QoE-Oriented Resource Allocation in Multiuser OFDM Systems

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Abstract—**Quality of experience (QoE) is a widely accepted criteria to measure the satisfaction of users nowadays. In this paper, we investigate the QoE-oriented resource allocation in multiuser orthogonal frequency division multiplexing (OFDM) systems. The optimization objective is to maximize the minimum mean opinion score (MOS) of users that incorporates with subjective human perception of quality. Our general problem formulation leads to an intractable mixed integer programming problem. We first employ a two-step procedure to convert it into an equivalent convex form. Then we develop a fast algorithm to solve it efficiently, where the key is to replace the time-consuming Newton step updating with an approximate linear complexity algorithm. Numerical results show that our proposal can always work out optimal solutions. Moreover, the proposed algorithm converges quickly, indicating it promising for applications.**

Index Terms—**Convex optimization, quality of experience (QoE), resource allocation.**

I. Introduction

Orthogonal frequency division multiplexing (OFDM) is deemed as a promising technique for wireless communication systems because it provides high data rate and flexibility in allocating radio resource, which makes it widely adopted in advanced mobile networks, e.g., Long Term Evolution (LTE). The basic idea of the OFDM systems is to divide broad available bandwidth into N orthogonal subchannels. As the bandwidth of subchannels is much smaller than the coherence bandwidth of wireless channel, subchannels suffer flat fading rather than frequency-selective fading. In multiuser scenarios, it yields independent channel attenuation for different users, which can be used to exploit multiuser diversity gain to improve system capacity. Therefore, adaptive resource allocation (RA) based on multiuser diversity is an important issue for OFDM systems, which has been extensively investigated during the past two decades.

A detailed survey on the RA algorithms for downlink OFDM systems can be found in [1] and the references therein. In [2], it is shown that the total throughput of a multiuser OFDM system can be maximized when each subchannel is assigned to the user with the highest channel gain over this subchannel with distributing powers among all subchannels by using water-filling algorithm. In [3], a proportional rate adaptive resource allocation algorithm for multiuser OFDM system is proposed, which provides each user a predefined data rate. Maximizing total data rate is always the core target [2] for exiting RA problems, where fairness [4] and quality of service (QoS) are also mentioned. However, few researches pay attention on the satisfaction of the subjective quality requirements from human users' perspective. Different from the typical network-oriented QoS, quality of experience (QoE) is a relative subjective metric that indicates not only the performance of services, but also the subjective opinions of users. We use the application-oriented mean opinion score (MOS) to measure the QoE of users in this work.

In [5], a QoE-based evaluation methodology is proposed to assess the LTE systems video capacity. The proposed QoE-aware radio resource management structure makes the network operators easy to increase the video capacity. In [6], a QoE-driven resource allocation scheme is proposed for cognitive radio networks. Scheduling multiple video users sharing time-varying wireless channel in LTE systems is investigated in [7], where a cross-layer video-QoE aware optimization framework is proposed for wireless resource allocation. In [8], two user-oriented joint subcarrier and power allocation algorithms are developed for real-time and interactive services.

In this paper, we study QoE-oriented RA algorithms in the downlink of multiuser OFDM system. We aim to maximize the minimum MOS of users under transmission power budget. We first introduce a QoE-based model to assess the OFDM system performance. Then we develop a two-step algorithm to solve the formulated problem efficiently. As the existence of binary and real variables makes it difficult to obtain optimal solutions, we apply a subchannels assignment scheme according to the channel gain, by which we can remove the integer constraints. Then, for a given subchannel assignment, we transform the intractable programming problem into a convex optimization one by using its hypograph form. Finally, we develop a fast algorithm by utilizing the special structure of the problem, decreasing computation load dramatically. Simulation results show that our proposal yields a promising performance.

The rest of this paper is organized as follows. In section II, we illustrate system model and formulate optimization problem. In section III, subchannel allocation scheme and power distribution algorithms are developed. Simulation results are presented in section IV, as well as discussions. Finally, conclusions are drawn in section V.

