{\nu}) \\ &s.t. \quad \lambda \geqslant 0, \mu \geqslant 0, \vec{\nu} \geqslant \mathbf{0} \end{aligned} \tag{10}$$

Notice that the Lagrangian function $\mathcal{L}(\{P_{k,n}\},\lambda,\mu,\vec{\nu})$ is linear in λ,μ and $\vec{\nu}$ for fixed $\{P_{k,n}\}$ and $g(\lambda,\mu,\vec{\nu})$ is the maximum of these linear functions, so the problem (10) is convex.

In order to facilitate the solving process, we decompose the problem (9) into N optimization sub-problems, which are solved on each subcarrier independently, which is:

$$\begin{aligned} g(\lambda,\mu,\vec{\nu}) = &\sum_{n=1}^{N} H_n(\lambda,\mu,\vec{\nu}) + \lambda P_{tot} + \mu I_{th} \\ &- \sum_{k\in K_{DS}} \nu_k\psi_k - qP_C \end{aligned} \tag{11}$$

where,

$$\begin{aligned} H_n(\lambda,\mu,\vec{\nu}) = &\max_{\{P_{k,n}\}} \{\sum_{k=1}^{K} R_{k,n} - (\lambda+q\varepsilon)\sum_{k=1}^{K} P_{k,n} \\ &- \mu\sum_{k=1}^{K} P_{k,n}\varphi_{k,n} + \sum_{k\in K_{DS}} \nu_k R_{k,n}\} \end{aligned} \tag{12}$$

Eq.(12) indicates a rule for allocating subcarrier which is to search the SU k^* for a specific subcarrier n that maximizes Eq.(12). Let $P^*_{k,n}$ denote the optimal solution for given subcarrier n and SU k. Applying Karush-Kuhn-Tucker (KKT) condition [18], by taking the derivation of $\mathcal{L}(\{P_{k,n}\},\lambda,\mu,\vec{\nu})$ with respect to $P_{k,n}$, we have:

$$\begin{cases} P^*_{k,n} = [\dfrac{\Delta f}{\ln 2(q\varepsilon+\lambda+\mu\varphi_{k,n})} - \dfrac{\sigma^2}{g_{k,n}}]^+, & k \in K_{DT} \\ P^*_{k,n} = [\dfrac{(\nu_k+1)\Delta f}{\ln 2(q\varepsilon+\lambda+\mu\varphi_{k,n})} - \dfrac{\sigma^2}{g_{k,n}}]^+, & k \in K_{DS} \end{cases} \tag{13}$$

Here, $[x]^+ = max(0,x)$ and K_{DS} denotes the set of the DT-SUs. Substituting Eq.(13) into Eq.(12), we obtain:

$$\begin{aligned} H_n(\lambda,\mu,\vec{\nu}) = &\max_{\{k\}} \{\sum_{k=1}^{K} R^*_{k,n} - (\lambda+q\varepsilon)\sum_{k=1}^{K} P^*_{k,n} \\ &- \mu\sum_{k=1}^{K} P^*_{k,n}\varphi_{k,n} + \sum_{k\in K_{DS}} \nu_k R^*_{k,n}\} \end{aligned} \tag{14}$$

Here $R^*_{k,n}$ is obtained using Eq.(1) for optimum $P^*_{k,n}$.

Note that there are several LDMs in our case, sub-gradient method [18] supplied to update these LDMs can guarantee to converge to the global optimal solution. These LDMs are updated as follows:

$$\begin{cases} \lambda^{l+1} = [\lambda^l - \theta^l_\lambda(P_{tot} - \sum_{k=1}^{K}\sum_{n=1}^{N} P^*_{k,n})]^+ \\ \mu^{l+1} = [\mu^l - \theta^l_\mu(I_{th} - \sum_{k=1}^{K}\sum_{n=1}^{N} P^*_{k,n}\varphi_{k,n})]^+ \\ \nu^{l+1}_k = [\nu^l_k - \theta^l_{\nu_k}(\sum_{n=1}^{N} R^*_{k,n} - \psi_k)]^+, k \in K_{DS} \end{cases} \tag{15}$$

where l deotes the iteration index and θ^l_λ, θ^l_μ, $\theta^l_{\nu_k}$ are the proper positive step-size sequences. After the convergence of these LDMs, the optimal solution $P^*_{k,n}$ can be obtained by substituting λ^*, μ^* and ν^*_k into Eq.(13). And combining with Eq.(14), the optimal subcarrier allocation is derived via solving N independent optimization sub-problems mentioned above.

