QoE-Driven Resource Allocation Method for Cognitive Radio Networks

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Abstract—**Since user experience plays a more and more important role in the development of today's communication systems, quality of experience (QoE) becomes a widely used metric, which reflects the subjective experience of end users for wireless services. In this paper, a QoE-driven radio resource allocation scheme is proposed for multi-user orthogonal frequency division multiplexing (OFDM) based cognitive radio (CR) networks. By introducing a QoE-based assessment model, our optimization task is formulated to maximize the overall QoE of the considered system subject to the total transmit power and interference constraints. We first propose a user-oriented subcarrier allocation algorithm. Secondly, for a given subchannel assignment, we propose a fast barrier method to tackle the optimal power allocation problem, where the key is to replace Newton step with complexity $O(N^3)$ in the barrier method by a procedure with approximate linear complexity, which is developed by exploiting the structure of the optimization problem. Simulation results validate that our method can always reach a better performance in terms of both single user QoE and the overall QoE with lower complexity.**

I. INTRODUCTION

With the rapid development of wireless communication technology, mobile networking business is becoming more and more abundant, which leads to the explosive growth of traffic flow in almost all wireless networks. According to the investigations in [1], global mobile data has been growing sharply since 2012 and is estimated to be 12 exabytes per month by 2017. It obviously indicates that the capacity of today's network is far from satisfaction, which will finally affect the quality of experience (QoE) for end users. As a novel technology, cognitive radio (CR) has changed the traditional paradigm of spectrum utilization by allowing the CR user to access the licensed spectrum authorized by the government, targeting the efficient spectrum utilization. Hence, CR is a new method to alleviate the looming spectrum shortage crisis to some degree [2]. Orthogonal frequency division multiplexing (OFDM) is widely accepted as the most popular air interface in cognitive radio systems owing to its inherent advantages, such as adaptive parameter adjustment and dynamic resource allocation.

In the field of wireless communications, end users are directly effected by mobile Internet business, whose experience becomes a key factor that impacts on the diffusion of mobile Internet services. Different from the traditional objective metrics that used to evaluate the performance of wireless networks (such as packet loss, delay and jitter.), QoE, as a subjective metric, which can not only indicate the performance of wireless communication services, but also the subjective opinions of users, becomes more and more important and popular, which may seriously affect the profits of the service providers. The International Telecommunication Union (ITU) has proposed a series of standards on subjective assessment methods for various application scenarios. There are growing studies on wireless communication quality assessment models that can estimate QoE, among which mean opinion score (MOS) is the most widely used QoE metric [3].

Many works on wireless transmissions over cognitive radio networks have been proposed since the concept of cognitive radio was firstly introduced more than 15 years ago [2]. Dynamic resource allocation and optimization algorithms for OFDM-based cognitive radio networks are hot topics in the past years. In [4], the authors develop a fast optimal power distribution algorithm with lower complexity, which not only obtains a significant capacity gain but also perfectly satisfies the proportional fairness. In [5], by taking considerations of many practical limitations, the formulated problem can finally be further converted into an equivalent convex optimization problem to maximize the system energy-efficiency. Actually, there have been many works on resource allocation in different QoE-driven wireless communications in recent years. In [6], the authors first introduce a MOS model, in which MOS of an end user is related to the allocated data rate. Secondly an algorithm for MOS-Based resource assignment has been proposed to maximize the total MOS. In [7], a QoE-oriented resource allocation strategy based on game theory for an OFDMA-based system is investigated to maximize QoE. In [8], a QoE-based optimization algorithm is introduced for video delivery in Long Term Evolution (LTE) mobile networks, in which simulation results show that the network resource can be saved significantly.

In this paper, we study the QoE-oriented resource allocation technique in the downlink of OFDM-based cognitive radio networks. We first introduce a QoE-based assessment model, after which we formulate an optimization task to maximize the overall QoE subject to the total transmit power and interference constraints. Since the involved integer constraints make it intractable, we develop a heuristic subchannel assignment, in which we jointly consider the channel gain and the interference to primary users (PUs) and remove the intractable integer constraints. Secondly, for a given subchannel assignment, by exploiting the structure of the problem, a fast optimal

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power allocation algorithm that has a much lower complexity than standard convex optimization techniques is developed to maximize the overall QoE.

