Abstract—In this paper, a MOS-driven energy efficient power allocation scheme (MEEPA) is proposed for video transmission over downlink orthogonal frequency division multiple access (OFDMA) networks. In the proposed framework, system power consumption and MOS for users based on end-to-end video distortion have been jointly optimized. We also define a novel energy efficient utility as the unifying metric based on the MOS model and the system power consumption. The main objective is to maximize the energy efficiency by balancing the MOS and the power consumption for each user. The power allocation problem is solved by using constrained particle swarm optimization (CPSO). Moreover, simulation results show that the proposed algorithm can improve energy efficiency greatly in terms of lower power consumption with a comparable video quality performance compared with the traditional algorithm.

Keywords—MOS; energy efficient; power allocation; video streaming; CPSO

I. INTRODUCTION

Due to the widespread applications of wireless video communications, a great number of challenges have been posed to wireless communications, which include the problem of scarce radio resources, stringent energy constraints and extensive variations of the wireless channel. Orthogonal frequency division multiple access (OFDMA) is a prospective technology adopted in multimedia broadcast multicast services in some cellular standards such as IEEE802.16 and the 3GPP Long Term Evolution (LTE) to guarantee high speed mobility as well as high rates for nomadic and mobile users. Although the future wireless network technologies not only promise communication more reliable but also use spectrum more efficiently, the problem on how to minimize transmission power consumption at the base station (BS) and to provide better quality of experience (QoE) for users within the next generation mobile communication networks has not been resolved perfectly [1] [2] [3] [4].

Recently, energy efficiency has attracted more and more attentions in the field of wireless video streaming transmission. In [1], the problem of transmitting data to multi-users over a shared wireless channel in a way that minimizes power consumption and prevents the receivers’ buffers from emptying is considered. Diverse energy efficiency schemes for video streaming transmission in single user and multiuser wireless systems are presented in [2]. Source coding and transmission transmission process are optimized to determine the energy efficiency for wireless video streaming jointly [4] [5]. In [6], a gradient projection based cross-layer optimized framework for multimedia streaming is proposed. The end-to-end distortion of video applications and user scheduling have been jointly considered. However, the QoE for users is not considered in [6]. It is seen that most of the previous works on energy efficiency are based on the wireless channel condition and the source content and aim to guarantee quality of service (QoS) of wireless video communications. There is not much work on transmission power consumption at BS in OFDMA systems and considering QoE for users within the network.

A practicable metric to weight QoE for users is the mean opinion score (MOS) [7] [8] [9], which has been used in the field of telephony networks to obtain user's attitude on the quality of the telephony service. MOS is beneficial to evaluate user's satisfaction subjectively, but it is unsuitable to be applied in the field of online video evaluation due to its own defects such as time-consuming, labor-consuming. So most previous works on the MOS focus on designing the objective video quality metric, which predicts perceived quality of sequences with video compression-induced impairments based on the mean squared error (MSE) between the received video and the one transmitted by BS. Energy efficient power allocation based on MOS has not drawn much attention.

In our work, MOS-driven energy efficient power allocation scheme (MEEPA) is proposed for wireless video transmission. Our contributions can be expressed summarily as follows. First, we focus on the power allocation at the BS for video streaming transmission in downlink OFDMA systems and maximize the transmission energy efficiency. Second, a MEEPA model is proposed which not only can guarantee QoS of wireless video communications but also can provide better MOS for users. Furthermore, we introduce a novel constrained particle swarm optimization (CPSO) to find out the suboptimal solution for power allocation problem.

The rest of this paper is organized as follows. Section II describes the system for video transmission over downlink OFDMA networks. MOS model is predicted in Section III. Section IV provides the proposed MOS-driven energy efficient power allocation scheme algorithm. Section V evaluates performance of the proposed algorithm by simulations. Finally, Section VI concludes the whole work.
the distributed to different users [10]. At the BS transmitter, let

corresponding mobile client. It is assumed that different users

video server through optical fiber to the BS, and then to the

corresponding data will be transmitted from the

A BS servers K mobile users. When a video stream is requested

videostreaming in OFDMA downlink wireless network, where

is the corresponding mobile client. It is assumed that different users

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require various video applications respectively [6] [9].