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II. System Model and Problem Formulation

A. Network Model

Consider the downlink of a multiuser OFDM system with K users, denoted by $\mathcal{K} = \{1, 2, \ldots, K\}$. The whole available bandwidth B is divided into N subchannels, denoted by $\mathcal{N} = \{1, 2, \ldots, N\}$. Each subchannel is assumed to be assigned to exclusive user, by which the intra-cell interference can be avoided. We assume that the estimated channel state information (CSI) can be obtained at the receiver with the aid of pilot symbols transmitted from its corresponding transmitter. $p_{k,n}$ is the power assigned to user k on subchannel n. The channel gain from base station to the kth user over the nth subchannel is denoted as $h_{k,n}$. Then, the achievable transmission rate of the nth subchannel occupied by the kth user can be denoted as follows,

$$r_{k,n} = \log_2\left(1 + \frac{p_{k,n} h_{k,n}^2}{\Gamma N_0 B/N}\right), \tag{1}$$

where N_0 is the power spectral density of additive white Gaussian noise (AWGN) and Γ is the signal-to-noise ratio (SNR) gap. Γ is associated with a given bit-error-rate (BER) requirement under the situation of an uncoded MQAM [9], where $\Gamma = -\ln(5BER)/1.6$. We introduce $H_{k,n}$ to denote the SNR of the kth user with unit power on the nth subchannel,

$$H_{k.n} = \frac{h_{k,n}^2}{\Gamma N_0 B/N}. \tag{2}$$

Thus, the transmission rate of the kth user is

$$R_k = \frac{B}{N} \sum_{n=1}^{N} c_{k,n} \log(1 + p_{k,n} H_{k,n}), \tag{3}$$

where $c_{k,n}$ is either 1 or 0. It indicates whether the nth subchannel is assigned to the kth user or not.

B. MOS Model for Web Browsing

MOS takes the subjective user perceived quality into consideration. In real wireless networks, there exists three different classes of services: audio, video and web browsing. In this paper, we focus on web browsing applications, which is one of the most popular application in wireless networks. Our proposed method can be extended to other applications with necessary modifications. The MOS model for the web browsing application can be defined as follows [8],

$$MOS_{web} = -K_1 \ln(d(R_{web})) + K_2, \tag{4}$$

where R_{web} is the data rate and MOS_{web} is a real score to reflect the user perceived quality. The higher the score is, the better the human perception of quality is. K_1 and K_2 are given constants. $d(R_{web})$ represents the time elapsed between the user requests a web page and the page is totally displayed by the browser. $d(R_{web})$ is related to the web page size (PS), the round trip time (RTT), and the types of the protocols, e.g., TCP and HTTP. When TCP and HTTP protocols are used in the systems, $d(R_{web})$ can be modeled as [10]

$$\begin{aligned} d(R_{web}) = &3RTT + \frac{PS}{R_{web}} \\ &+ L\left(\frac{MSS}{R_{web}} + RTT\right) - \frac{2MSS(2^L - 1)}{R_{web}}, \end{aligned} \tag{5}$$

where MSS is the maximum segment size. The parameter $L = \min[L_1, L_2]$ is the number of slow start cycles with idle periods. The number of cycles that the congestion window required to reach the bandwidth-delay product are denoted as L_1. And L_2 is the required number of slow start cycles before PS is totally transferred. L_1 and L_2 can be denoted as

$$L_1 = \log_2\left(\tfrac{R_{web} RTT}{MSS} + 1\right) - 1,$$
$$L_2 = \log_2\left(\tfrac{PS}{2MSS} - 1\right) - 1.$$

