Joint Performance Optimization of Primary Networks and Cognitive Radio Networks

Jingyi Dai and Shaowei Wang
School of Electronic Science and Engineering, Nanjing University, Nanjing 210023, China
E-mail:MG1523077@smail.nju.edu.cn, wangsw@nju.edu.cn

***Abstract*—In this paper, we study the resource allocation issues related to OFDM-based multiuser cognitive radio cellular networks, where both of primary network and secondary network are investigated to make an all-round evaluation of the network performance, including the Quality of Experience (QoE) of the primary users (PUs) and the minimal rate requirement of the secondary users (SUs). Since the general resource allocation optimization task we formulate leads to challenging mixed integer nonlinear programming problems, we first propose a heuristic subchannel allocation method to remove the awkward integer constraints. Then an efficient distribution algorithm, which yields nearly linear computational complexity, is developed to work out the optimal power allocation. Simulation results indicate that our proposed resource allocation scheme works better under different performance metrics as compared to others. Moreover, our proposed distribution algorithms converge stably and quickly.**

I. Introduction

The rapid development of information and communication technology (ICT) has led to the tremendous growth of traffic data in various aspects of mobile service and each year the corresponding energy consumption is increasing at an amazing speed of $16\% - 20\%$ [1]. It is predicted that mobile data traffic will grow up to 1000-fold by 2020 [2] due to the increase of broadband services and the burst traffic of point to point transmission in cloud platforms [3]. The energy consumption issue in different wireless communication systems has been investigated in the literature [4–6], where the optimization problems are around the system energy efficiency while taking into consideration of practical constraints such as interference and channel uncertainty.

Meanwhile, the scarcity and low utilization efficiency of spectrum resource has also gained accelerating focus in the past decades. Since the multimedia industry witnessed the boom of the tremendous growth of "smart" devices such as laptops and smartphones, and also the growth of various multimedia applications in our daily life, the current available spectrum resource can not afford such a big burden, which requires mobile operators and research institutions to come up with advanced spectrum sharing strategies. Cognitive radio (CR), where secondary users (SUs) in secondary network (SN) can opportunistically access the available vacant spectrum holes licensed by primary network (PN) without causing harmful interference to the primary users (PUs), is a natural solution to cope with the diverse, exploding and random traffic data in current mobile communications [7].

Another notable issue of wireless communication networks is the quality representation metrics which can reasonably reflect the network performance [8]. Conventional signal quality metrics and system quality metrics such as Peak-Sinal-to-Noise-Ratio (PSNR) and Quality of Service (QoS) are successfully applied in various multimedia communications. However, those conventional objective metrics do not include user perceived quality, which may not subjectively reflect users' requirement and experience. As a result, Quality of Experience (QoE), a user-oriented evaluation metric is formally introduced [9], which aims at overcoming the shortage of conventional objective metrics. Additionally, there are quite a few evaluation models for QoE assessment, among which Mean Opinion Score (MOS) is mostly promoted [10].

In [11], QoE-based multichannel allocation problem for small-cell users in 5G heterogeneous networks (HetNets) is investigated. In [12], a novel spectrum sharing paradigm is proposed, in which a base station (BS) offload strategy is introduced to enhance the users' QoE and spectrum utilization efficiency. However, as far as the authors have known, much emphasis is always put on the downlink OFDM-based cognitive network (secondary network), while the network performance of PN are paid much less attention to. Since the performance of both the PN and SN are important in wireless mobile communication, we address the resource allocation issue for both of them in this paper. First, we study the QoE-oriented resource allocation method for PUs in PN, where we introduce an assessment model, MOS, for QoE at first and then try to maximize the sum MOS values subject to the total transmit power limit and interference constraints afterwards. Then, as for SN, we try to maximize the total system throughput while taking into consideration of many practical constraints including QoS requirement of SUs, transmission power budget and interference constraints of SN. Since both of the two optimization task we formulate are mixed integer nonlinear programming (MINLP) problems that are NP-hard, a heuristic subchannel allocation method is firstly introduced to remove the integer constraints, after which an efficient power distribution algorithm is designed to obtain the optimal power allocation. Since the computational complexity of our proposed method is nearly linear, we conclude that it worth applying in practical.