It is assumed that different subsets of subchannels are

distributed to different users [10]. At the BS transmitter, let

the nth (1 ≤ n ≤ N ) subchannel allocate to user k (1 ≤ k ≤ K ),

and the corresponding assigned power is Pk,n . Then the

instantaneous signal-to-noise ratio (SNR) of user k on the

subchannel n is defined as:

\[ \gamma_{k,n} = P_{k,n} |h_{k,n}|^2 / \sigma^2 \]  

where \( h_{k,n} \) is the corresponding channel gain, \( N_0 \) is noise

power spectral density and \( \sigma^2 = N_0 B / N \) is additive white

Gaussian noise (AWGN) power.

III. MOS MODEL ANALYSIS

A. MOS Definition

MOS as a practicable metric to weight QoE for users is used in

this paper. In voice and video communications, user’s

experience usually dictates the quality of the wireless

transmission. MOS uses subjective measurements that are

averaged in a mathematical way to get a quantitative marker of

the system performance [9]. It is the arithmetic mean of all the

scores of the individual, which is expressed in a number

ranging from 1 to 5. The MOS number indicates the quality of

video streamings. That is to say, the MOS number 5 means the best

video quality, while 1 means the worst video quality.

MOS is a subjective evaluation method, which relies on

subjective sense of large groups of non-professional testers for

video quality evaluation. It can be used of non-professional testers for

video quality evaluation. It can be used to reflect the subjective

feelings of people with high accuracy directly. However, the

approach can’t be used in online video evaluation, because it

has obvious defects intrinsically, such as time-consuming,
labor-consuming and so on. So in this paper, a model based on

the video parameters in a mathematical manner is set up to

estimate the MOS quality. We will specialize in the analysis in

the following.

B. PSNR Analysis based on Distortion

Peak signal-to-noise ratio (PSNR) is generally applied as an

objective quality indicator on the quality of received video

because of the simplicity and high degree of correlation with

subjective quality. In this paper, we introduce MOS model

based on PSNR, which can be shown as follows [6] [9]:

\[ \text{PSNR} = 10 \log_{10} \frac{255^2}{\text{MSE}} \]  

According to the previous work [9] [11], MSE can be

expressed in terms of the end-to-end distortion of video data.

Let D denote the distortion between the received video

streaming at mobile terminal and the transmitted one at BS. It

generally accepted that the video source distortion can be

expressed as an exponential function of the rate of encoding.

Meanwhile, the channel distortion of the video streaming is

dependent on the amount of lost packets.

In this paper, we adopt the idea of source distortion that is

introduced in [12], and assume that the loss distortion is

related with packet error probability (PEP) linearly [9]. The

MSE distortion metric can be expressed definitely as follows:

\[ D = D_s + D_L = \alpha R + \beta \text{PEP} \]  

where \( \alpha \), \( \beta \) and \( \xi \) are different parameters. Dc is the source

distortion depending on the source rate of the video signal \( R \).

Dl is the channel loss distortion in reference to PEP. The

following model is introduced to get the PEP of user k:

\[ \text{PEP}_k = 1 - (1 - P_{c,m}(\gamma_k^{\text{eff}}))^\xi \]  

where \( \sigma \) is the packet size in bytes. \( \gamma_k^{\text{eff}} \) is the exponential
effective SNR, that can be defined as [13]:

\[ \gamma_k^{\text{eff}} = -\lambda \ln \left( \frac{\sum_{i=1}^{N_x} e^{-\frac{\gamma_k}{\lambda}}}{N_x} \right) \]  

where \( \lambda \) is a parameter that must be optimized from link-level

simulation results for every modulation and coding rate

combination.

A technique known as link adaptation through adaptive

modulation and coding (AMC) [14] [15] [16] has been used
generally to achieve a robust link performance. The objective

of AMC is to maximize the data rate in link level by adjusting

transmission parameters to the corresponding channel

condition. The bit error rate (BER) of AMC can be defined as

[6] [11]:

\[ P_{c,m}(\gamma_k^{\text{eff}}) = \frac{a_m}{\delta^2 e^{\frac{-\gamma_k}{\delta}}} \]  

where m is the mode index of modulation and coding schemes

and coefficients \( a_m \) and \( b_m \) can be obtained in [6]. Then the

received distortion for user k can be expressed as [9] [12]:

Fig. 1. Framework of wireless video transmission

II. WIRELESS VIDEO TRANSMISSION

As shown in Fig. 1, there is a typical scenario of

video streaming in OFDMA downlink wireless network, where

a BS servers K mobile users. When a video stream is requested

by a user, the corresponding data will be transmitted from the

video server through optical fiber to the BS, and then to the

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approach can’t be used in online video evaluation, because it

has obvious defects intrinsically, such as time-consuming,
where the parameters are the corresponding values for user k.