According to [8], the sensitivity of the MOS function to the RTT is much less significant than the sensitivity to the data rate and the web page size. Moreover, LTE release 8 already achieves lower RTT than the currently supported 10 ms. Thus, it is reasonable that we assume that $RTT \approx 0$ ms. Therefore, (5) can be simplified as

$$d(R_{web}) = PS/R_{web}. \tag{6}$$

By combining (3), (4), and (6), we can obtain $MOS_{web}^k(R_k)$ of the user k for web browsing, which is denoted as follows,

$$\begin{aligned} &MOS_{web}^k(c_{k,n}, p_{k,n}) \\ &= -K_1 \ln\left(\frac{PS_k}{\frac{B}{N}\sum_{n=1}^{N} c_{k,n} \log_2(1 + H_{k,n} p_{k,n})}\right) + K_2, \end{aligned} \tag{7}$$

where we rewrite $MOS_{web}^k(R_k)$ as $MOS_{web}^k(c_{k,n}, p_{k,n})$, i.e., a function of $c_{k,n}$ and $p_{k,n}$. Further, (7) can be transformed into the following form

$$\begin{aligned} MOS_{web}^k(c_{k,n}, p_{k,n}) = \; & K_1 \ln\left(\sum_{n=1}^{N} c_{k,n} \log_2(1 + H_{k,n} p_{k,n})\right) \\ & + K_3, \end{aligned} \tag{8}$$

where $K_3 = K_2 + K1 * \ln(\frac{B}{PS_k N})$.

C. Problem Formulation

In this paper, we aim to maximize the minimum of whole users' MOS under the transmission power budget. Hence, the optimization task can be formulated as

$$\begin{aligned} \max_{c_{k,n}, p_{k,n}} \quad & \min_k MOS_{web}^k \\ s.t. \quad C1: \quad & \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \leq P_{total}, \\ C2: \quad & p_{k,n} \geq 0, \forall k, n, \\ C3: \quad & c_{k,n} \in \{0, 1\}, \forall k, n, \\ C4: \quad & \sum_{k=1}^{K} c_{k,n} \leq 1, \forall n, \end{aligned} \tag{9}$$

where P_{total} is the total transmission power budget of users. C1 guarantees power allocated to users is under the total power limit. C3 and C4 are constraints on users' subchannel allocation, which indicates that each OFDM subchannel cannot be shared by different users.

III. INTEGER SUBCHANNEL ALLOCATION AND OPTIMAL POWER ALLOCATION

A. Integer Subchannel Allocation

Apparently, (9) is a mixed integer programming problem since both binary variables $c_{k,n}$'s and real variables $p_{k,n}$'s are involved. Intuitive exhaustive search, which is the main approach to solve (9), generates K^N possible subchannel assignments because of the existence of integer constraint C3. A general method to tackle the integer programming is time-sharing, by which integer variables are relaxed into continuous ones so that efficient linear/nolinear optimization methods can be employed.

For the relaxation form, the fractional $c_{k,n}$ can be regarded as a metric to determine the exact assignment of subchannels. [11] has proved that only few subchannels are shared among users for $K \ll N$, which means $c_{k,n}$ is mostly either 1 or 0. And further more, each subchannel is prohibited from being shared among multiuser in practical OFDM systems. So each subchannel is assigned to only one user, which means that the allocation indexes $c_{k,n}$'s are limited to be 0's or 1's. The subchannel allocation depends on the following equation:

$$c^*_{k,n} = \begin{cases} 1, & \text{for all } |H_{k,n}| \geq |H_{j,n}|, \forall j \in \mathcal{K}, \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

B. Power Distribution with Given Subchannel Assignment

Given a subchannel assignment, the integer constraints in problem (9) have been vanished and power distribution across subchannels follows. Let Ω_k denote the set of subchannels allocated to the kth user, the original problem can be transformed to the power distribution problem as follows:

$$\begin{aligned} \max_{p_{k,n}} \quad & \min_k \left(K_1 \ln\Big(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\Big) + K_3 \right) \\ s.t. \quad C1: \ & \sum_{k=1}^{K} \sum_{n\in\Omega_k} p_{k,n} \leq P_{total}, \\ C2: \ & p_{k,n} \geq 0, \forall k, n. \end{aligned} \tag{11}$$

1) Equivalent transformation in hypograph form: (11) defines a non-linear fractional programming problem what is still difficult to solve. Nevertheless, (11) has an equivalent transformation via its hypograph form [12], since the objective function is concave in $p_{k,n}$'s. The hypograph form of (11) is followed as,

$$\begin{aligned} \max_{p_{k,n},y} \quad & y \\ s.t. \quad & \text{C1} \sim \text{C2 in (9)}, \\ & K_1 \ln\Big(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\Big) + K_3 \geq y, \forall k, \\ & y \geq 0. \end{aligned} \tag{12}$$

Such a transformation guarantees that (12) is equivalent to (11). Namely, we maximize y over the hypograph of MOS^k_{web}, subject to the constrains in (11), which is equivalent to solve (11) directly.