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

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. MOS Model

MOS is described as a utility function, which is most widely used to characterize QoE. MOS value reflects users' opinions on services, which ranges from totally unacceptable to fully satisfied as discussed in [9]. In [10, 11], the authors investigate the bounded logarithmic relationship between quality of service (QoS) (e.g., data rate) and QoE for different applications such as video streaming, FTP, etc. Let MOS_k and R_k denote secondary user (SU) k's mean opinion score (MOS) and rate, respectively, the mathematical expression of QoE used in this paper is defined as

$$MOS_k = \alpha \log(\beta R_k), \tag{1}$$

where α, β are fixed coefficients, which are directly related to business characteristics and users' behavior [12] and in this work, $\alpha = 2.3473$ and $\beta = 0.2667$. As can be seen from (1), the QoE utility is described as increasing, strictly concave and continuously differentiable function of throughput.

B. Problem Formulation

Consider the downlink of a multiuser OFDM-based CR network with K SUs, denoted by $\mathcal{K} = \{1, 2, \dots, K\}$, coexisting with L PUs in a licensed system. Assume that perfect channel state information is available at the transceivers of the SUs and PUs. The total bandwidth W is divided into N OFDM subchannels in the CR system, denoted by $\mathcal{N} = \{1, 2, \dots, N\}$. The bandwidth of the nth subchannel spans from $f_0 + (n-1)W/N$ to $f_0 + nW/N$, where f_0 is the starting frequency and W/N is the bandwidth of each OFDM subchannel. The nominal band of PU l ranges from to f_l to $f_l + W_l$, where f_l and W_l are the starting frequency and the bandwidth of the lth PU. The interference to the lth PU introduced by SU must be kept below I_l^{th}. The power spectrum density (PSD) of the OFDM subcarrier is

$$\phi(f) = T\left(\frac{\sin(\pi f T)}{\pi f T}\right)^2, \tag{2}$$

where T is the OFDM symbol duration. The interference to the lth PU introduced by SU's access on the nth subchannel with unit transmission power is

$$I_{l,n}^{SP} = \int_{f_l - f_0 - (n-1/2)W/N}^{f_l + W_l - f_0 - (n-1/2)W/N} g_{l,n}^{SP} \phi(f)\, df, \tag{3}$$

where $g_{l,n}^{SP}$ is the power gain from an SU's transmitter to the lth PU's receiver on the nth subchannel.

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

$$I_{l,k,n}^{PS} = \int_{(n-1)W/N - (f_l + 1/2W_l)}^{nW/N - (f_l + 1/2W_l)} g_{k,n}^{PS} \phi(f)\, df, \tag{4}$$

where $g_{k,n}^{PS}$ is the power gain from a PU's transmitter to the kth SU's receiver on the nth subchannel. Denote the signal-to-noise ratio (SNR) of the the kth SU on the nth OFDM subchannel with unit power as $h_{k,n}$,

$$h_{k,n} = \frac{g_{k,n}}{\Gamma(N_0 W/N + \sum_{l=1}^{L} I_{l,k,n}^{PS})}, \tag{5}$$

where N_0 is the PSD of the additive white Gaussian noise, $g_{k,n}$ is the power gain of the kth SU on the nth OFDM subchannel with unit power. Γ is the SNR gap, which can be represented as $\Gamma = -\ln(5BER)/1.5$ for an uncoded multilevel quadrature amplitude modulation with specified bit-error-rate (BER) [13].

Let $r_{k,n}$ denote the transmission rate of the kth SU on the nth subchannel, we have

$$r_{k,n} = \frac{W}{N} \log_2(1 + p_{k,n} h_{k,n}), \tag{6}$$

where $p_{k,n}$ is the power allocated to the kth SU on the nth subchannel. Denote R_k as the sum rate of the kth SU,

$$R_k = \sum_{n=1}^{N} c_{k,n} \frac{W}{N} \log_2(1 + p_{k,n} h_{k,n}), \tag{7}$$

where $c_{k,n}$ can be either 1 or 0, informing whether the kth SU occupies the nth subchannel or not.

