QoE Optimized Resource Allocation in Multiuser OFDM Systems

Abstract. The resource allocation in multiuser Orthogonal Frequency Division Multiplexing (OFDM) systems is addressed, which aims to maximize the user-perceived quality of services instead of the conventional objective metrics. By introducing the previous application-centric Mean Opinion Score (MOS) assessment model, the problem is formulated as a bounded optimization problem, which is non-concave and difficult to develop a closed-form solution. A heuristic algorithm, which couples bound relaxation technique with further fix and drop operations is then proposed for the final solution. Simulation results indicate that our proposal can improve the overall perceived quality from users’ perspective as well as the fairness between users, in comparison with the classical throughput-oriented algorithm.

Streszczenie. Artykuł analizuje system OFDM (orthogonal frequency division multiplexing) do alokacji zasobów w systemie OFDM przy wielu użytkownikach i przesyłaniu duży wielkości danych. Metoda wykorzystuje serwisy QoS – Quality of service i QoE – quality of experience. (Optymalizowana alokacja zasobów w systemie OFDM przy wielu użytkownikach)

Keywords: OFDM, MOS, Quality of Service (QoS), Quality of Experience (QoE), bound relaxation.

1. Introduction
The emerging demand of delivering large volumes of data in next generation networks motivates intelligent multiuser Radio Resource Management (RRM) designs. As an effective multi-carrier solution for broadband wireless transmission, OFDM systems have been widely dealt with for the optimal allocation of power and subcarrier resources. Many approaches have been proposed to maximize the overall system performance (e.g., maximum throughput) or tradeoff between it and fairness (see [1, 2] and references therein). Although they perform well in providing the perfect objective metrics, they could not however directly reflect the perceived quality of services by users, which may cause a waste of radio resources. Thus, network operators have turned their focuses from network Quality of Service (QoS) to user Quality of Experience (QoE) [3]. QoE-aware resource allocation, which enhances the performance of a network from the user perspective, are drawing more and more attentions.

Inspired by the research on QoS-QoE mappings [4, 5], there have been several works focusing on the QoE-based optimization. Khan et al. have firstly proposed a cross-layer optimization framework as well as some novel strategies and algorithms in [6], which has been already proved to substantially enhance the user-perceived quality. Xie, et al. presented a QoE-aware power allocation technique with the objective of maximizing the overall QoE and meanwhile improving the single user QoE, comparing to the water-filling algorithm [7]. Based on the game theory concepts, Sacchi et al. [8] modeled OFDMA RRM as a marketplace and proposed a negotiation strategy aiming at maximizing the minimum MOS experienced by the users, which ensures a balance between efficiency and fairness. But, the dynamic subcarrier allocation together with adaptive power allocation for QoE optimization has not been yet studied, which could yield certain improvements on users’ perceived quality, as shown in section 4.

In this paper, the resource allocation in the downlink multiuser OFDM systems is investigated, with the objective to optimize the users’ perceived quality of services, rather than the typical objective metrics. Based on the existing MOS-based QoS-QoE mapping functions [4], the problem is modeled as a bounded optimization problem under certain constraints, which shows a property of non-concave and hard to be solved directly. By means of bound relaxation technique, the problem is firstly decomposed to an unbounded sub-problem, which can be solved via dynamic subcarrier assignment and adaptive power allocation algorithm. Fix and drop operations are further utilized to obtain the final solution. System simulations validate that certain improvements in terms of QoE and fairness between users are achieved by our proposal.

The reminder of this paper is structured as follows. Section 2 introduces the system model and formulates the optimization problem. In Section 3, our proposal for QoE optimization is presented by means of decomposition and transformation. The proposal’s performance is evaluated via experimental simulations in Section 4, followed by the final conclusion in the last section.

2. System Model

2.1 MOS-based QoE Model
Since several factors including subjective and objective ones contribute to users’ perceived quality (i.e., QoE) [3-5], QoE assessment inherently becomes a challenge, which draws plenty of attentions from either academia or industry. As originally proposed for estimating voice quality, Mean Opinion Score (MOS) is now extended to evaluate the quality of other services, such as video, web browsing, whose value ranges from 1 to 5, representing the users’ experience on services from poor to excellent [3].

The logarithmic relationship between QoS (e.g., data rate here) and QoE has been found by using either subjective tests [3, 4] or the theories of economics and psychology [5], which is expressed as

\[ d_{QoS} = d_{QoE} \] (1)

Thus, the mapping function between date rate and MOS score is then given by

\[ MOS_x(R_x) = \begin{cases} 1.0 & R_{x,10} < R_x \\ \alpha_x \ln(\beta_x R_x) + \phi_x & R_{x,10} \leq R_x \leq R_{x,4.5} \\ 4.5 & R_x > R_{x,4.5} \end{cases} \]

where \( \alpha_x \) and \( \beta_x \) are the scaling factors with respect to the on-going service, while \( \phi_x \) is a constant. Although other forms of QoS to QoE mapping functions are suggested in literature [5], the original intention of this paper remains steady, which aims at providing a new methodology of QoE optimization.