Thus, (12) can be transformed into a convex optimization problem as follows,

$$\begin{aligned} & K_1 \ln\Big(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\Big) + K_3 \geq y \\ \Longleftrightarrow\ & K_1 \ln\Big(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\Big) + K_3 - y \geq 0. \end{aligned} \tag{13}$$

Then the equivalent hypograph form of (12) can be written as follows,

$$\begin{aligned} \max_{p_{k,n},y} \quad & y \\ s.t. \quad & \text{C1} \sim \text{C2 in (9)}, \\ & K_1 \ln\Big(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\Big) + K_3 - y \geq 0, \forall k, \\ & y \geq 0. \end{aligned} \tag{14}$$

Obviously, (14) defines a convex optimization problem, to which the optimal solutions are the same as (12). Since there are fully developed algorithms to solve such kind of problems, it is reasonable to work out the optimal solution to (12) by solving (14).

2) Fast barrier method: Barrier method is regarded as a standard technique to solve convex optimization problems. The computation of Newton step, which needs matrix inversion with a complexity of $\mathcal{O}(N^3)$ for our problem, mainly decides the computational complexity of the barrier method. There exists thousands of subchannels in a practical OFDM system, which causes that the complexity is too high for the system to apply, especially for the problem that should be tackled in limited time. In this work, we exploit the special structure of the matrix to decrease computational complexity as the similar methods proposed in [13–15].

To employ the barrier method, we transform the objective function y in (14) into a twice differentiable function $U(y)$ [16] as follows,

$$\begin{aligned} \max_{p_{k,n},y} \quad & \log(1 + y) \\ s.t. C1: \ & K_1 \ln\Big(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\Big) + K_3 \\ & -y \geq 0, \forall k, \\ C2: \ & \sum_{k=1}^{K} \sum_{n\in\Omega_k} p_{k,n} \leq P_{total}, \\ C3: \ & p_{k,n} \geq 0, \forall k, n, \\ C4: \ & y \geq 0, \end{aligned} \tag{15}$$

where $U(y) = \log(1 + y)$, which is monotone increasing. Obviously, the transformed problem (15) is equivalent to the original form (14).

Then we convert all inequality constraints into a logarithmic

TABLE I
THE BARRIER METHOD

Initialization
Feasible point $x \in R^{N+1\times 1}$, $\epsilon > 0$, $\epsilon_n > 0$, $t = t^{(0)} > 0$, $\mu > 1$, $\alpha \in (0, 1/2)$, $\beta \in (0, 1)$.
repeat
  Newton method
  Starting point **x**, subject to constraints
  repeat
    Compute $\triangle \mathbf{x}_{nt}$ and $\lambda^2 = -\bigtriangledown \psi_t(\mathbf{x})^T \triangle x_{nt}$
    Backtracking line search
    $s = 1$;
    while $\psi_t(\mathbf{x} + s \triangle \mathbf{x}_{nt}) > \psi_t(\mathbf{x}) - \alpha s \lambda^2$
      $s = \beta s$;
    end while
    Update $\mathbf{x} = \mathbf{x} + s \triangle \mathbf{x}_n t$
  until $\lambda^2/2 \le \epsilon_n$
  $t = \mu t$
until $(K + N + 2)/t < \epsilon$
return x

barrier function $\phi(\mathbf{x})$,

$$\begin{aligned}\phi(\mathbf{x}) = & -\sum_{k=1}^{K} \log\left(K_1 \ln\left(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\right) + K_3 - y\right) \\ & - \log\left(P_{total} - \sum_{k=1}^{K}\sum_{n\in\Omega_k} p_{k,n}\right) \\ & - \sum_{k=1}^{K}\sum_{n\in\Omega_k} \log p_{k,n} - \log y, \end{aligned} \tag{16}$$

where all variables are collected into one vector **x**, i.e. $\mathbf{x} = \{p_1, p_2, \ldots, p_N, y\}$.