We try to maximize the sum MOS value of the SUs while considering the total transmission power budget of the CR system and the interference constraints of the PUs. Mathematically, the optimization problem can be described as follows,

$$\begin{aligned} &\max_{p_{k,n}} \sum_{k=1}^{K} MOS_k, \\ s.t.\quad & C_1: \sum_{k=1}^{K} \sum_{N=1}^{N} p_{k,n} \le P_T, \\ & C_2: p_{k,n} \ge 0, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \\ & C_3: \sum_{k=1}^{K} \sum_{N=1}^{N} p_{k,n} I_{l,n}^{SP} \le I_l^{th}, \forall l \in \mathcal{L}, \\ & C_4: \sum_{k=1}^{K} c_{k,n} = 1, \forall n \in \mathcal{N}, \\ & C_5: c_{k,n} \in \{0, 1\}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \end{aligned} \tag{8}$$

where P_T is the power limit of the access point in the CR system and I_l^{th} is the interference power threshold of the lth PU. C_1 and C_2 are the transmission power constraints, while C_3 is the interference constraints of the PUs. C_4 and C_5 guarantee that each subchannel is kept from being shared among the SUs.

III. SUBCHANNEL ALLOCATION SCHEME

Obviously, both continuous variable $p_{k,n}$ and binary variable $c_{k,n}$ are involved in the optimization problem defined by (8). It defines a mixed binary integer programming problem that is generally hard to solve. Thus, we propose a heuristic subchannel allocation method to remove the integer constraints. In the previous works, a subchannel is always allocated to the user with the largest SNR in order to obtain the highest transmission rate with a given power budget [14]. But in an OFDM-based cognitive network, a subchannel with high SNR may also generate more interference to the PUs, which makes it impossible to transmit with the maximum available power over this subchannel. This indicates that these methods for conventional OFDM systems are no longer suitable for CR scenarios. Thus, it requests us to jointly consider the SNR of a subchannel and the interference generated to the PUs in OFDM-based CR networks. The highest achievable rate of subchannel n for SU k is given by

$$r_{k,n}^{M} = \frac{W}{N}\log(1 + p_{k,n}^{M} h_{k,n}), \tag{9}$$

where $p_{k,n}^{M}$ is the maximum power allocated to subchannel n for SU k,

$$p_{k,n}^{M} = \min(P_T, \min_{l \in \mathcal{L}}(\frac{I_l^{th}}{I_{l,n}^{SP}})), \tag{10}$$

we can see that the constraints C_2 and C_3 in (8) are satisfied in (10), which means the power on subchannel n is always bounded by the total power P_T of the CR system and the interference constraints laid by the PUs.

We propose a two-round subchannel allocation procedure among the SUs. In the first ground, we allocate each SU a subchannel, over which the SU can achieve the highest possible rate among all available subchannels. In the second ground, the user who suffers the severest unjustness, has the priority to choose a subchannel with the highest achievable rate among the remaining ones. The allocation process is repeated until all subchannels are consumed. This allocation scheme guarantees a coarse proportional fairness among SUs and the maximization of the MOS value will be ultimately accomplished after power disribution among subchannels. The subchannel allocation scheme is described in Table I, in which $\mathcal{K}$, $\mathcal{L}$ and $\mathcal{N}$ are the set of SUs, PUs and subchannels, respectively. The set of subchannels allocated to SU k is denoted as Ω_k.

TABLE I
SUBCHANNEL ALLOCATION

```
Algorithm: Subchannel Allocation
Initialization:
  Set $R_k = 0,\ \Omega_k = 0,\ \forall k \in \mathcal{K},\ \mathcal{K}_t = \mathcal{K},\ \mathcal{N}_t = \mathcal{N}$;
First round:
  for $i = 1$ to $K$
    Find $k^*, n^*$ that $r_{k^*,n^*}^M \geq r_{k,n}^M, \forall k \in \mathcal{K}_t, \forall n \in \mathcal{N}_t$;
    $\Omega_{k^*} = \Omega_{k^*} \quad n^*,\ \mathcal{K}_t = \mathcal{K}_t \backslash k^*,\ \mathcal{N}_t = \mathcal{N}_t \backslash n^*$;
    $R_{k^*} = r_{k^*,n^*}^M$.
  end for
Second round
  while $\mathcal{N}_t \neq \varnothing$
    Find $k^* = \arg(\min_{k \in \mathcal{K}} R_k)$;
    Find $n^*$ that $r_{k^*,n^*}^M \geq r_{k^*,n}^M, \forall n \in \mathcal{N}_t$;
    $\Omega_{k^*} = \Omega_{k^*} \quad n^*,\ \mathcal{N}_t = \mathcal{N}_t \backslash n^*$;
    $R_k = R_k + r_{k^*,n^*}$.
  end while
```

IV. OPTIMAL POWER ALLOCATION: A FAST BARRIER METHOD

For a given subchannel assignment, the constraints C_4 and C_5 in (8) vanish, and the optimization problem is transformed into the following form,

$$\begin{aligned} &\max_{p_{k,n}} \sum_{k=1}^{K} \alpha \log(\beta \sum_{n \in \Omega_k} r_{k,n}), \\ &s.t. \quad C_1 \sim C_3 \ in \ (8), \end{aligned} \tag{11}$$

where $r_{k,n} = \frac{W}{N}\log_2(1 + p_{k,n}h_{k,n})$, which is a monotropic function of $p_{k,n}$.