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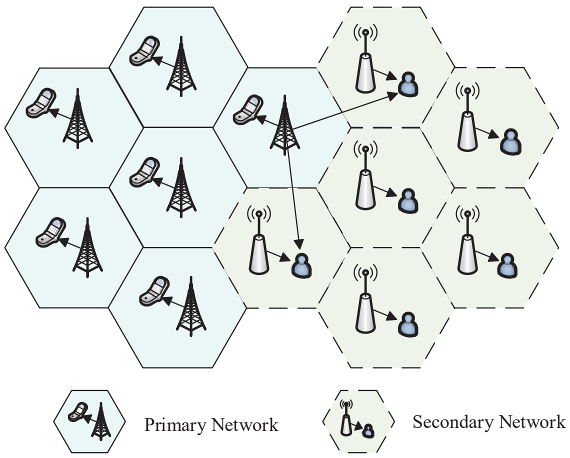

Fig. 1. System model

The rest of this paper is organized as follows. Section II illustrates system model and Section III presents the optimization problems. In Section IV, we discuss the subchannel allocation scheme and the optimal power distribution algorithm . Simulation results and discussions are presented in Section V and conclusions are drawn in Section VI.

II. System Model

Consider the downlink of a multiuser OFDM-based CR network, where K secondary users (SUs) in secondary network (SN), denoted by $\mathcal{K} = \{1, 2, \ldots, K\}$, share the spectrum with L primary users (PUs) in primary network (PN), denoted by $\mathcal{L} = \{1, 2, \ldots, L\}$, while both of PN and SN are deployed in a hexagonal cells model of equal sizes as can be seen from Fig. 1. We assume perfect channel state information (CSI) is available at the transceivers of the SUs and the PUs. The SUs use different OFDM subchannels, as well as the PUs. There exists inter-tier interference between the SUs and the PUs and the interference to the lth PU introduced by the SUs must be kept below I_l^{P-th} while the interference to the kth SU introduced by the PUs must be kept below I_k^{S-th}.

A. Interference Model

Let $\mathcal{N} = \{1, 2, \ldots, N\}$ denote N OFDM subchannels while the starting frequency is f_0 and the bandwidth of each subchannel is W/N, where W is the total bandwidth of our considered system. Denote the interference to the lth PU introduced by the kth SU's access on the nth subchannel with unit transmission power as $I_{l,k,n}^{SP}$,

$$I_{l,k,n}^{SP} = \int_{f_l - f_0 - (n-1/2)W/N}^{f_l + W_l - f_0 - (n-1/2)W/N} g_{l,k,n}^{SP} \phi(f)\, df, \tag{1}$$

where f_l and w_l are the staring frequency and the bandwidth of the lth PU, $\phi(f)$ is the power spectrum density (PSD) of the OFDM subchannel, and $g_{l,k,n}^{SP}$ is the power gain from the kth SU's transmitter to the lth PU's receiver on the nth subchannel.

Similarly, the interference introduced to the kth SU by the lth PU on the nth subchannel with unit transmission power is

$$I_{k,l,n}^{PS} = \int_{(n-1)W/N - (f_l + 1/2W_l)}^{nW/N - (f_l + 1/2W_l)} g_{k,l,n}^{PS} \phi(f)\, df. \tag{2}$$

B. MOS Model

As aforementioned, MOS is the most widely used metric of QoE, which is a utility function of the transmission rate and links the technical objective parameters with the subjective user perceived quality [13]. As investigated in [14] , different MOS models are suitable to different media applications such as Voice over Internet Protocol (VoIP), Internet Protocol Television (IPTV) and File Download (FD). In [15], it is investigated that there exists a bounded logarithmic relationship between the objective QoS metric and subjective QoE metric. In this paper, we consider the MOS model for FD, which consists of elastic services including file transfer and web browsing. Let MOS_l and R_l denotes the lth user's MOS value and transmission rate, respectively, we can conclude the mathematical expression of QoE used in this paper as follows,

$$MOS_l = A \log(BR_l), \tag{3}$$

where A=2.3473, B=0.2667 are constants which are determined by an analysis of the experimental results for FD services.

III. Problem Formulation

Our objective is to maximize the sum MOS value of the PUs in PN and the sum throughput of SUs in SN, respectively.

A. Primary Network

Define $r_{l,n}$ as the achievable data rate of the lth PU on the nth subchannel,

$$r_{l,n} = \frac{W}{N} \log_2(1 + p_{l,n} H_{l,n}), \tag{4}$$

where $p_{l,n}$ is the power allocated to the lth PU on the nth subchannel and $H_{l,n}$ is the signal-to-noise ratio (SNR) of the the lth PU on the nth OFDM subchannel with unit power. Then the sum rate of the lth PU can be defined as follows,

$$R_l = \sum_{n=1}^{N} \rho_{l,n} \frac{W}{N} \log_2(1 + p_{l,n} H_{l,n}), \tag{5}$$

where the binary variable $\rho_{l,n} = 1$ indicates the nth subchannel is occupied by the lth PU and $\rho_{l,n} = 0$ otherwise.