Thus, the optimal solution to (15) can be approximated by solving the following minimization problem,

$$\min \psi_t(\mathbf{x}) = -t \log(1 + y) + \phi(\mathbf{x}), \tag{17}$$

where t is a parameter to control the accuracy of solution. As t increases, the approximation solution will close to the optimal solution gradually. The outline of the barrier method is detailed in Table I. Denoted the tolerances of the barrier method and the Newton step by ϵ and ϵ_n, respectively. α and β are two constants introduced in backtracking line search with $\alpha \in (0, 0.5)$ and $\beta \in (0, 1)$. s is the step length of the backtracking line search with $s > 0$. The tradeoff between inner iterations and outer iterations is realized by introducing parameters t and μ.

Because of the quadratic convergence property of Newton method, it is better to compute the central point in the inner loop of the barrier method. With a given parameter t, Newton step $\triangle \mathbf{x}_{nt}$ and its related dual variables ν satisfy the following Karush-Kuhn-Tucker (KKT) conditions,

$$\begin{pmatrix} \bigtriangledown^2 \psi_t(\mathbf{x}) & \mathbf{B}^T \\ \mathbf{B} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \triangle \mathbf{x}_{nt} \\ \nu \end{pmatrix} = \begin{pmatrix} -\bigtriangledown \psi_t(\mathbf{x}) \\ \mathbf{0} \end{pmatrix}, \tag{18}$$

where $\mathbf{B} \in \Re^{1\times N+1}$. $\bigtriangledown^2 \psi_t(\mathbf{x})$ and $\bigtriangledown \psi_t(\mathbf{x})$ are the Hessian and gradient of $\psi_t(\mathbf{x})$, respectively.

If we solve (18) directly, it will generate a complexity of $\mathcal{O}(N^3)$, which is too high to apply in practice. We analyze problem (16) and utilize its special structure to compute the Newton step quickly. For simplicity, denote

$$\begin{aligned} f_0 &= P_{total} - \sum_{k=1}^{K}\sum_{n\in\Omega_k} p_{k,n}, \\ f_k &= K_1 \ln\left(\sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n})\right) + K_3 - y, \forall k, \\ g_k &= \sum_{n\in\Omega_k} \log_2(1 + H_{k,n}p_{k,n}), \forall k, \end{aligned} \tag{19}$$

then the gradient of $\psi_t(\mathbf{x})$ is

$$\begin{aligned} \frac{\partial \psi_t}{\partial p_{k,n}} &= -\frac{1}{f_k}\left(\frac{K_1}{g_k}\frac{H_{k,n}}{1+H_{k,n}p_{k,n}}\frac{1}{\ln 2}\right) + \frac{1}{f_0} - \frac{1}{p_{k,n}}, \\ \frac{\partial \psi_t}{\partial y} &= -\frac{t}{1+y} - \frac{1}{y} + \sum_{k=1}^{K}\frac{1}{f_k}. \end{aligned} \tag{20}$$

And the Hessian of $\psi_t(\mathbf{x})$ can be calculated as follows,

$$\begin{aligned} \bigtriangledown^2 \psi_t(\mathbf{x}) &= \begin{pmatrix} D_1 & & & \\ & \ddots & & \\ & & D_N & \\ & & & Y \end{pmatrix} \\ & \quad + \frac{\bigtriangledown f_0 \bigtriangledown f_0^T}{f_0^2} + \sum_{k=1}^{K}\frac{\bigtriangledown f_k \bigtriangledown f_k^T}{f_k^2} + \sum_{k=1}^{K}\frac{K_1}{f_k}\frac{\bigtriangledown g_k \bigtriangledown g_k^T}{g_k^2} \\ &= \mathbf{D} + \sum_{i=1}^{2K+1} \mathbf{q}_i \mathbf{q}_i^T, \end{aligned} \tag{21}$$

