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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 przy wielu użytkownikach i przesyle dużych wielkości danych. Metoda wykorzystuje serwisy QoS – Quolity 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.
Słowa kluczowe: przesył danych, system OFDM

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 has 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 $dQoS \propto QoS \cdot dQoE$. Thus, the mapping function between date rate and MOS score is then given by

$$MOS_k(R_k) = \begin{cases} 1.0 & R_k < R_{1.0} \\ \alpha_k \ln(\beta_k R_k) + \phi_k & R_{1.0} \le R_k \le R_{4.5} \\ 4.5 & R_k > R_{4.5} \end{cases} \tag{1}$$

where α_k and β_k are the scaling factors with respect to the on-going service, while Φ_k 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 $\mathbf{K}=\{1,2,...,K\}$ and $\mathbf{N} = \{1,2,..., N\}$ as the set of users and sub-carriers respectively. The data rate of user k in bit/s is given as

(2) $$R_k = \sum_{n=1}^{N} r_{k,n} = \sum_{n=1}^{N} \frac{B}{N} \rho_{k,n} \log_2(1+\gamma_{k,n})$$

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 nth 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 nth subcarrier for the kth user and is expressed as

(3) $$\gamma_{k,n} = p_{k,n} H_{k,n}$$

(4) $$H_{k,n} = \frac{l_k h_{k,n}^2}{\Gamma N_0 B / N}$$

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. Γ is the SNR gap and determined by a desired Bit Error Ratio (BER), i.e., $\Gamma=-\ln(5BER)/1.5$. 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 constrains is then formulated as follows:

(5) $$\max_{\boldsymbol{\rho},\mathbf{p}} \sum_{k=1}^{K} MOS_k(R_k)$$

subject to

(6) $$\begin{aligned} &C1: \rho_{k,n} \in \{0,1\}, \forall k, n \\ &C2: \sum_{k=1}^{K} \rho_{k,n} \le 1, \forall n \\ &C3: p_{k,n} \ge 0, \forall k, n \\ &C4: \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \le P_T \end{aligned}$$

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: $S_K \subseteq \mathbf{K}$, $S_N \subseteq \mathbf{N}$, where the objective can be rewritten as

(7) $$\max_{\boldsymbol{\rho},\mathbf{p}} \sum_{k=1}^{S_K} \alpha_k \ln(\beta_k \sum_{k=1}^{S_K}\sum_{n=1}^{S_N} \rho_{k,n} p_{k,n})$$

(8) $$\begin{aligned} &C1': \rho_{k,n} \in \{0,1\}, \forall k \in S_K, n \in S_N \\ &C2': \sum_{k=1}^{S_K} \rho_{k,n} \le 1, \forall n \in S_N \\ &C3': p_{k,n} \ge 0, \forall k \in S_K, n \in S_N \\ &C4': \sum_{k=1}^{S_K}\sum_{n=1}^{S_N} p_{k,n} \le P_{avi} \end{aligned}$$

where P_{avi} 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 $\boldsymbol{\lambda}=[\lambda_1, \lambda_2, .., \lambda_N]^+$ collecting the Lagrange multiplier for $C2'$ and μ denoting the Lagrange multiplier associated with the power constraints $C4'$ respectively, the Lagrangian for (7) is then defined as

$$\begin{aligned} L(\boldsymbol{\rho},\mathbf{p},\boldsymbol{\lambda},\mu) &= \sum_{k=1}^{S_K} \alpha_k \ln\left(\beta_k \sum_{n=1}^{S_N} \rho_{k,n} r_{k,n}\right) + \sum_{n=1}^{S_N} \lambda_n \left(1 - \sum_{k=1}^{S_K} \rho_{k,n}\right) \\ &\quad + \mu\left(P_{avi} - \sum_{k=1}^{S_K}\sum_{n=1}^{S_N} p_{k,n}\right) \\ &= \sum_{k=1}^{S_K}\left[\alpha_k \ln\left(\beta_k \sum_{n=1}^{S_N} \rho_{k,n} r_{k,n}\right) - \sum_{n=1}^{S_N} \lambda_n \rho_{k,n} - \mu \sum_{n=1}^{S_N} p_{k,n}\right] \\ &\quad + \sum_{n=1}^{N} \lambda_n + \mu P_{avi} \end{aligned}$$

Thus, the corresponding Lagrange dual function is

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

and the dual problem of (6) is $\min_{\lambda>0,\mu>0} G(\lambda,\mu)$, which can be decomposed to two subproblems as