The optimal power and subcarrier allocation are solved via the DDM above, which is based on the assumption that the parameter q is a constant. However, our ultimate goal is to find the solution of $F(q) = 0$ which represents the optimal EE value in this paper. Furthermore, because the $F(q)$ is strictly monotonic decreasing with respect to q and the optimal solution is obtained if and only if when $F(q) = 0$, a bisection method can be used to search the optimal solution. With given λ, μ and $\vec{\nu}$, the bisection method is given in Algorithm 1.

Notice that the Algorithm 1 is based on that the value of λ, μ and $\vec{\nu}$ is given in advance. However, the value of these LDMs is unknown originally. In this paper, the DDM is proposed to obtain the optimal value of λ, μ and $\vec{\nu}$. Sub-gradient methods can guarantee these LDMs to converge to the global optimal solution, and the DDM is detailed in Algorithm 2.

V. Numerical Results

In this section, we present some numerical results. For simplicity, we consider a scenario with 10 subcarriers and 2 SUs (in which SU 1 is the DS-SU and SU 2 is the DT-SU). σ^2, Δf and B are assumed to be 0.1, 0.15 kHz and 1.5 kHz,

Algorithm 1 Bisection method

Initialization:

λ, μ, $\vec{\nu}$, δ, a and b (error limitation $\delta > 0$, a, b satisfying $F(a) > 0$ and $F(b) < 0$); $q = (a + b)/2$;

Iteration:

1: **while** $F(q) > \delta$ **do**
2: **if** $F(a) \cdot F(q) \geqslant 0$ **then**
3: $a = q$;
4: **else**
5: $b = q$;
6: **end if**
7: $q = (a + b)/2$;
8: **end while**

Algorithm 2 Dual Decomposition Method

1: subcarrier set: $N = \{1, 2, \cdots, N\}$;
SU set: $K = \{1, 2, \cdots, K\}$, $K_{DT}, K_{DS} \subseteq K$, $K_{DT} \cup K_{DS} = K$ and $K_{DT} \cap K_{DS} = \phi$;
2: **Calculate optimal LDMs**
3: Use Eq.(11), Eq.(12) and Eq.(13), calculate the optimal LDMs;
4: **Joint subcarrier assignment and power allocation**
5: **while** $N \neq \phi$ **do**
6: 1)compute $P^*_{k,n}$ using the Eq.(12), $\forall$ k$\in$ K;
7: 2)find the optimal set S^*_k satisfying the Eq.(10);
8: 3)assign subcarrier n^* to user k^* according the S^*_k;
9: 4)update the optimal power $P^*_{k,n}$;
10: 5)$N = N - \{n^*\}$;
11: **end while**

respectively. The channel power gains $g_{k,n}$, $h_{k,n}$ and $h^{'}_{k,n}$ are assumed to be Rayleigh distributed random variables with mean -6 dB.

To evaluate the performance of the proposed scheme, we present the simulation results of SUs' EE with different total power constraint (P_{tot}), interferene constraint of PUs caused by SUs (I_{th}) and transmission rate requirement of the DS-SU (ψ_1), respectively. We first evaluate the impact of P_{tot} and I_{th} on the SUs' EE. Fig. 3 compares the EE of energy-efficient resource allocation scheme and spectral-efficient maximization (SE-max) [19] scheme in the downlink transmission [6]. It can be seen that the energy-efficient scheme always outperforms the SE-max scheme, and the EE of the energy-efficient scheme goes up when the P_{tot} increases, whereas the EE of SE-max scheme rises and falls as the P_{tot} increases. Similarly, as we can see in Fig. 4, the EE of energy-efficient scheme and SE-max scheme goes up when the I_{th} increases, and the EE of energy-efficient scheme outperforms the SE-max scheme significantly.