We try to maximize the sum MOS value of PN while taking into consideration of the total transmission power limit of PN and interference introduced to the SUs in SN. Thus, the mathematical expression of the optimization problem is described as follows,

$$\begin{aligned} \text{OP 1} \quad & \max_{p_{l,n}} \sum_{l=1}^{L} MOS_l, \\ s.t. \quad & C_1 : \sum_{l=1}^{L}\sum_{n=1}^{N} \rho_{l,n} p_{l,n} \le P_T^{\text{PN}}, \\ & C_2 : p_{l,n} \ge 0, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}, \\ & C_3 : \sum_{l=1}^{L}\sum_{n=1}^{N} \rho_{l,n} p_{l,n} I_{k,l,n}^{PS} \le I_k^{S-th}, \forall k \in \mathcal{K}, \\ & C_4 : \sum_{l=1}^{L} \rho_{l,n} = 1, \forall n \in \mathcal{N}, \\ & C_5 : \rho_{l,n} \in \{0,1\}, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}, \end{aligned} \tag{6}$$

where P_T^{PN} is the maximum transmitted power the PN can afford and I_k^{S-th} is the interference threshold of the kth SU. C_1 , C_2 and C_3 represent the power limit and interference constraint of PN, respectively. C_4 and C_5 guarantee that one subchannel can be allocated to at most one PU.

B. Secondary Network

For SN, we try to maximize the sum throughput of all SUs in SN while guaranteeing the QoS requirement of SUs, the total transmission power budget and the interference constraints of SN. Mathematically, the optimization problem can be described as follows,

$$\begin{aligned} \text{OP 2} \quad & \max_{p_{k,n}} \sum_{k=1}^{K} R_k, \\ s.t. \quad & C_1 : R_k \ge R_{\min}, \\ & C_2 : \sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n} p_{k,n} \le P_T^{\text{SN}}, \\ & C_3 : p_{k,n} \ge 0, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \\ & C_4 : \sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n} p_{k,n} I_{l,k,n}^{SP} \le I_l^{P-th}, \forall l \in \mathcal{L}, \\ & C_5 : \sum_{k=1}^{K} c_{k,n} = 1, \forall n \in \mathcal{N}, \\ & C_6 : c_{k,n} \in \{0,1\}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \end{aligned} \tag{7}$$

where $c_{k,n}$ is a binary variable and $c_{k,n} = 1$ indicates that the kth SU is allocated the nth subchannel and $c_{k,n} = 0$ otherwise. $R_{\min}$ is the minimal rate (QoS) requirement of SUs, P_T^{SN} is the maximum transmitted power the SN can afford and I_l^{P-th} is the maximum interference that PU l can bear. Thus, C_1 is the QoS requirement, C_2 and C_3 represent the power budget of SN while C_4 limits the interference introduced to the PUs. C_5 and C_6 are intuitive.

IV. Proposed PN and SN Algorithm

It is intuitive that both OP 1 and OP 2 are NP-hard because of the involved binary variables. Since OP 1 and OP 2 have similarities in structure, we develop a two-step procedure to address both of them. We give the detailed resource allocation scheme for OP 1 here.

TABLE I
SUBCHANNEL ALLOCATION

Algorithm:
Initialization:
Set $R_l = 0,\ \Omega_l = 0,\ \forall l \in \mathcal{L},\ \mathcal{L}_t = \mathcal{L},\ \mathcal{N}_t = \mathcal{N}$;
First round:
for $i = 1$ to L
Find l^*, n^* that $r_{l^*,n^*} \ge r_{l,n}, \forall l \in {}_t, \forall n \in \mathcal{N}_t$;
$\Omega_{l^*} = \Omega_{l^*} \quad \{n^*\},\ \mathcal{L}_t = \mathcal{L}_t \backslash l^* \ \ \mathcal{N}_t = \mathcal{N}_t \backslash n^*$;
$R_{l^*} = r_{l^*,n^*}$.
end for
Second round
while $\mathcal{N}_t \neq \varnothing$
Find $l^* = \arg\min_{l \in \mathcal{L}} R_l$;
Find n^* that $r_{l^*,n^*} \ge r_{l^*,n}, \forall n \in \mathcal{N}_t$;
$\Omega_{l^*} = \Omega_{l^*} \quad \{n^*\},\ \mathcal{N}_t = \mathcal{N}_t \backslash n^*$;
$R_l = R_l + r_{l^*,n^*}$.
end while