2.2 Problem Formulation
We now consider the downlink resource allocation of a single cell in the multiuser OFDM system, where the cell is equipped with a base station for several simultaneous transmissions coordination. Assume that there are \( K \) users sharing \( N \) subcarriers over \( B \) Hz (i.e., the total bandwidth of the system). Denote \( K = \{1, 2, \ldots, K\} \) and \( N = \{1, 2, \ldots, N\} \) as the set of users and sub-carriers respectively. The data rate of user \( k \) in bit/s is given as

\[ r_k = \text{bit/s} \]
where $r_{k,n}$ represents the data rate of user $k$ in subchannel $n$, $\rho_{k,n}$ is the subcarrier assignment index indicating whether the $n$th subcarriers is allocated to user $k$. $\rho_{k,n}=1$ means user $k$ occupies subcarrier $n$, while $\rho_{k,n}=0$ otherwise. $\gamma_{k,n}$ is the effective Signal to Noise Ratio (SNR) of the $n$th subcarrier for the $k$th user and is expressed as

$$\gamma_{k,n} = p_{k,n} H_{k,n},$$

subject to

$$H_{k,n} = \frac{1}{\gamma_{k,n}} l_k h_{k,n}$$

where $p_{k,n}$ and $H_{k,n}$ denote the allocated power and channel-to-noise ratio for user $k$ in subchannel $n$, $l_k$ and $h_{k,n}$ are the path loss coefficient and the channel gain, respectively. $N_0$ is the noise spectral density. $\Gamma$ is the SNR gap and determined by a desired Bit Error Ratio (BER), i.e., $\Gamma=\ln(5\text{BER})/1.5$. Note that the inter-cell interference is not taken into consideration in this paper.

Based on the above MOS-based QoE modeling, the problem of maximizing the total users’ satisfaction of the system under certain constraints is then formulated as follows:

$$\max_{\mathbf{p}, \mathbf{p}, \lambda} \sum_{k=1}^{K} \text{MOS}_k(R_k)$$

subject to

$$C1: \rho_{k,n} \in \{0, 1\}, \forall k, n$$

$$C2: \sum_{k=1}^{K} \rho_{k,n} \leq 1, \forall n$$

$$C3: \rho_{k,n} \geq 0, \forall k, n$$

$$C4: \sum_{k=1}^{K} \sum_{n=1}^{N} \rho_{k,n} \leq P_{\text{t}}$$

where the first two constraints ensure that each subcarrier is assigned to only one user, while $C4$ indicates that there is a power constraint on the total transmit power of the system.

3. Optimum Resource Allocation

As the aforementioned optimization problem is neither con-cave nor convex [7][9], a technique of bound relaxation is firstly utilized to produce a unbounded optimization problem in this section, followed with the analytical solution by Joint Dynamic Subcarrier allocation and Adaptive Power allocation (JDSAP) algorithm. And then we obtain the final solutions through further remove and drop operations.

3.1 Unbounded Optimization Subproblem

Consider an unbounded optimization subproblem within a subset of users and subcarriers: $S_k \subseteq K$, $S_n \subseteq N$, where the objective can be rewritten as

$$\max_{\mathbf{p}, \mathbf{p}, \lambda} \sum_{k=1}^{K} \alpha_k \ln \left( \beta \sum_{n=1}^{N} \rho_{k,n} p_{k,n} \right)$$

subject to

$$C1': \rho_{k,n} \in \{0, 1\}, \forall k \in S_k, n \in S_n$$

$$C2': \sum_{k=1}^{K} \rho_{k,n} \leq 1, \forall n \in S_n$$

$$C3': \rho_{k,n} \geq 0, \forall k \in S_k, n \in S_n$$

$$C4': \sum_{k=1}^{K} \sum_{n=1}^{N} \rho_{k,n} \leq P_{\text{av}}$$

where $P_{\text{av}}$ represents the available transmit power of these users. The above problem shows a property of concave and can be solved using a Lagrange dual approach [1][9].