Eq.(11) defines a convex optimization problem and can be solved by the barrier method discussed in [15, 16]. Table II shows the flow of the barrier method, where ϵ and ϵ_n are the tolerances of the barrier method and Newton step, respectively. α and β are two constants utilized in backtracking line search with $\alpha \in (0, 0.5)$ and $\beta \in (0, 1)$. The step size of the backtracking line search is s with $s > 0$. t and μ are parameters which are associated with the tradeoff between outer iterations and inner iterations. The computational complexity of the barrier method mainly lies in the computation of Newton step that needs matrix inversion with a complexity of $O(N^3)$. Since the number of subchannels N in a practical OFDM system is always several thousand and such a complexity is unacceptable the for the resource allocation problem that should be tackled in an online manner, in this work, we develop an efficient algorithm, fast barrier algorithm, to compute the Newton step by exploiting the structure of (11).

The barrier function of (11) is

$$\begin{aligned} \phi(P) = &-\sum_{n=1}^{N}\log(p_n) - \log(P_T - \sum_{n=1}^{N} p_n) \\ &-\sum_{l=1}^{L}\log(I_l^{th} - \sum_{n=1}^{N} p_n I_{l,n}^{SP}), \end{aligned} \tag{12}$$

where $P = (p_1, p_2, \ldots, p_N)$. Denote

$$f(P) = \sum_{k=1}^{K} log(\alpha \log(\beta \sum_{n \in \Omega_k} \log(1 + p_{k,n}h_{k,n}))),$$

the optimal solution of (11) can be approximated by solving the following unconstrained minimization problem

$$\min \psi_t(P) = -tf(P) + \phi(P), \tag{13}$$

where $t > 0$ is a parameter to control the accuracy of solution. As t increases, the approximation becomes more and more accurate. Newton method can efficiently solve this unconstrained minimization problem. Newton step at P, denoted by ΔP_{nt}, is given by

$$\nabla^2\psi_t(P)\Delta P_{nt} = -\nabla\psi_t(P), \tag{14}$$

where $\nabla^2\psi_t(P)$ is the Hessian and $\nabla\psi_t(P)$ is the gradient of $\psi_t(P)$, respectively. Now we develop an efficient algorithm to quickly calculate Newton step.

The gradient of $\psi_t(P)$ is

$$\begin{aligned}\nabla\psi_t(P) &= -t\nabla f(P) + \nabla\phi(P)\\ &= -t\alpha\frac{h_{k,n}}{\sum\limits_{n\in\Omega_k}\log(1+h_{k,n}p_{k,n})(1+h_{k,n}p_{k,n})}\\ &\quad -\frac{1}{p_n} + \frac{1}{P_T - P^N} + \sum_{l=1}^{L}\frac{I_{l,n}^{SP}}{I_l^{th} - \sum\limits_{n=1}^{N} p_n I_{l,n}^{SP}},\end{aligned}$$

and the Hessian of $\psi_t(P)$ is

$$\begin{aligned}\nabla^2\psi_t(P) &= -t\nabla^2 f(P) + \nabla^2\phi(P)\\ &= D + \sum_{l=0}^{L} g_l g_l^T,\end{aligned}$$

where

$$D = \begin{bmatrix}\lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_N\end{bmatrix},$$

$$\begin{aligned}\lambda_i &= t\alpha\frac{h_{k,i}^2[1+\sum\limits_{n\in\Omega_k}\log(1+h_{k,i}p_i)]}{\sum\limits_{n\in\Omega_k}\log^2(1+h_{k,i}p_i)(1+h_{k,i}p_i)^2} + \frac{1}{p_i^2},\\ g_0 &= (\frac{1}{P_T-P^N}, \frac{1}{P_T-P^N}, \ldots, \frac{1}{P_T-P^N})^T,\\ g_l &= \frac{1}{I_l^{th} - I_l^{tot}(P)}(I_{l,1}^{SP}, I_{l,2}^{SP}, \ldots, I_{l,N}^{SP}),\end{aligned}$$

where $I_l^{tot}(P) = \sum\limits_{n=1}^{N} p_n I_{l,n}^{SP}$, $P^N = \sum\limits_{n=1}^{N} p_n$.