C. MOS based on PSNR

In the traditional work [9], a simple linear mapping between PSNR and MOS is established. The maximum user satisfaction is achieved when PSNR is 40 dB while the minimum user satisfaction is achieved when PSNR is 20 dB.

The relationship between MOS and PSNR can be expressed as:

$$\text{MOS} = \begin{cases} 3.5 & \text{if } 20 < \text{PSNR} \leq 40 \\ 0 & \text{otherwise} \end{cases}$$  \hfill (8)

Based on the above analysis, the MOS of each video application is known by our scheme.

IV. MOS-DRIVEN ENERGY EFFICIENT POWER ALLOCATION

A. Energy Efficient Utility

It is assumed that BS lies in the center of a cell, and the served users are randomly spread all over the service available area. The update process of the state information of all users and the power allocation decision process are made every TTI (Transmission Time Interval).

What is particularly to be mentioned, the proportional fair (PF) scheme [17] is adopted in this paper because subchannel allocation should be allocated before power allocation. After subchannel allocation, the MOS-driven energy efficient power allocation process will be executed.

We define a power allocation matrix as $[P]_{k,n} = p_{k,n}$, in which $p_{k,n}$ is the allocated power value for user k on the subchannel n. We can get $p_{k,n} = 0$ if the subchannel n is not assigned to user k. In mathematical manner, the power allocation problem is formulated as:

$$\max \left( \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \right)$$  \hfill (9-1)

subject to:

$$\begin{cases} p_{k,n} \geq 0, & \forall k, \forall n \\ \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \leq P_{\text{max}} \end{cases}$$  \hfill (9-2)

where $P_{\text{max}}$ is the system maximum energy that the users can be allocated. The first one constraint means that every user’s allocated power is nonnegative. The other indicates that the total power allocated to the users should be smaller than the system maximum power. The energy efficiency of the system can be maximized by finding the optimal solution of (9-1) under constraint (9-2).

B. CPSO Optimization Algorithm

Particle swarm optimization (PSO) [18-20] has been proved to take great effect at solving engineering unconstrained problems as a new evolutionary computation algorithm. However, engineering optimization is usually subject to various constraints. In [19], Kim and Maruta proposed a novel constrained PSO targeted to solve engineering optimization problems containing various constraints. It has been proved to be simple and efficient. In this paper, we adopt this simple and efficient constrained PSO (CPSO) to solve our constrained optimization problem.

To use the CPSO algorithm, the constrained problems mentioned above have to be converted as follows:

$$\min f(A) = -\max \left( \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \right)$$  \hfill (10-1)

subject to:

$$\begin{cases} h_1(A) = -p_{k,n} \leq 0, & \forall k, \forall n \\ h_2(A) = \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} - P_{\text{max}} \leq 0 \end{cases}$$  \hfill (10-2)

where A is the power allocation set and $p_{k,n}$ is its corresponding element.

In order to make original constrained optimization problem unconstrained, the objective function is modified as follows:

$$\min \ell(A) = \begin{cases} \ell(A) = h_{\text{max}}(A), & \text{if } h_{\text{max}}(A) > 0 \\ \ell(A) = \text{atan}[f(A)] - \frac{\pi}{2}, & \text{otherwise} \end{cases}$$  \hfill (11)

where $h_{\text{max}}(A) = \max[h_1(A), h_2(A)]$ and $\text{atan}[\cdot]$ denotes inverse tangent.

After the preparations, the following procedure for CPSO is summarized as follows:

Step 1: Consider a power allocation swarm containing $m_p$ individual power allocation particles: $A_1, A_2, ..., A_{m_p}$.