With $\lambda=[\lambda_1, \lambda_2, \ldots, \lambda_K]$ collecting the Lagrange multiplier for $C2'$ and $\mu$ denoting the Lagrange multiplier associated with the power constraints $C4'$ respectively, the Lagrangian for (7) is then defined as

$$L(\mathbf{p}, \lambda, \mu) = \sum_{k=1}^{K} \alpha_k \ln \left( \beta \sum_{n=1}^{N} \rho_{k,n} r_{k,n} \right) + \sum_{n=1}^{N} \lambda_n \left( 1 - \sum_{k=1}^{K} \rho_{k,n} \right)$$

$$+ \mu \left( P_{\text{av}} - \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \right)$$

$$= \sum_{k=1}^{K} \alpha_k \ln \left( \beta \sum_{n=1}^{N} \rho_{k,n} r_{k,n} \right) - \sum_{k=1}^{K} \lambda_n \rho_{k,n} - \mu \sum_{k=1}^{K} p_{k,n}$$

$$+ \sum_{n=1}^{N} \lambda_n$$

Thus, the corresponding Lagrange dual function is

$$G(\lambda, \mu) = \max_{\mathbf{p}, \mathbf{p}, \lambda} L(\mathbf{p}, \lambda, \mu)$$

and the dual problem of (6) is $\min_{\lambda, \mu} G(\lambda, \mu)$, which can be decomposed to two subproblems as

$$\max_{\lambda} \sum_{n=1}^{N} \lambda_n \rho_{k,n} + \mu P_{\text{av}}, s.t. \lambda \geq 0, \mu \geq 0$$

Using the Karush-Kuhn-Tucker (KKT) conditions [10], the optimal power allocation can be found as

$$p_{k,n} = \frac{\alpha_k W}{\mu R_k \ln 2} - \frac{1}{g_{k,n}}$$

where $[x]^+ = \max\{x, 0\}$. And then the criterion of subcarrier assignment is derived as follows:

$$< k^*, n^* > = \arg \max_{k,n} \{ r_{k,n} / R_k \}$$

i.e., $p_{k,n}=1$, $\rho_{k,n}=0, \forall k \neq k^*, n \neq n^*$.

Further, the optimal multipliers are obtained by solving the dual problem using gradient projection iterations [9], given by

$$\mu(i+1) = \left( \mu(i) - \gamma \left( P_{\text{av}} - \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \right) \right)$$

Finally, this unbounded concave optimization problem will be solved through an iterative algorithm, which joints SDA and APA with continuous rate adaptation (JDSAP), described as follows:

JDSAP Algorithm:

1. Initial iteration of power multiplier: $i=0$, $\mu(0)>0$
2. Initial iteration of data rate: $j=0$ and $R_k(0)=0, \forall k \in S_k$
3. For $n = 1:S_N$
   a. Get $p_{k,n}$ and $\rho_{k,n}$ using (13) and (2), respectively;
   b. Assign subcarrier $n$ to user $k^*$
4. Update $R_k$ with step-size $\delta \in (0,1)$, using :

$$R_k(j+1) = (1-\delta)R_k(j) + \delta \sum_{n=1}^{N} \rho_{k,n}(j)p_{k,n}(j)$$
5 \( j \leftarrow j+1 \), goto 3 until
\[
\sum_{j} \alpha_k \left( R_k(j) - R_k(j+1) \right) < \varepsilon
\]
where \( \varepsilon \) is sufficiently small.
6 \( i \leftarrow i+1 \), Update \( \mu \) with step-size \( \gamma \), using (15)
goto 2 until \( p_k(j+1) < \varepsilon, \forall k \in S_k, n \in S_k \)

3.2 Upper Bounded Problem

We further restrict (7) by upper bounding the MOS value, reformulate the objective as
\[
\max_{k} \sum R_k \text{MOS}^** \left( R_k \right)
\]
with
\[
\text{MOS}^** \left( R_k \right) = \begin{cases} 
\alpha_k \ln \left( \beta_k R_k \right) + \phi_k & R_k < R_{k, min} \\
4.5 & R_k = R_{k, min} \\
R_k > R_{k, min} 
\end{cases}
\]

From (17), we know that if the allocated resources have made \( R_k < R_{k, min} \), then the remaining served resources, by removing all the spare resources, through perceived QoE.

Thus, we should drop these users’ rate to \( R_{k, min} \) and therefore the resources, by removing all the spare resources, through the following algorithm:

1 Initially, set \( S_k, S_k \) from subsection 3.3.
2 Solve unbounded problem (7) via JDSAP Algorithm
3 Users with \( \text{MOS}^* \left( R_k \right) \text{MOS}_{k+1} \text{MOS}^* \left( R_k \right) \geq 4.5 \) are removed from \( S_k \).
4 Reallocate the subcarriers and power of user \( k \) until \( R_k > R_{k, min} \).
5 Go to 4 until \( R_k > R_{k, min} \).
6 Go to 2 until all users’ \( \text{MOS}^* \left( R_k \right) \text{MOS}_{k+1} \text{MOS}^* \left( R_k \right) \leq 4.5 \).