Define $D_i = D + \sum\limits_{l=0}^{i} g_l g_l^T, i = 0, 1, 2, \ldots, L$, we have the following theorem:

Theorem 1. *All D_i's are positive definite.*

proof: D is diagonal and $\lambda_i > 0$, so D is obviously positive definite. $g_0 g_0^T$ is positive semidefinite, then $H_0 = H + g_0 g_0^T$ is positive definite. Since $g_l g_l^T$ is always positive semidefinite, H_i's are positive define sequentially.

Since the matrix of (14) is invertible and the Hessian H_L can be treated as the sum of a diagonal matrix and L+1 number of rank-one matrices, we can use this special structure to calculate the Newton step ΔP_{nt} with approximate linear complexity.

Theorem 2. *The equation (14) can be solved with the complexity of $O(L^2N)$.*

TABLE II
THE BARRIER METHOD

```
Algorithm:
Initialization
Feasible point $p \in R^{N+1\times1}$, $\epsilon > 0$, $\epsilon_n > 0$, $t = t^{(0)} > 0$, $\mu > 1$,
$\alpha \in (0, 1/2)$, $\beta \in (0, 1)$.
repeat
  Newton method
    Starting point P, subject to constraints
    repeat
      Compute $\triangle P_{nt}$ and $\lambda^2 = -\nabla\psi_t(P)^T \triangle P_{nt}$
      Backtracking line search
        $s = 1$;
        while $\psi_t(P + s\triangle P_{nt}) > \psi_t(P) - \alpha s\lambda^2$
          $s = \beta s$;
        end while
        Update $P = P + s\triangle P_{nt}$
  until $\lambda^2/2 \le \epsilon_n$
  $t = \mu t$
until $(L + N + 1)/t < \epsilon$
return P
```

The proof is given in Appendix. In practical wireless systems, the number of PUs $L \ll N$, so the complexity of the algorithm has a significant advantage over the standard convex optimization technique, which yields a complexity of $O(N^3)$.

V. SIMULATION RESULTS AND DISCUSSIONS

Considering an OFDM-based CR system, each PU occupies random bandwidth which spans continuous subchannels, and all users are randomly located in a 3×3 km area, while each receiver is uniformly distributed in the circle within 0.5 km from its transmitter. The noise power is 10^{-13} W. The interference thresholds of all PUs are set to 5×10^{-13} W. The channel suffers from frequency selective fading. The path loss exponent is 4. The variance of logarithmic normal shadow fading is 10 dB and the amplitude of multipath fading is Rayleigh. The parameters of the MOS model and the barrier method are set to the typical values discussed in [17] and [18], respectively. The parameters of the barrier method are also initialized with a strictly feasible solution generated by

$$p_n = \min\{P_T/N, \min_n\{\min_l I_l^{th}/I_{l,n}^{SP}\}\}, \tag{15}$$

we choose two traditional power allocation algorithms for comparison, Max-Throughput Algorithm (MTA) and Max-Min resource allocation scheme, both of which aim at maximizing the overall data rates of all end users.

As discussed above, the computational load of the proposed algorithm mainly lies in the computation of Newton step. Fig. 1 shows the number of Newton iterations with 100 random instances and the cumulative distribution function (CDF) of the number of Newton iterations over 1000 instances for solving the optimal power allocation with $L = 2, N = 64, K = 4$ and $P_T = 1$ W. As can be seen from the results, the number of Newton iterations is not large (the average number of Newton iterations is 108) and varies in a narrow range (80% of the