A. Subchanel Allocation

First, we propose a heuristic subchannel allocation method to remove $\rho_{l,n}$ in OP 1. Let $p_{l,n}^M$ and $r_{l,n}^M$ denotes the maximum power allocated to subchannel n for PU l and the highest rate PU l can achieve over the subchannel n, respectively. We have

$$\begin{aligned} p_{l,n}^M &= \min(P_T^{\text{PN}}, \min_{l \in \mathcal{L}}(\frac{I_{th}^{S-k}}{I_{k,l,n}^{PS}})), \\ r_{l,n}^M &= \frac{W}{N}\log(1 + p_{l,n}^M H_{l,n}). \end{aligned} \tag{8}$$

Obviously, the SNR of subchannels and the interference constraint are jointly taken into consideration for our considered CR network, in other words, the power allocated to the subchannels are always bounded by the total power limit P_T^{PN} and interference threshold I_{th}^{S-k}.

The key idea shown in Table I is that we allocate the subchannel to the users over which they can achieve the highest possible rate among all available ones. $\mathcal{L}$ and $\mathcal{N}$ are the set of PUs and subchannels, respectively. The set of subchannels allocated to SU l is denoted as Ω_l.

B. Power Distribution

For a given subchannel assignment, the binary variable $\rho_{l,n}$ and the constraints C_4 and C_5 vanish, OP 1 can be rewritten as follows:

$$\begin{aligned} \text{OP 3} \quad & \max_{p_{l,n}} \textstyle\sum_{l\in\mathcal{L}} MOS_l, \\ s.t. \quad & C_1 : \textstyle\sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l} p_{l,n} \le P_T^{\text{PN}}, \\ & C_2 : p_{l,n} \ge 0, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}, \\ & C_3 : \textstyle\sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l} I_{k,l,n}^{PS} \le I_k^{S-th}, \forall l \in \mathcal{L}. \end{aligned} \tag{9}$$

Intuitively, OP 3 requires us to work out the maximum MOS values of PN while satisfying the power limits and interference threshold of the considered system. Such a power distribution problem is easy to be proved as a convex problem because the objective function is convex and all the constraints are affine [16]. It can be solved by standard convex optimization techniques in which barrier method that is quadratic convergence is generally used. However, the high computation cost of barrier method prevents its online applications since the computation complexity of solving OP 3 with barrier method is $O(N^3)$ that is impractical. Thus, we take a fast algorithm [17] to efficiently solve OP 3.

The barrier function of (9) is

$$\begin{aligned}\phi(P) = &-\sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l}\log(p_{l,n}) - \log(P_T^{\mathrm{PN}} - \sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l} p_{l,n}) \\ &- \sum_{k\in\mathcal{K}}\log(I_k^{S-th} - \sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l} p_{l,n} I_{k,l,n}^{PS}),\end{aligned} \tag{10}$$

where $P = (p_{1,1}, \ldots, p_{L,N})$. Denote

$$f(P) = \sum_{l\in\mathcal{L}}\log(\alpha\log(\beta\frac{W}{N}\sum_{n\in\Omega_l}\log_2(1+p_{l,n}H_{l,n}))).$$

Then, by introducing a logarithmic barrier function with a parameter t, we can convert OP 3 into a sequence of minimization problems, in which t is a parameter to control the accuracy of solution. Thus, OP 3 can be approximated by solving the following unconstrained minimization problem

$$\min \psi_t(P) = -tf(P) + \phi(P). \tag{11}$$

Generally, Newton method is recommended to solve such kind of unconstrained minimization problems because of its quadratic convergence property [16]. Newton step at *P*, denoted by ΔP_{nt}, is given by

$$\nabla^2\psi_t(P)\Delta P_{nt} = -\nabla\psi_t(P), \tag{12}$$

where $\nabla^2\psi_t(P)$ and $\nabla\psi_t(P)$ are the Hessian and the gradient of $\psi_t(P)$, respectively. For simplicity, we denote

$$\begin{aligned}f_0 &= P_T^{\mathrm{PN}} - \sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l} p_{l,n}, \\ f_l &= \alpha\log(\beta\sum_{n\in\Omega_l}\frac{W}{N}\log_2(1+p_{l,n}H_{l,n})), \\ g_k &= I_k^{S-th} - \sum_{l\in\mathcal{L}}\sum_{n\in\Omega_l} p_{l,n} I_{k,l,n}^{PS}.\end{aligned}$$

