Energy-Efficient Power Allocation with QoS Guarantee in OFDMA Wireless Networks

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***Abstract*—The explosive growth of high-data-rate multimedia services, with diverse quality-of-service (QoS) requirements, in wireless networks will lead to enormous energy consumption. Thus, the main challenge in designing recent wireless networks is to utilize network resources as efficiently as possible while ensuring the QoS for users. In this paper, we investigate the energy-efficient power allocation with QoS considered in the downlink of wireless multimedia networks with orthogonal frequency division multiple access (OFDMA). Firstly, energy-efficient power allocation problem is molded as the maximization of energy efficiency (EE) under different QoS requirements. Subsequently, an energy-efficient power allocation algorithm with chaotic particle swarm optimization (CPSO) is proposed. Finally, simulation results show that the proposed algorithm can converge much faster, compared with water-filling power allocation (WFPA), but both of them improve the EE greatly, compared with equal-power power allocation (EPPA).**

***Keywords*-QoS, OFDMA, energy efficiency, CPSO**

I. Introduction

As smart mobile terminals become popular, the wireless networks carry a variety of multimedia services, such as delay-sensitive applications (e.g., video teleconferencing) and delay-tolerant ones (e.g., web browsing and file downloading), with different QoS requirements. In addition, the explosive growth of high-data-rate multimedia services in wireless networks will lead to enormous energy consumption, which will result in large operational expense at the base station side. As reported in [1], the energy consumed at radio access part has taken up more than 70% of the total consumption for most operators. Obviously, it's inevitable to take energy efficiency into consideration in the development of wireless communication technologies. Therefore, energy-efficient resource allocation in wireless networks, especially multimedia wireless networks, has become increasingly significant and prompted new waves of research and standard development activities.

OFDMA is a prospective technology adopted in multimedia broadcast multicast services in some cellular standards, such as WiMAX and the 3GPP LTE, guaranteeing high-speed mobility as well as high rates for mobile users. While extensive research has been done to improve throughput, limited has been conducted for energy efficient communications in OFDMA systems [2], [3]. Recently, more attentions have been paid to energy efficiency in OFDMA wireless networks. Energy efficiency, measured in bits/joule, has been defined as the number of delivered bits for each energy-unit used in transmission [4]. Energy-efficient OFDM, which maximizes the EE with circuit energy consumption considered, has been addressed by [5]. In papers [6], [7], it has been demonstrated that a unique global maximum EE exists. However, there is limited work on the energy-efficient power allocation with QoS guarantee, which is urgent in multimedia wireless networks.

Particle swarm optimization (PSO) is a high-efficiency and simply-operated heuristic optimization technique. Its heuristic searching procedure is based on a group of randomly distributed particles, named as swarm, that fly in the solution space with velocity dynamically adjusted, based on the flying experience of its own and companions in the swarm [8]. As the heuristic process depends on the previous experience, the swarm will keeping heading to the best optima in the solution at each iteration. However, PSO may fail to search the global optimal solution because of the centralization of the particles in the initialized swarm. As chaotic optimization introduced, chaotic PSO (CPSO) improves the performance of PSO and converge fast. Therefore, it will be introduced into our power allocation algorithm.

In this paper, we address energy-efficient power allocation, ensuring various QoS requirements for various sorts of users, in wireless networks. Apparently, different kinds of users require different QoS requirements. For instance, such delay-sensitive services as video teleconferencing and live football games watching demand more minimum date rates, while delay-tolerate ones, such as emailing and web browsing, will require no minimum date rates. Firstly, we model the problem as the maximization of general EE under minimum-data-rate QoS constraints, properly decided by the delay-sensitive categories. Subsequently, an energy-efficient CPSO-based power allocation (CPSOPA) is proposed. Simulation results demonstrate that the proposed algorithm can converge faster than WFPA, and both of them can improve the EE greatly, compared with EPPA.

The remainder of the paper is organized as follows. In Section II, we describe the system model and formulate the EE optimization problem provisioning QoS. In Section III, the CPSO-based power allocation algorithm is proposed. Subsequently, we present the simulation results to analyze the performance of the proposed algorithm and the tradeoff between QoS and EE in Section IV. Finally, in Section V, we conclude the paper.