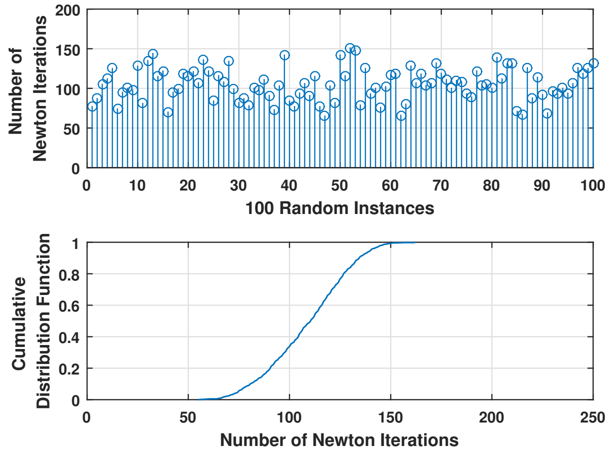

Fig. 1. Number of Newton iterations and CDF of number of Newton iterations over 1000 instances of the algorithms with $L = 2, N = 64, K = 4$ and $P_T = 1$ W.

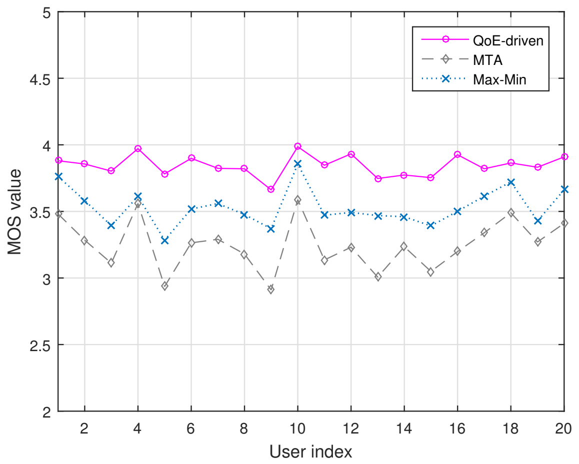

Fig. 2. MOS value of each SU obtained by the algorithms with $L = 2, N = 64, K = 20$ and $P_T = 1$ W.

number of Newton iterations of is less than 125), indicating our proposed algorithm is efficient.

Fig. 2 shows the MOS value of each SU obtained by the above three algorithms with $L = 2, N = 64$ and $K = 20$. As can be seen from the result, our QoE-driven resource allocation algorithm obtains a high and relatively stable MOS value, which is better and more acceptable than the other two. We also present the simulation results of the SU's average MOS value (per user) for a different number of SUs and different transmit power limit for CR System in Fig. 3 and Fig. 4 with $L = 2$ and $N = 64$, respectively. As can be seen from Fig. 3, the average MOS value of each user decreases as the number of users increases, this is owing to the decrease of each SU's sum rate, which is affected by the number of subchannels allocated to each SU. Besides, it is observed in Fig. 4 that the average MOS value of each user increases as the transmit power limit for CR System increases. Both of the simulation results show that our proposed method can always obtain the highest MOS value, indicating that our QoE-driven resource allocation scheme outperforms both MTA and Max-Min and users who take our method can enjoy the best user experience. Thus, our QoE-driven resource allocation algorithm is promising for practical systems.

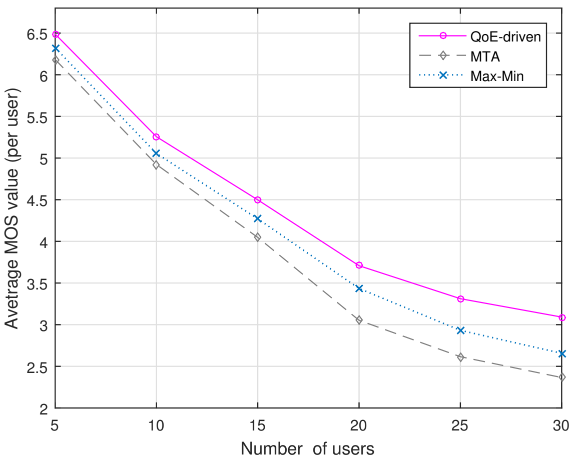

Fig. 3. Average MOS value of all SUs obtained by the algorithms with $L = 2, N = 64$ and $P_T = 1$ W.

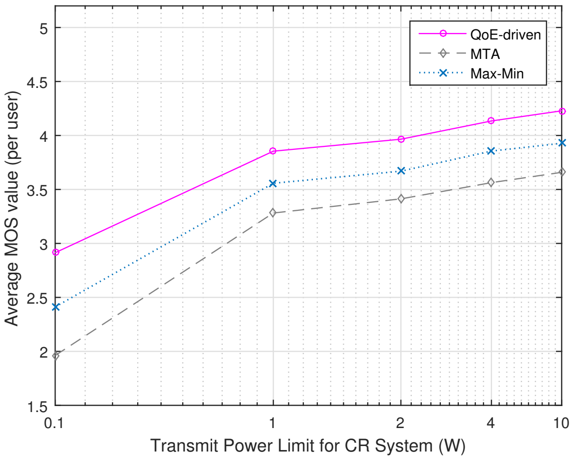

Fig. 4. Average MOS value of all SUs obtained by the algorithms with $L = 2, N = 64, K = 20$ and $P_T = 1$ W.