The Hessian of $\psi_t(P)$ is

$$\begin{aligned}\nabla^2\psi_t(P) =& D + \frac{\nabla f_0\nabla f_0^T}{f_0^2} + \sum_{l\in\mathcal{L}}\frac{\nabla f_l\nabla f_l^T}{f_l^2} + \sum_{k\in\mathcal{K}}\frac{\nabla g_k\nabla g_k^T}{g_k^2} \\ &+ \frac{\nabla^2 f_0}{f_0} + \sum_{l\in\mathcal{L}}\frac{\nabla^2 f_l}{f_l} + \sum_{k\in\mathcal{K}}\frac{\nabla^2 g_k}{g_k} \\ &= D + \sum_{i=1}^{K+L+1}\mathbf{q}_i\mathbf{q}_i^T\end{aligned} \tag{13}$$

where $D = \mathrm{diag}(\lambda_1, \ldots, \lambda_N)$,

$$\begin{aligned}\lambda_i &= t\alpha\frac{h_{l,i}^2[1+\sum_{n\in\Omega_l}\log_2(1+h_{l,i}p_{l,i})]}{\ln 2[\sum_{n\in\Omega_l}\log_2(1+h_{l,i}p_{l,i})(1+h_{l,i}p_{l,i})]^2} + \frac{1}{p_{l,i}^2}, \\ \mathbf{q}_i &= \begin{cases}\frac{\nabla f_0}{f_0}, & i=1, \\ \frac{\nabla f_l}{f_l}, & l=1,\ldots,L, i=l+1, \\ \frac{\nabla g_k}{g_k}, & k=1,\ldots,K, i=k+L+1,\ldots,K+L+1.\end{cases}\end{aligned}$$

Matrix $\mathbf{D}$ is positive definite and all $\mathbf{q}_i\mathbf{q}_i^T > 0$. Thus, it can be concluded that the Hessian (13) is positive definite and also invertible. Consider the special structure of the Hessian of $\psi_t(P)$, an efficient algorithm can be developed to calculate the Newton step. According to the decomposition in (13), the Hessian can be written into

$$\mathbf{\Lambda}_i = \mathbf{D} + \sum_{m=1}^{i}\mathbf{q}_m\mathbf{q}_m^T, \ i = 1, 2, \ldots, M, \tag{14}$$

where $M = K + L + 1$. Then we develop an $(M+1)$-step iterative algorithm to quickly calculate the Newton step. The detailed description of the algorithm is given in Table II, which yields a computation complexity of $O(K^2N)$ that is proved in [17]. Thus, we can conclude that our proposed efficient power allocation method has a significant advantage over the standard convex optimization technique since $K \ll N$ in practical.

TABLE II
FAST CALCULATING NEWTON STEP

Step 1 Decompose Λ_M, $\Lambda_M = \Lambda_{M-1} + \mathbf{q}_M\mathbf{q}_M^T$.
Then we have $u^0 = u_1^1 - \frac{\mathbf{q}_M^T u_1^1}{1+\mathbf{q}_M^T u_2^1}u_2^1$,
Where $\Lambda_{M-1}u_1^1 = -\nabla\psi_t(P)$ and $\Lambda_{M-1}u_2^1 = \mathbf{q}_M$
After Step 1, we can figure out the $\triangle P_{nt}$ by solving u_1^1 and u_2^1,
Step 2 Decompose Λ_{M-1} with $\Lambda_{M-1} = \Lambda_{M-2} + \mathbf{q}_{M-1}\mathbf{q}_{M-1}^T$
Similarly, u_1^1 and u_2^1 can be obtained by
$u_i^1 = u_i^2 - \frac{\mathbf{q}_{M-1}^T u_i^2}{1+\mathbf{q}_{M-1}^T u_i^2}u_3^2, i = 1, 2,$
where $\Lambda_{M-1}u_1^2 = -\nabla\psi_t(P)$, $\Lambda_{M-1}u_i^2 = \mathbf{q}_{M+2-i}, i = 2, 3.$
⋮
Continue this process to Step M,
Step M
We can obtain $M+1$ variables by solving $M+1$ linear equations,
$\mathbf{D}u_1^M = -\nabla\psi_t(P)$
$\mathbf{D}u_i^M = \mathbf{q}_{M+2-i}, i = 2, 3, \ldots, M+1.$

Similarly, OP 2 can be solved by the proposed two-step RA algorithm efficiently and the evaluation of the performance of our proposed algorithms are investigated in the following section.