where D_n and Y are defined, respectively, as follows,

$$\begin{aligned} D_n &= \frac{K_1}{f_{k^*} g_{k^*} \ln 2}\left(\frac{H_{k^*,n}}{1+H_{k^*,n}p_{k^*,n}}\right)^2 + \frac{1}{p_{k^*,n}^2}, \\ Y &= t/(1+y^2) + 1/y^2 \end{aligned} \tag{22}$$

where k^* is the user that owns subchannel n. Denote $\mathbf{D} = diag(D_1, D_2, \ldots, D_N, Y)$ and $\mathbf{q} \in \Re^{N+1\times 1}$ with

$$\mathbf{q}_i = \begin{cases} \frac{\bigtriangledown f_0}{f_0}, & i = 1, \\ \frac{\bigtriangledown f_k}{f_k}, & k = 1, \ldots, K, i = k + 1, \\ \sqrt{\frac{K_1}{f_k}}\frac{\bigtriangledown g_k}{g_k}, & k = 1, \ldots, K, i = K + k + 1, \end{cases} \tag{23}$$

the matrix **D** is positive definite and all $\mathbf{q}_i \mathbf{q}_i^T \ge 0$, hence the Hessian is positive definite. Moreover, since **B** is a full row rank matrix, the KKT matrix at the left-side of (18) is invertible. However, the computational complexity of matrix inversion for solving the KKT matrix is $\mathcal{O}(N^3)$, which prohibits its application in practical wireless systems since there exists thousands of OFDM subchannels.

Consider the Hessian of $\psi_t(\mathbf{x})$, based on the matrix inversion lemma, we derive a fast algorithm to speed up the computation of Newton step. Define Λ_i as follows,

$$\Lambda_i = \mathbf{D} + \sum_{m=1}^{i} \mathbf{q}_m \mathbf{q}_m^T, i = 1, 2, \ldots, M, \tag{24}$$

where $M = 2K + 1$. And we propose an $(M + 1)$-step iterative algorithm to calculate the Newton step quickly. The detail of the algorithm is given in Table II. After the Mth step, we obtain $M + 1$ variables based on the $M + 1$ matrix systems. According to Table II, we can find that we can utilize the $M + 1$ variables in Step M to calculate the M variables in

TABLE II
FAST CALCULATING OF 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 $\Lambda_{M-1} u_1^1 = -\bigtriangledown \psi_t(\mathbf{x})$ and $\Lambda_{M-1} u_2^1 = \mathbf{q}_M$
After Step 1, we can figure out the $\triangle \mathbf{x}_{nt}$ by solving u_1^1 and u_2^1, instead of using (15).

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 $\Lambda_{M-1} u_1^2 = -\bigtriangledown \psi_t(\mathbf{x})$, $\Lambda_{M-1} u_i^2 = \mathbf{q}_{M+2-i}, i = 2, 3.$
⋮
Continue this process to Step M,

Step M
We can obtain $M+1$ variables by solving $M+1$ liner equation,
$\mathbf{D} u_1^M = -\bigtriangledown \psi_t(\mathbf{x})$
$\mathbf{D} u_i^M = \mathbf{q}_{M+2-i}, i = 2, 3, \ldots, M+1.$

Step $M-1$. Hence, the Newton step can be indirectly figured out by an M-step reverse computation. Furthermore, since $\mathbf{D}$ is a diagonal, the $M+1$ variables $u_i^M, i = 1, 2, \ldots, M+1$ can be obtained by solving each set of equations in Step M.

3) Warm start: A strictly feasible starting point is necessary in the beginning of the barrier method. Thus, a preliminary procedure is essential to acquire a feasible point or prove its nonexistence. We implement the warm start procedure with two steps. First, a feasible point p^0, which satisfies the constraints that $MOS(R_k) > 0$ for all user k and C1 ~ C2 in (9), should be found. Then, we obtain the value of y from the interval $(0, minMOS(R_k))$ and denoted as y^0. The optimization problem defined in the first step is similar to (9). Therefore, we can also apply the proposed fast algorithm discussed in Section III-B to solve it. If no feasible point exists for warm start procedure, we regard such a case as system outage.