Each individual power allocation particle $A_i$ is a $K \times N$ matrix and the velocity $v_i$ is also a $K \times N$ dimensional matrix, $i \in [1, 2, ..., m_p]$. The positions of individual power allocation particles, as well as their velocities, are initialized randomly in the search space.

Step 2: Calculate the energy efficiency fitness of every particle in current position:

$$\text{fitness}_i = \min \ell(A_i)$$  \hfill (12)

Step 3: Update the vector of velocity iteratively [20]:

$$A_i^{t+1} = A_i^t + v_i^{t+1}$$  \hfill (13)

$$v_i^{t+1} = \chi [v_i^t + c_1 \omega_i^t (A^{\text{best},t} - A_i^t) + c_2 \omega_i^t (A^{\text{opp},t} - A_i^t)]$$  \hfill (14)

where $c_1$ is the cognitive scaling factor, $c_2$ is the social scaling factor, and $\chi$ is the constriction factor which is expressed as:
The term $c_2T_i (A_{\text{best},i} - A_i')$ is related with cognition, since it only cares about the best position of the particle’s own experience. Meanwhile, $c_2T_i (A_{\text{swarm}} - A_i')$ represents the social interaction of all particles.

Step 4: Update $A_{\text{best},i}$ and $A_{\text{swarm}}$ by (16) and (17) iteratively.

Step 5: Go to step 2, if the criterion of terminating iteration is unsatisfied. Otherwise, jump out of the circulation.

V. SIMULATION RESULTS AND ANALYSIS

A. Simulation Parameters

In this section, the performance of the proposed MEEPA algorithm is evaluated by simulations. We adopt the related video parameters described in [16] for simplicity. The scalable parameters are configured according to the values listed in Table I.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>User number</td>
<td>10</td>
</tr>
<tr>
<td>Cell size</td>
<td>1 km</td>
</tr>
<tr>
<td>System bandwidth</td>
<td>5 MHz</td>
</tr>
<tr>
<td>Number of subcarriers</td>
<td>300</td>
</tr>
<tr>
<td>Number of subchannels</td>
<td>10</td>
</tr>
<tr>
<td>Maximum transmission power</td>
<td>5 W</td>
</tr>
<tr>
<td>Power spectral density of AWGN</td>
<td>$10^8$ W/Hz</td>
</tr>
</tbody>
</table>

B. Performance Analysis

We compare the investigated optimization MEEPA approach and the fix power allocation scheme called GQCS proposed in [6] whose main objective is to maximize video system parameters quality by reducing the end-to-end distortion. The results are based on numbers of simulation TTIs.

First of all, the energy efficiency performance difference between the two strategies is compared in our experiments. The simulation result is shown in Fig. 2, where 30 TTIs are simulated. It is proposed MEEPA algorithm improves the energy efficiency performance greatly compared with GQCS method. That is because our proposed method aims to maximize the transmission energy efficiency which considers the MOS value and the power consumption for each user together. The MEEPA strategy updates the power allocation
result every TTI based on the system energy efficiency, differently from GQCS power allocation which doesn’t consider MOS or the system power consumption, but just optimizes the end-to-end distortion.

Furthermore, we evaluate the quality of the video streamings. Based on the above analysis, it is known that MOS can capture user satisfaction and indicate the video quality exactly. So we compare the MOS performance of the two strategies. Fig. 3 shows system average MOS differences between different strategies. In order to make the graphics more clear, we just display 15 TTIs in the figure. It is obvious that our MEEPA scheme performs analogously compared with GQCS method. It is seen that the proposed MEEPA scheme can guarantee the video quality of the system as well as GQCS.

In the end, total system power consumption is evaluated. As illustrated in Fig. 4, total power consumption of MEEPA is less than GQCS scheme. Moreover, in nearly 40% of the TTIs, MEEPA scheme reduces the power consumption by more than 6%. Evidently, the system energy computation cost of MEEPA scheme is less than GQCS, while the MEEPA scheme brings similar performance compared with GQCS method.

VI. CONCLUSION

In this paper, a MOS-driven energy efficient power allocation algorithm for video streaming over OFDMA based wireless networks is proposed. MOS and system power consumption have been optimized jointly. Moreover, the power allocation problem is solved by using constrained simple and efficient constrained particle swarm optimization. Experimental results show that the proposed framework can improve energy efficiency greatly with analogous video quality performance but lower power consumption.

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