II. System Model and Problem Formulation

In this section, we introduce the system model and formulate the problem of energy efficiency optimization in downlink of the multimedia wireless network.

A. System Model

As is shown in figure 1, K active mobile users in a single cell connect to the Internet through mobile core network server and request multimedia services from media server and web server in Internet. The media server provides delay-sensitive services, such as video teleconferencing and live football games watching, and the other one provides delay-tolerate services, such as web browsing and file downloading. The multimedia data stream from these two servers will be transmitted to each user by the base station.

The total system bandwidth B is divided into N subchannels, each with a bandwidth of $W = B/N$, and every subchannel is allocated to at most one user in each time internal to avoid interference among different users. Denote $\mathcal{N}$ and $\mathcal{K}$ as the set of all the subchannels and that of all the active users, respectively. $\mathcal{N}_k$ is the set of subchannels allocated to the user k. Obviously $\mathcal{N}_k$ should satisfy $\bigcup\limits_{k=1}^{K} \mathcal{N}_k = \mathcal{N}$ and $\mathcal{N}_k \bigcap \mathcal{N}_j = \emptyset (k \neq j)$.

Let subchannel $n(n \in \mathcal{N})$ be allocated to user $k(k \in \mathcal{K})$, and the corresponding power gain and assigned power are respectively $g_{k,n}$ and $p_{k,n}$. According to Shannon's theorems, the achievable data rate of the user k on the subchannel n is accordingly

$$r_{k,n} = W \log_2(1 + \frac{p_{k,n} g_{k,n}}{N_0 W}), \tag{1}$$

where, N_0 is the single-sided noise spectral density.

Then, the aggregate rate for user k is accordingly

$$R_k = \sum_{n \in \mathcal{N}_k} r_{k,n} = \sum_{n \in \mathcal{N}_k} W \log_2(1 + \frac{p_{k,n} g_{k,n}}{N_0 W}), \tag{2}$$

Therefore, the aggregate date rate at the BS(base station) can be calculated by

$$R = \sum_{k \in \mathcal{K}} R_k = \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}_k} W \log_2(1 + \frac{p_{k,n} g_{k,n}}{N_0 W}), \tag{3}$$

Practically, the total transmit power at the base station is limited. Thus, any possible power allocation matrix, $\mathbf{P} = [p_{k,n}]_{K \times N}$, should be subject to

$$\begin{array}{c} \mathbf{P} \in \{[p_{k,n}]_{K \times N} | p_{k,n} \geq 0, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}; \\ \sum\limits_{k \in \mathcal{K}} \sum\limits_{n \in \mathcal{N}_k} p_{k,n} \leq P_{\max}\} \end{array}, \tag{4}$$

where, $P_{\max}$ represents the maximum total transmit power at base station for downlink transmission.

In addition, the circuit energy consumption, incurred by active circuit blocks, should also be considered and the overall power consumption at the base station, P_{total}, is given by [9]

$$P_{total} = \zeta P + P_c, \tag{5}$$

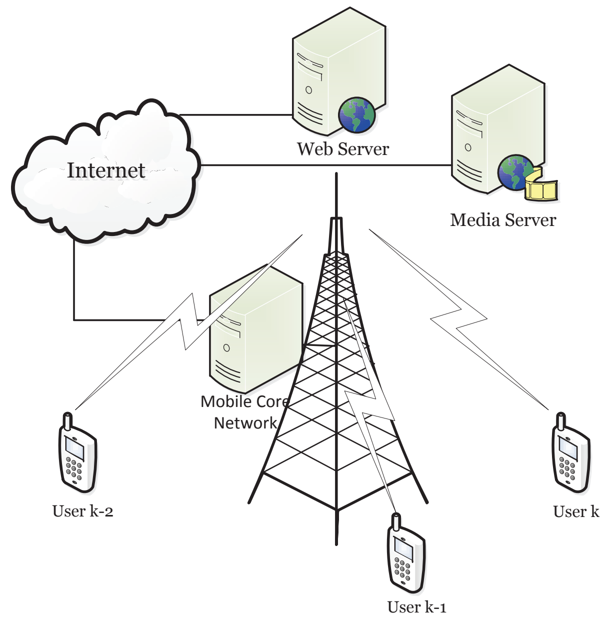

Fig. 1: A Multimedia Wireless Network

where, ζ is the reciprocal of drain efficiency of power amplifier and P_c is the circuit power.