V. SIMULATION RESULTS AND DISCUSSIONS

In this section, a series of experimental simulations are conducted to evaluate the performance of the proposed algorithms. Consider the downlink of multiuser OFDM-based CR cellular network, where all SUs and PUs randomly locate in a 3×3 km area and each receiver is uniformly distributed within the radiation radius of the transmitter, which is assumed to be 0.5 km. Besides, we take the following channel model: (i) The channel suffers from frequency selective fading; (ii) The path loss exponent is 4 while the variance of logarithmic normal shadow effect is 10 dB; (iii) The amplitude of multipath fading is Rayleigh. Besides, the noise power is 10^{-13} W and the interference thresholds are set to 5×10^{-13} W.

First, we evaluate the performance of our proposed algorithm for PN. To evaluate the sum MOS value of PN, we compare our proposed algorithm with other representative algorithms, including equal power allocation (EPA), interference-factor power allocation (IFPA) and maximum SNR power allocation (MSPA). The EPA and IFPA algorithms are investigated in [18]. Specifically, the EPA makes the assumption that the transmission power is equally allocated among subchannels, while the IFPA guarantees that the transmission power distributed to each subchannel is inversely proportional to the interference level. Besides, the MSPA performs subchannel allocation according to user's SNR over subchannels, in which users are always allocated the subchannel over which they can obtain the highest SNR.

Fig. 2 shows the average MOS value of PUs as a function of the transmission power limit. There are 32 OFDM subchannels and the number of PUs and SUs are set to 2 and 4, respectively. As can be seen from Fig. 2, the average MOS value increases as the transmission power limit grows and our proposed algorithm outperforms the others since we take joint consideration of the SNR of subchannels and the interference constraint. Note that when the transmission power limit is small, EPA performs well and when the transmission power limit grows larger, the performance of IFPA improves obviously, this is because as the increase of transmission power limit, the subchannels tend to be interference limited rather than power limited and IFPA which allocates subchannels to users with the minimal interference level performs well.

Fig. 3 shows the average MOS value of PUs as a function of the interference threshold. There are 2 PUs and 4 SUs in the considered system and the number of subchannels is 32 while the transmission power budget is 1 W. From Fig. 3 we can observe that the average MOS value increases with the growth of interference threshold, since more power can be consumed to maximize the sum MOS value of PN as long as the interference introduced to SUs is within the interference threshold. Note that our proposed algorithm always performs better than the others while the gap between our proposed algorithm and EPA becomes smaller as the increase of interference threshold. This is because when the interference threshold is small, most of the subchannels are interference limited. However, with the continuous growth of interference threshold, the subchannels tend to be power limited rather than interference limited, and EPA, which is power limited, improves more obviously than the others.

Then, we evaluate the performance of our proposed algorithm for SN. Fig. 4 shows the sum rate of SUs as a function of the transmission power limit. There are 2 PUs and 4 SUs in our

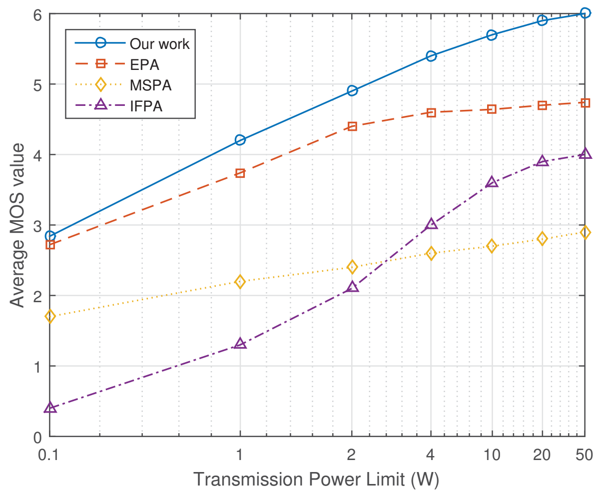

Fig. 2. Average MOS value of PUs as a function of the transmission power limit with $N = 32, L = 2$ and $K = 4$.