3.3 Final Solution

To approach the bounded optimization problem (5), we firstly determine the users who cannot be served, and then solve the upper bounded problem. Note that once the dropped users are exactly selected, the remaining served users will always gain the satisfying data rate and thus the perceived QoE.

Therefore, the bounded problem (5) can be optimally solved by the following iterative algorithm, where set \( S_k^\text{stop} \) denotes the set of users who will be excluded in case that the boundary condition is satisfied in this allocation interval.

1 Initially, all users are served.
2 Solve upper bounded problem (16) with the subset \( S_k, S_k^\text{stop} \) and the available power \( P_{av} \).
3 If the boundary condition is fulfilled, drop the users \( k^* \text{arg min}_k \text{MOS}^* \left( R_k \right) \) by releasing all the resource allocated as
4 Goto 2

In this algorithm, the boundary condition determines whether the user cannot be satisfied, given by
\[
R_k(\varepsilon) < R_k(0), \exists k
\]
where \( R_k(0) \) denotes the data rate of minimum requested MOS, i.e., \( R_k(0) = \text{MOS}^* \left( R_k \right) \text{min} \). Note that \( \text{MOS}_{k+1} \text{MOS}^* \left( R_k \right) \) is variable and belongs to \( [1, 4.5] \). By setting the value of \( \text{MOS}_{k+1} \text{MOS}^* \left( R_k \right) \), a certain flexibility of our algorithm can be provided, in a way of admission control.

3.4 Computational Complexity

In order to indicate the availability of our algorithm, the computational complexity is calculated by considering the worst case run time. Note that in each iteration, at least one user is dropped, which may result in at most \( K \) iterations in the outer loop, while in the inner loop, the number of iterations at most equals to the number of served users.

Thus, the total number of iterations is upper bounded by \( K(K+1)/2 \), which means most users could be served in our observation. Hence, the number of iterations of the outer loop and inner loop is significantly lower than that in the above analysis, which means that our solution can be made more operationally.

4. Performance Evaluation

In this section, system simulations are executed to show the superiority of our proposal from the viewpoint of users, in comparison with the traditional Max-Throughput algorithm (MTA) mentioned in [1, 2]. Note that WINNER ubran macro-cell is utilized to model the radio channel [6], while the other parameter settings are detailedly listed in Table 1, where the MOS threshold is set to 1.0 here. Users randomly walk in the cell with a maximum velocity of 5 m/s.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier frequency</td>
<td>2.4 GHz</td>
</tr>
<tr>
<td>System bandwidth</td>
<td>10 MHz</td>
</tr>
<tr>
<td>Number of subcarriers</td>
<td>250</td>
</tr>
<tr>
<td>Transmit power</td>
<td>10 W</td>
</tr>
<tr>
<td>Shadowing</td>
<td>Log-normal, 8 dB</td>
</tr>
<tr>
<td>Path loss</td>
<td>38.4+35log_{10} dB</td>
</tr>
<tr>
<td>Cell radius</td>
<td>500 m</td>
</tr>
<tr>
<td>Noise spectrum density</td>
<td>-174 dBm/Hz</td>
</tr>
<tr>
<td>Target BER</td>
<td>10^{-2}</td>
</tr>
</tbody>
</table>

Fig.1 is a snapshot of 100 timeslots simulation of 16 users totally, with respect to the system throughput and average MOS achieved by the two optimization algorithms, respectively. It can be observed that, owing to the inherent property of QoE maximization, our proposal performs better in terms of user-perceived quality of services (i.e., QoE), while MTA fails to providing a sufficiently high degree of satisfaction to the users (always lower than 2.6 as shown in Fig. 1a), even though the system throughput is maximized. So, from the users’ perspective, it’s evidently demonstrated that our method is more applicable for future radio resource management, since the users are the service consumers and final payers.

The cumulative distribution function (CDF) curves of users’ MOS obtained by the above two algorithms are also plotted and compared in Fig. 2, which is produced by a long-term simulation. As shown, by using MTA, there are about 20% of users having MOS lower than 1, and all user are always not satisfied since the maximum MOS is only 2.7, while the user experience is very satisfying for all users in our proposal (always higher than 3). This picture provides a strong evidence that again our proposal outperforms MTA in providing the user-perceived quality of services.
achieve the maximum overall QoE with the constraint in total transmit power. Since the difficulty in getting a close-form solution of the optimization problem, bound relaxation technique coupling with fix and drop operation are proposed. Simulation results show that our proposal contributes to the system performance enhancement in term of QoE, while achieving satisfying fairness between users.

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