In practical multimedia wireless networks, more delay-sensitive services need much more minimum date rates, while delay-torrent ones needn't. For simplicity, we have classified them into M groups according to the degree of their delay sensitivity. Denote $R_k^{\min}$ as the minimum rate the user k needs to guarantee its QoS, then the following condition should be satisfied:

$$\begin{cases} R_k^{\min} = 0, \quad k \in A_0 \\ R_k^{\min} = R_{A_1}, \; k \in A_1 \\ \quad \vdots \\ R_k^{\min} = R_{A_{M-1}}, \; k \in A_{M-1} \end{cases} \tag{6}$$

where $\{A_m\}(m = 0, ...M-1)$ represents the service classification set, where the category with larger m has higher delay sensitivity and A_0 is the delay-tolerant one.

B. EE for Downlink Transmission

EE is commonly defined as information bits per unit of transmit energy [10] as follows,

$$\eta = \frac{R}{P_{total}} \tag{7}$$

The definition of the EE means the tradeoff between aggregate rate and energy consumption. Obviously, excessive transmission power, though bring much higher data rate, will consume extravagant energy, therefore the EE won't be very high. Thus, a appropriate subchannel and transmission power allocation should be designed to achieve the best energy efficiency.

In this paper, to focus EE optimization problem on power allocation, we assume that the subchannel allocation has been accomplished, namely $\mathcal{N}_k$ is given. Subsequently, in consideration of the QoS requirement for each user, the EE optimization problem at the base station for the downlink transmission can be mathematically formulated as follows:

$$\overset{\wedge}{\eta} = \max_{\mathbf{P}} \frac{\sum\limits_{k\in K}\sum\limits_{n\in N_k} W\log_2(1+\frac{p_{k,n}g_{k,n}}{N_0 W})}{\zeta\sum\limits_{k=1}^{K}\sum\limits_{n\in N_k} p_{k,n} + P_c} \tag{8}$$

subject to

$$R_k \geq R_k^{\min}, \forall k \in K, \tag{9}$$

$$p_{k,n} \geq 0, \forall k \in K, \tag{10}$$

$$\sum_{k\in K}\sum_{n\in N_k} p_{k,n} \leq P_{\max}, \forall k \in K, \tag{11}$$

where, $\overset{\wedge}{\eta}$ represents the optimal downlink EE and $\mathcal{N}_k$ is given as the accomplished subchannel allocation.

III. Power Optimization with CPSO

A. Chaotic Particle Swarm Optimization

The optimization procedure of PSO is based on the movement of a randomly initialized particle swarm that fly in the solution space with velocity dynamically adjusted, based on the flying experience of its own and companions[8]. Each particle in the swarm has a position vector $\mathbf{X}$ and a velocity vector $\mathbf{V}$, respectively representing a candidate solution and the step size with which it flies from the last iteration to the present.

The performance of particle is evaluated by the *fitness function* using $\mathbf{X}$ as input. The higher is the fitness, the better is the position. At each iteration, each particle records its personal best, which represents best position it has achieved so far. At the same time, the swarm records the global best, which represents the best position searched among all the particles. Each particle updates its velocity and position from the present iteration to the next according to three factors: previous velocity, local personal experience and social experience. After each update, they record the best particle and finally the particle swarm will find a optimal position in the solution space.

PSO algorithm is easily-operated and can converge fast, for it has few parameters to control and follows to optima always. However, it may fail to search the global optimal solution because of the centralization in the initialized swarm. As chaotic optimization introduced, CPSO improves the performance of PSO and converge fast. Therefore, it will be introduced into our power allocation algorithm.

B. Power Allocation with CPSO

In this subsection, CPSO is applied to solve the energy-efficient power allocation problem formulated in Section II. The number of the dimension is N, which is the count of the subchannels. The position vector equals to the transmission power vector, $\mathbf{X} = \mathbf{P} = (p_1, p_2, \cdots, p_N)$, then each position represents a power allocation schedule. The general EE is the *fitness function* for each particle, which can be calculated when the power allocation is given.