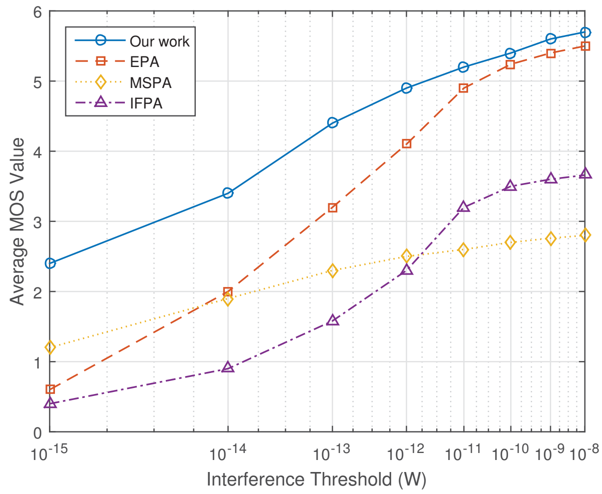

Fig. 3. Average MOS value of PUs as a function of interference threshold with $N = 32, L = 2, K = 4$ and $P_T = 1$ W.

considered system. As can be seen from Fig. 4, the sum rate of SUs increases with the increase of transmission power limit, this is because the growth of power budget offers abundant transmission power for SUs to maximize their transmission rate. It can also be seen from the figure that the sum rate of SUs also increases as the number of subchannels increases, which can be explained as the channel diversity in wireless environment. Anyway, our proposed algorithm ourperforms EPA in different cases.

Fig. 5 show the number of Newton iterations of our proposed algorithm with 200 random instances with different setting of N. The transmission power limit is 1 W, while the number of PUs and SUs are set to 2 and 4, respectively. As can be seen from Fig. 5 , the number of Newton iterations, which directly indicates the computational complexity of our proposed power distribution method which is discussed in

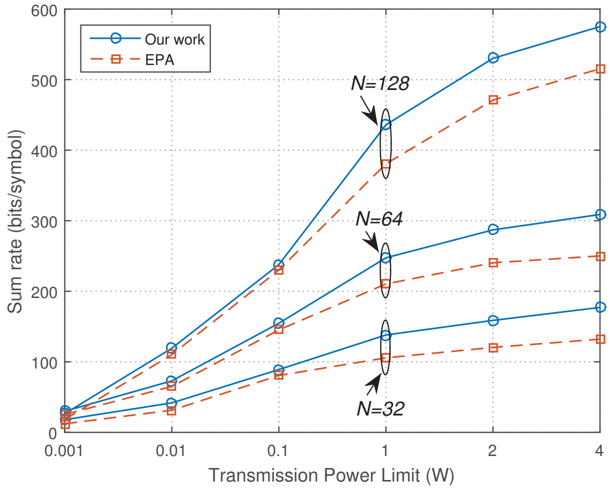

Fig. 4. Sum rate of SUs as a function of transmission power limit with $L = 2$ and $K = 4$.

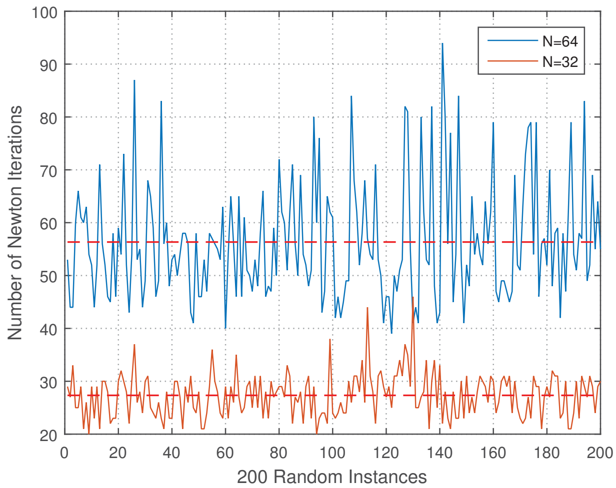

Fig. 5. Number of Newton iterations over 200 instances of the algorithms with $L = 2, K = 4$ and $P_T = 1$ W.

section IV, is not large with given number of subchannels. It is also noted that the variation of the number of Newton iterations is slight, indicating our proposed algorithm is efficient and promising in practical applications.