VI. CONCLUSIONS

In this paper, we presented a novel QoE-driven radio resource allocation algorithm for the downlink of OFDM-based cognitive radio networks, in which our target was to maximize the total QoE of all SUs. By introducing the QoE-based assessment model, a mixed binary integer programming problem is formulated, which is hard to solve. Thus a subchannel allocation scheme based on the joint consideration of the SNR of a subchannel and the interference generated to the PUs is introduced to remove the integer constraints. Then for a given subchannel assignment, we propose a fast barrier method with a low complexity of $O(L^2N)$ to tackle the formulated problem. Simulation results demonstrate that our proposed algorithm can significantly improve the overall perceived quality of experience from the user's perspective in comparison with the traditional QoS-oriented algorithms. In future work, more practical scenarios should be considered to verify the effectiveness and the efficiency of our proposed method.

APPENDIX

Proof of *Theorem 2*:

Rewrite (15) as

$$D_L u^0 = -\nabla\psi_t(P) \tag{16}$$

where $u^0 = \Delta P_{nt}$. Recall $D_L = D_{L-1} + g_L g_L^T$, (16) can be written as

$$(D_{L-1} + g_L g_L^T)u^0 = -\nabla\psi_t(P) \tag{17}$$

Since H_i's are positive define and invertible, then

$$u^0 = (D_{L-1} + g_L g_L^T)^{-1}(-\nabla\psi_t(P)) \tag{18}$$

Using matrix inversion lemma [19], we have

$$u^0 = D_{L-1}^{-1}(-\nabla\psi_t(P)) - \frac{g_L^T D_{L-1}^{-1}(-\nabla\psi_t(P))}{1 + g_L^T D_{L-1}^{-1} g_L} D_{L-1}^{-1} g_L \tag{19}$$

Step 1: Denote two intermediate variables $u_1^1, u_2^1 \in R^n$ as the solutions of the following two sets of linear equations,

$$\begin{aligned} D_{L-1}u_1^1 &= -\nabla\psi_t(P) \\ D_{L-1}u_2^1 &= g_L \end{aligned} \tag{20}$$

then (19) can be written as

$$u^0 = u_1^1 - \frac{g_L^T u_1^1}{1 + g_L^T u_2^1} u_2^1 \tag{21}$$

It means that u^0 can be worked out if u_1^1 and u_2^1 have been calculated.

Step 2: Similarly, u_1^1 and u_2^1 can be obtained by solving the following three sets of linear equations,

$$\begin{aligned} D_{L-2}u_1^2 &= -\nabla\psi_t(P) \\ D_{L-2}u_2^2 &= g_L \\ D_{L-2}u_3^2 &= g_{L-1} \end{aligned} \tag{22}$$

where $u_1^2, u_2^2, u_3^2 \in R^n$ are other intermediate variables.

Continue this process to *Step* L+1, L+1 variables $u_1^L, u_2^L, \ldots, u_{L+1}^L \in R^n$ are obtained by solving L+2 sets of linear equations.

$$\begin{aligned} Du_1^{L+1} &= -\nabla\psi_t(P) \\ Du_2^{L+1} &= g_L \\ &\vdots \\ Du_{L+2}^{L+1} &= g_0 \end{aligned} \tag{23}$$

Since H is diagonal, each set of equations in (23) can be solved at a cost of $O(N)$. The computation cost of solving (23) is $O(LN)$. Using (21), we calculate all $u_i^L, i = 1, 2, \ldots, L+1$ with $O(LN)$ complexity. Carry out the iteration process inversely, we can calculate all the intermediate variable $u_1^{i-1}, u_2^{i-1}, \ldots, u_i^{i-1}$ with a cost of at most $O(LN)$ until u^0 is worked out. The total cost is $O(L^2N)$. Notice that all H_i's are positive definite, the condition of using the matrix inversion lemma is always satisfied during the computations.

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