(10) $$\max L_k = \alpha_k \ln\left(\beta_k \sum_{n=1}^{S_N} \rho_{k,n} r_{k,n}\right) - \sum_{n=1}^{S_N} \lambda_n \rho_{k,n} - \mu \sum_{n=1}^{S_N} p_{k,n}$$

subject to

(11) $$\begin{aligned} &C1': 0 \le \rho_{k,n} \le 1, \forall k \in S_K, n \in S_N \\ &C3': p_{k,n} \ge 0, \forall k \in S_K, n \in S_N \end{aligned}$$

and further

(12) $$\max_{\boldsymbol{\lambda},\mu} \sum_{n=1}^{S_N} \lambda_n + \mu P_{avi}, s.t. \boldsymbol{\lambda} \ge \mathbf{0}, \mu \ge 0$$

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

(13) $$p_{k,n} = \left[\frac{\alpha_k W}{\mu N R_k \ln 2} - \frac{1}{g_{k,n}}\right]^+$$

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

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

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

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

(15) $$\mu(i+1) = \left[\mu(i) - \gamma\left(P_T - \sum_{k=1}^{S_K}\sum_{n=1}^{S_N} p_{k,n}\right)\right]^+$$

Finally, this unbounded concave optimizaiton problem will be solved through an iterative algorithm, which Joints DSA 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 $r_{k,n}$ using (13) and (2), respectively;

b) Assign subcarrier n to user k^*

End

4 Update R_k, with step-size $\delta \in (0,1)$, using :

$$R_k(j+1) = (1-\delta) R_k(j) + \delta \sum_{k=1}^{S_K}\sum_{n=1}^{S_N} \rho_{k,n}(j) p_{k,n}(j)$$

5 $j \leftarrow j+1$,goto **3** until

$$\sum_k \frac{\alpha_k}{R_k(j)}\left(R_k(j+1) - R_k(j)\right) < \varepsilon$$

where ε is sufficiently small.

6 $i \leftarrow i+1$, Update μ with step-size γ, using (15) goto **2** until $p_{k,n}(j+1)$-$p_{k,n}(j)<\varepsilon, \forall k \in S_K, n \in S_N$

3.2 Upper Bounded Problem

We further restrict (7) by upper bounding the MOS value, reformulate the objective as

$$\max_{\boldsymbol{\rho},\mathbf{p}} \sum_{k=1}^{K} MOS'_k(R_k) \quad (16)$$

with

$$MOS'_k(R_k) = \begin{cases} \alpha_k \ln(\beta_k R_k) + \phi_k & R_{1.0} \le R_k \le R_{4.5} \\ 4.5 & R_k > R_{4.5} \end{cases} \quad (17)$$

From (17), we know that once the allocated resources have made R_k>$R_{4.5}$ holds, more resources will be wasted, since the user perceived QoE has already been optimal. Thus, we should *fix* these users' rate to $R_{4.5}$ and therefore the resources, by removing all the spare resources, through the following algorithm:

1 Initially, set S_K,S_N from subsection 3.3.

2 Solve unbounded problem (7) via ***JDSAP Algorithm***

3 Users with $MOS(R_k)$>4.5 are removed from S_K Reallocate the subcarriers and power of user k until R_k=$MOS^{-1}(4.5)$, where $MOS^{-1}(x)$ is the inverse funcion of (1), and then release all spare resources.

$$S_K \leftarrow S_K - \{k\}, S_N \leftarrow S_N \cup C_k, P_{avi} \leftarrow P_{vi} + P_k$$

Where C_k and P_k represents the spared subcarriers and the sum of spared power of user k.

4 Goto 3 until all users' $MOS(R_k)$≤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 uses 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 algoritgm, where set S_{drop} 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_N and the available power P_{avi}.

3 If the *boundary condition* is fullfilled,

drop the user k^*=$\arg\min_k MOS(R_k)$ by releasing all the resource allocated as

$$S_K \leftarrow S_K - \{k^*\}, S_N \leftarrow S_N \cup A_{k^*}, P_{avi} \leftarrow P_{vi} + P_{k^*}$$

where A_{k^*} and P_{k^*} denote the subcarriers and the sum of power allocated to user k^*.

else, stop.