For this N-dimensional PSO optimization, the present position and velocity of the power particle m can be denoted as $X_m(t) = (x_{m,1}(t), x_{m,2}(t), \cdots, x_{m,N}(t))$ and $V_m(t) = (v_{m,1}(t), v_{m,2}(t), \cdots, v_{m,N}(t))$, respectively. In addition, each particle records its personal best as $Q_m(t) = (q_{m,1}(t), q_{m,2}(t), \cdots, q_{m,N}(t))$, and the swarm record their global best as $G(t) = (g_1(t), g_2(t), \cdots, g_N(t))$. Each power particle updates its velocity and position as follows:

$$V(t+1) = \omega V(t) + c_1 r_1 (Q(t) - X(t)) + c_2 r_2 (G(t) - X(t)), \tag{12}$$

$$X(t+1) = X(t) + V(t+1), \tag{13}$$

where r_1 and r_2 are random numbers independently and uniformly distributed in the range [0,1]. $(Q(t) - X(t))$ and $(G(t)-X(t))$ respectively represent each particle's individual experience and social experience. c_1 and c_2 are the corresponding learning factors, which are usually both set to 2.0 based on the trial results. ω is the inertia weight to obtain tradeoff between the local and global searching. The larger the ω, the stronger the global searching ability. Obviously, global researching ability should be stronger at first, while the local one should be stronger at the end. In this paper, a linear iteration-decreasing inertia weight is introduced as follow

$$\omega(t) = \frac{t_{\max} - t}{t_{\max}}(\omega_{\max} - \omega_{\min}) + \omega_{\min}, \tag{14}$$

where, $\omega_{\max}$ and $\omega_{\min}$ are respectively the maximum and the minimum inertia weight, $t_{\max}$ is the maximum times of iteration.

In chaotic optimization algorithm, the logistic formulation for the dth dimension of a high-dimensional complex problem can be defined as [11]

$$z_d^{t+1} = \mu z_d^t (1 - z_d^t), 0 < z_0 < 1, \tag{15}$$

where, $\mathrm{t} = 0, 1, 2 \cdots$ is the chaotic iteration index and $z_d \notin \{0, 0.25, 0.5, 0.75, 1\}, \mu = 4$. With the iteration of (15), we can produce a lot of ergodic pseudo random numbers in the range (0,1) without repeat. Usually, there exists two kinds of usages of the logic formulation as follows:

$$y_d = (b - a) z_d + a, \tag{16}$$

$$u_d = x_d + r \cdot (z_d - 0.5), \tag{17}$$

where, z_d is a chaotic variable in the range $(0, 1)$. With (16), the chaos expands to the range [a,b], and with (17), we can introduce the chaos into the range $(x_d - \frac{r}{2}, x_d + \frac{r}{2})$, which is near x_d.

At the beginning, we initialize the power particles with chaotic formulation, which satisfy (9), (10) and (11), in range $[0, P_{\max}]$. Subsequently, with PSO algorithm, a underlying optimal power allocation solution will be achieved, which is denoted as $G^* = (g_1^*, g_2^*, \cdots, g_N^*)$. Finally, with (16), (17) we will find the optimal power allocation solution $\mathbf{P}^*$ near G^*, which make the general EE highest.

C. CPSO-based power allocation algorithm

The base station allocates energy-efficiently its transmit power by executing the power optimization algorithm shown in **Algorithm 1**.