4) Complexity analysis: In an M-user and N-subchannel system, the computational complexity of our proposed algorithm can be counted as follows. First, solving the equations in Step M yields a complexity of $\mathcal{O}(MN)$, which figures out M variables. We can carry out the iteration process inversely until u^0 is worked out. Thus, the computational complexity of working out the optimal solution to (9) is $\mathcal{O}(M^2N)$. Since we can also solve the warm start problem by applying the developed fast algorithm, the computation complexity of warm start is equal to that of solving (9). Hence, we can conclude that the complexity of our proposal for the considered problem is $\mathcal{O}(M^2N)$.

As for the complexity of two algorithms mentioned in [8], the complexity of the Max-Min MOS is $\mathcal{O}(MN+2N^2)$ while the complexity of the QoE-aware algorithm is $\mathcal{O}(2MN + N^2 + N^{*2})$, where N^* is the number of iterations required to achieve the minimum MOS for all users. Table III gives the complexity of the mentioned algorithms. We can see that the computation load of our proposed algorithm is much lower than others.

TABLE III
COMPLEXITY COMPARISON OF DIFFERENT RESOURCE ALLOCATION ALGORITHMS

Our proposed algorithm	$\mathcal{O}(M^2N)$
Max-Min MOS algorithm in Ref.[10]	$\mathcal{O}(MN+2N^2)$
QoE-aware algorithm in Ref.[10]	$\mathcal{O}(2MN+N^2+N^{*2})$

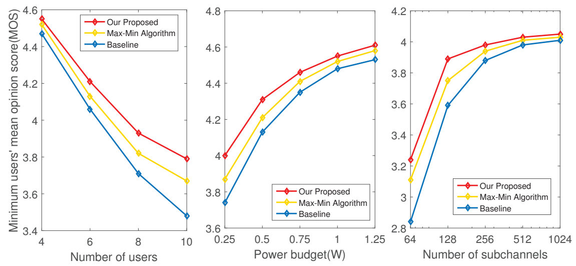

Fig. 1. MOS as a function of the number of users in (a), transmission power limit in (b) and number of subchannels in (c). (a) $N = 256$, $P_{total} = 1W$; (b) $N = 256$, $K = 4$; (c) $K = 4$, $P_{total} = 0.25W$.

IV. Numerical Results and Discussions

Consider a multiuser OFDM system, where the OFDM subchannels is frequency-selective. The path loss exponent is 4 and the variance of shadowing effect is $10dB$. The noise power is set to $10^{-13}W$ and $\Gamma = 1$. All users located in a 3×3 km area randomly. Each receiver is uniformly distributed in the circle within $0.5km$ from its transmitter.

Fig.1 shows the minimum achieved MOS of users for our proposal. We take Max-Min MOS algorithm proposed in [8] for comparison. The Max-Min MOS algorithm prior assigns the user that has minimum MOS value with subchannel, on which it has the best channel gain. Then, it uses the water-filing strategy to allow power among subchannels belonging to a given user. Moreover, we take the average power allocation scheme as the baseline, where the subchannel allocation algorithm proposed in Section III-A is applied. All the results are averaged by 1000 different realizations. We adopt simplified model of web browsing application. Users access web pages with the following web page sizes,

$$
\begin{aligned}
K = 4 &\longrightarrow FS = [30, 100, 320, 500]\ kb \\
K = 6 &\longrightarrow FS = [30, 100, 200, 320, 500, 1000]\ kb \\
K = 8 &\longrightarrow FS = [18, 30, 100, 200, 320, 320, 500, 1000]\ kb \\
K = 10 &\longrightarrow FS = [18, 30, 50, 100, 200, 320, 320, 500, \\
&\qquad 650, 1000]\ kb
\end{aligned}
$$

As can be seen in Fig.1.(a), the minimum achieved MOS decreases with the increasing of the number of users. The number of subchannels $N = 256$ and the total transmission power limit $P_t = 1W$. This is because the increase of the number of users brings the decrease of the benefits of channel diversity on system performance, as well as the MOS. Notice that the performance of our proposal is better than the Max-Min MOS algorithm. More than 3.2% performance improvement is obtained when the number of users is 10.