4 goto **2**

In this algorithm, the *boundary condition* determines when the algorithm will stop by considering whether the user can not be satisfied, given by

$$R_k(t) < R_k(0), \exists k \quad (18)$$

where $R_k(0)$ denotes the data rate of minimum requested MOS, i.e., $R_k(0)$=$MOS^{-1}(MOS_{\min})$. Note that $MOS_{\min}$ is variable and belongs to [1, 4.5]. By setting the value of $MOS_{\min}$, 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 interations 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 outter 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 propoasal 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 1. Simulation Parameters

Carrier frequency	2.4 GHz
System bandwidth	10 MHz
Number of subcarriers	250
Transmit power	10 W
Shadowing	Log-normal, 8 dB
Path loss	$38.4+35\log_2 d$ dB
Cell radius	500 m
Noise spectrum density	-174 dBm/Hz
Target BER	10^{-3}

Fig.1 is a snapshot of 100 timeslots simulation of 16 users totally, with respect to the system throughput and average MOS achieved by 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.

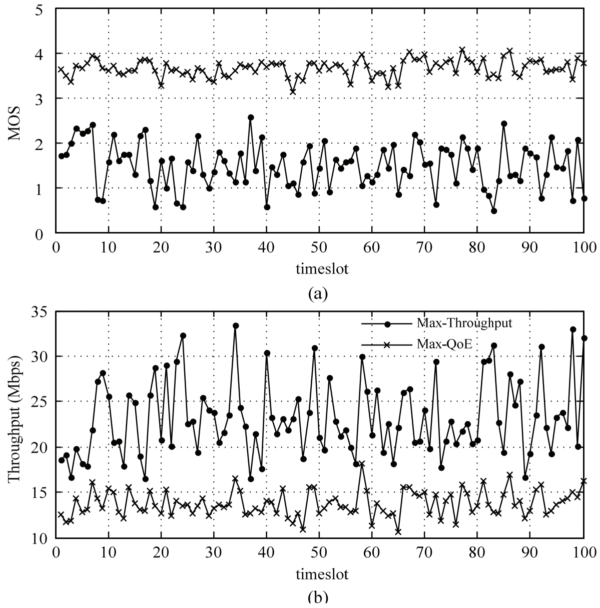

Fig. 1 Average MOS and system throughput achieved by those two optimization algorithms

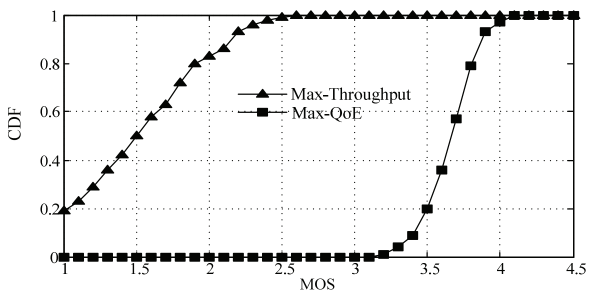

Fig. 2 CDF of average MOS gained by two optimization algorithms

To exhibit the potential advantages of our algorithm in the fairness guarantee between users, Fairness Index (FI) is statistically defined as

(19) $$FI = \left(\sum_{k=1}^{K} S_k \right)^2 \Bigg/ \left(K \sum_{k=1}^{K} S_k^2 \right)$$

where S_k is the average data rate of user k in a large time scale. As plotted in Fig. 3, compared to MTA, our proposal achieves a substantial improvement of fairness between users, where FI is always larger than 0.8 by our algorithm, while it decreases to 0.4 or less by MTA. This is because that MTA aims at obtainling the maximum throughput by allocating resources to the users in good channel states, while leaves the user in poor channel states into starvation. Different from MTA, our objective is to optimize the sum of log-form rate, which provides a smoothness of resource allocation between users. Moreover, the subsequent *fix* and *drop* operations further improve the former fairness by sparing the redundant resources of users whose MOS has already been higher than 4.5 to others.

5. Conclusion

In this paper, the resource allocation including dynamic subcarrier assignment and power allocation is presented for downlink multiuser OFDM systems. Based on the existing MOS-based QoS-QoE mapping functions, the allocation problem is modeled as a bounded optimization problem to 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.

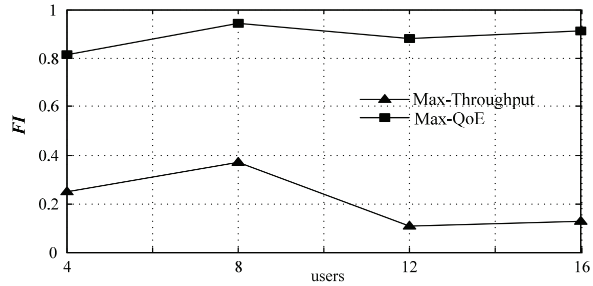

Fig. 3 Fairness measure by different optimization algorithms

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