VI. Conclusions

In this paper, we presented novel resource allocation s-trategies for OFDM-based multiuser cognitive radio cellular networks, in which we take consideration of subjective and objective assessment metric for the PN and SN, respectively. A QoE-based user-oriented assessment model is firstly introduced to evaluate the performance of the PN and an optimization task that aims to maximize the sum MOS value of the PUs is formulated, while another optimization task which aims at maximizing the total system throughput subject to the QoS requirement of the SUs is also formulated for the SN afterwards. Since the formulated optimization problems are NP-hard, we tackle them with two steps: subchannel allocation and power distribution. A heuristic subchannel allocation scheme is proposed to remove the integer constraints to make the problem trackable, followed by an efficient power distribution algorithm with low complexity, which obtains the optimal power allocation solution by exploiting the special structure of the problem. Simulation results show that our proposed resource allocation algorithms is robust and converges stably and quickly, and can achieve better performance when comparing with other algorithms.

References

[1] Y. Luo, L. Gao, and J. Huang, "An integrated spectrum and information market for green cognitive communications," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3326–3338, Dec. 2016.

[2] W. Han, Y. Zhang, X. Wang, M. Sheng, J. Li, and X. Ma, "Orthogonal power division multiple access: A green communication perspective," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3828–3842, Dec. 2016.

[3] J. Xu, L. Duan, and R. Zhang, "Cost-aware green cellular networks with energy and communication cooperation," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 257–263, May 2015.

[4] S. Wang, W. Shi, and C. Wang, "Energy-efficient resource management in OFDM-based cognitive radio networks under channel uncertainty," *IEEE Trans. Commun.*, vol. 63, no. 9, pp. 3092–3102, Sept. 2015.

[5] W. Zhao and S. Wang, "Traffic density based RRH selection for power saving in C-RAN," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3157–3167, Dec. 2016.

[6] S. Wang, M. Ge, and W. Zhao, "Energy-efficient resource allocation for OFDM-based cognitive radio networks," *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3181–3191, Aug. 2013.

[7] A. Gupta and R. K. Jha, "A survey of 5G network: Architecture and emerging technologies," *IEEE Access*, vol. 3, pp. 1206–1232, July 2015.

[8] T. Zhao, Q. Liu, and C. W. Chen, "QoE in video transmission: A user experience-driven strategy," *IEEE Commun. Surv. Tutor.*, no. 10, Oct. 2016.

[9] A. R. Sebastian Moller, *Quality of Experience. Advanced Concepts, Applications and Methods*, 2014.

[10] T. Hossfeld, L. Skorin-Kapov, P. Heegaard, and M. Varela, "Definition of QoE fairness in shared systems," *IEEE Commun. Lett.*, vol. 21, no. 1, pp. 184–187, Jan. 2016.

[11] D. Wu, Q. Wu, Y. Xu, J. Jing, and Z. Qin, "QoE-based distributed multichannel allocation in 5G heterogeneous cellular networks: A matching-coalitional game solution," *IEEE Access*, vol. 5, pp. 61–71, 2016.

[12] M. Srinivasan, V. J. Kotagi, and C. S. R. Murthy, "A Q-learning framework for user QoE enhanced self-organizing spectrally efficient network using a novel inter-operator proximal spectrum sharing," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 11, pp. 2887–2901, Nov. 2016.

[13] Y. Wu, Y. Chen, J. Tang, D. K. C. So, Z. Xu, C. L. I., P. Ferrand, J. M. Gorce, C. H. Tang, P. R. Li, K. T. Feng, L. C. Wang, K. Borner, and L. Thiele, "Green transmission technologies for balancing the energy efficiency and spectrum efficiency trade-off," *IEEE Commun. Mag.*, vol. 52, no. 11, pp. 112–120, Nov. 2014.

[14] X. Deng, Q. Gao, S. Mohammed, L. Chen, F. Wang, and Z. Fei, "A QoE-Driven resource allocation strategy for OFDM multiuser-multiservice system," in *Proc. IEEE CIT'14*, Dhaka, Bangladesh, Sept. 2014.

[15] B. Li, S. Li, C. Xing, Z. Fei, and J. Kuang, "A QoE-based OFDM resource allocation scheme for energy efficiency and quality guarantee in multiuser-multiservice system," in *Proc. IEEE GC 2012 Wkshps*, California, USA, Dec. 2012.

[16] S. P. Boyd and L. Vandenberghe, "Convex optimization," *Cambridge University Press*, 2004.

[17] J. Dai and S. Wang, "QoE-driven resource allocation method for cognitive radio networks," in *Proc. IEEE ICC'16*, Kuala Lumpur, Malaysia, May 2016.

[18] S. M. Almalfouh and G. L. Stuber, "Interference-aware radio resource allocation in OFDMA-based cognitive radio networks," *IEEE Trans. Veh. Tech.*, vol. 60, no. 4, pp. 1699–1713, May 2011.