We also evaluate the performance of EE versus ψ_1. In Fig. 5, as ψ_1 increases, the the EE of energy-efficient scheme decreases slightly and the the EE of SE-max scheme increases observably. It is notable that the gap of the two schemes is very large when ψ_1 is small, and the EE of energy-efficient scheme outperforms the SE-max scheme when $\psi_1 < 0.9$ bit/s. With increasement of ψ_1, the gap of the two schemes will gradually dwindle until the results of both schemes coincide. This is probably because more resource tends to be allocated to the DS-SU as the delay constraint increases. The extreme case, which makes results of the two schemes coincide, would be that the DS-SU has to "monopolize" all the resource while its rate (delay) requirement is extremely high (low). Anyway, the energy-efficient scheme proposed in this paper achieve superior performance over the SE-max scheme in most cases.

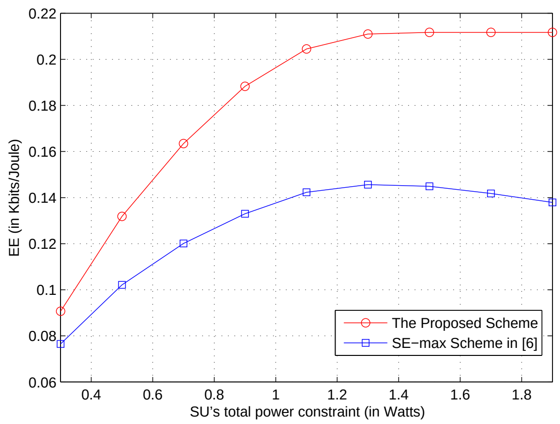

Fig. 3. Energy efficiency of the proposed and SE-max schemes vs P_{tot}

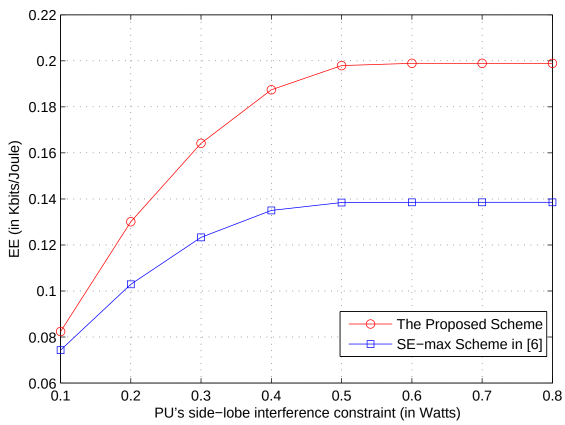

Fig. 4. Energy efficiency of the proposed and SE-max schemes vs I_{th}

VI. Conclusion

In this paper, we propose a novel resource allocation scheme for an interference-limited OFDM-based CR system aimed at EE maximization, which takes into account the heterogeneous QoS requirements of DS-SUs. Then we formulate the problem as a nonlinear fraction programming problem, which can be transformed into an equivalent parametric programming problem, and it can be solved efficiently with the bisection

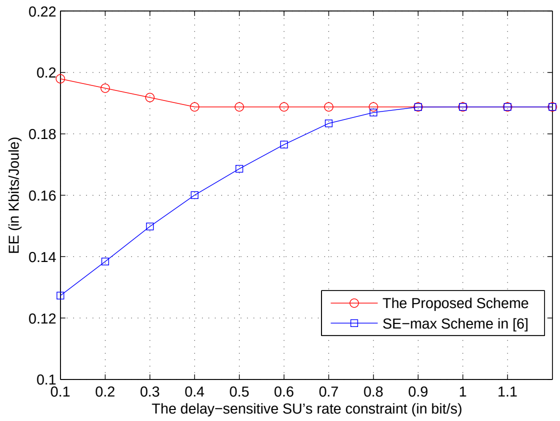

Fig. 5. Energy efficiency of the proposed and SE-max schemes vs ψ_1

method and DDM. Different from conventional approaches, the proposed algorithm achieves optimal EE and significantly improve the system performance while protecting PUs from intolerable interference. The simulation results validate our proposed scheme which outperforms SE-max scheme observably. Further study may focus on the EE optimization with the imperfect channel sensing and distributed resource allocation while only local information is available for each SU.

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