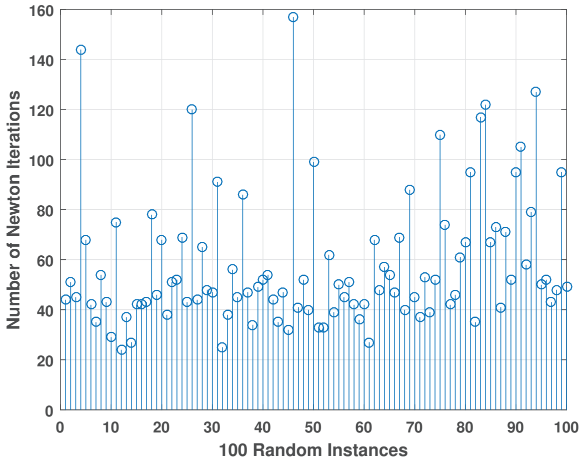

Fig. 2. Number of Newton iterations. $K = 4$, $P_{total} = 1W$, $N = 128$.

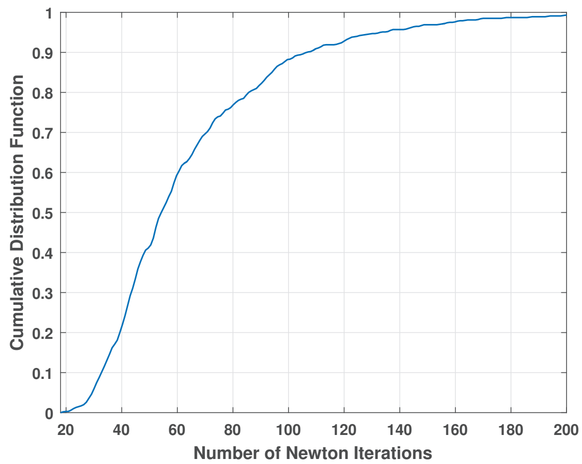

Fig. 3. CDF of the number of Newton iterations. $K = 4$, $P_{total} = 1W$, $N = 128$.

Fig.1.(b) illustrates the minimum MOS versus the transmission power budget. The number of users and subchannels are $K = 4$ and $N = 256$, respectively. It is shown in Fig.1.(b) that the minimum MOS increases rapidly at the beginning as the increase of the transmission power budget. The system can satisfy all users' rate requirements when the transmission power budget is sufficiently enough. Again, our proposed optimal power allocation performs better than the Max-Min MOS algorithm. We also evaluate the minimum MOS versus the number of subchannels in Fig.1.(c). The number of users $K = 4$. The total transmission power budget $P_t = 0.25W$. We can observe that the minimum user's MOS increases with the growth of the number of subchannels. The reason is that many subchannels have good channel gains in such a scenario.

The convergence of our proposed algorithm is shown in Fig.2-3. Fig.2 shows the number of Newton iterations of the barrier method required for convergence with 100 channel realizations. The majority of Newton iterations lies in interval $(20, 60)$. The proportion of Newton iterations which is larger than 100 is less than 10 %. Moreover, for 80% instances, Newton iterations for convergence are less than 85 as can be seen from Fig.3. Both Fig.2 and Fig.3 illustrate that the number of Newton iterations is small and varies in a narrow range, which confirms that our proposed algorithm is effective and efficient.

V. Conclusion

In this paper, we studied the QoE-oriented optimal power allocation problem in the downlink of the multiuser OFDM system. We formulated a general optimization task which tries to maximize the mean opinion score of the users. We develop efficient algorithm to address the intractable problem. Numerical results indicate that our proposed algorithm can significantly improve the QoE of the users as compared to other representative methods.

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