Algorithm 1: CPSO-based Power Optimization Algorithm

Step 1: Power particle swarm initialization.
  Initialize the position, $\mathbf{X}$, of each particle with chaotic optimization in the swarm, which should satisfy (9), (10) and (11).
  Initialize the velocity, $\mathbf{V}$, of each particle randomly;
  Calculate each particle's fitness with (8);
  For each particle $m \in \mathcal{M}$, set particle m's personal optima, $Q_m(0)$, to its initial position;
  Set the swarm $\mathcal{M}$'s optima, $G(0)$, to the best particle among the initial swarm.
Step 2: Begin to search the underlying global optima.
  while($t \leq t_{\max}$) **do**
  Update each particle's velocity with (12);
  Update each particle's position with (13);
  Update each particle's personal optima: if $f(X_m(t)) > f(Q_m(t-1))$, then update $Q_m(t)$ to its present position, otherwise don't.
  Update the swarm's global optima: if there exists $Q_k(t)$ satisfying $f(Q_k(t)) > f(G(t-1))$, then update $G(t)$ to $Q_k(t)$, otherwise don't.
  end while
After step 2, we have found the optimization problem's underlying global optima $G^* = (g_1^*, g_2^*, \cdots, g_N^*)$.
Step 3: Search the global optima with chaotic optimization algorithm.
  Produce a random vector of N dimensions, $(z_1, z_2, \cdots, z_N)$, each component is in the range (0,1);
  for $t = 1 : T_{max}$ **do**
  Update the position with (15) and (17);
  Calculate its fitness with (8);
  if $f(X(t)) > f(G^*)$ **then** update G^* to X.
end for
Step 4: Output the final global optima G^* as the best power allocation result, $\mathbf{P}^*$.

IV. Simulation and Numerical Analysis

In this section, we present simulation results to demonstrate the performance of the CPSOPA algorithm, compared with WFPA and EPPA. Subsequently, the influence of the number of video users on the EE has been demonstrated. Finally, the tradeoff between energy efficiency and minimum-data-rate QoS has been exhibited.

Monte Carlo method has been utilized in the simulation, a MATLAB-based simulator has been used to model the experience environment. For simplicity, two kinds of services are considered in this paper, consisting of delay-sensitive video service with the minimum rate, $R_{\min}$, and delay-tolerant service with zero as its minimum data rate. Since each user undergoes flat fading, we assume the subchannels allocated to the same user have the same power gains.

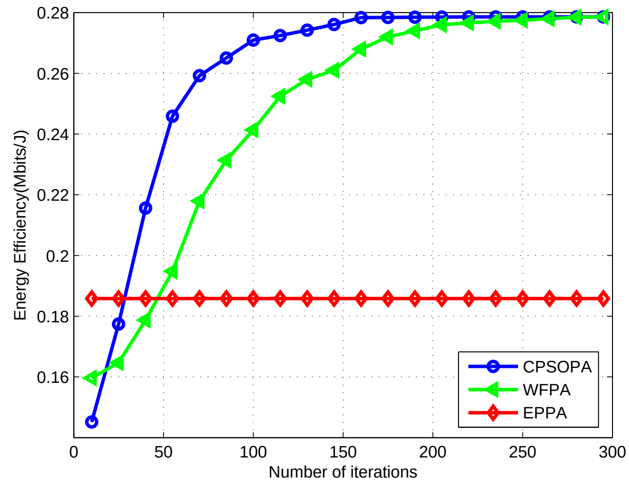

Fig. 2: EE vs. number of iterations for different number of video users

TABLE I: Simulation Parameters

Parameter	Value
System bandwidth B	150KHz
Subchannel number N	10
Base station's transmit power P_{max}	2W
Circuit power p_c	2W
Active multimedia users K	5
The drain efficiency of power amplifier	50%
$R_{\min}$	300Kps

The mainly scalable parameters are configured according to the values listed in **Table I**. As shown in the table, there are five active users and $\mathcal{K} = \{1, 2, 3, 4, 5\}$. The system bandwidth is 150KHz, which is divided into 10 subchannels. The circuit power and the maximum transmission power are both set to 2W, and the drain efficiency of power amplifier is 50%. Here, in order to focus our attention on power allocation, we utilize the simplest subchannel allocation strategy and allot them two by two in order. Therefore, the first two subchannels are occupied by the user UE 1, and their power gains, $g_{1,1}$ and $g_{1,2}$, are both 1. The second two subchannels are allocated to UE 2 and accordingly $g_{2,3}$ and $g_{2,4}$ are both 1. Similarly, $g_{3,5}$ and $g_{3,6}$ are both 10, $g_{4,7}$ and $g_{4,8}$ are both 2 and $g_{5,9}$ and $g_{5,10}$ are 2. In addition, the minimum rate $R_{\min}$ is set to 300Kps and the single-sided noise spectral density N_0 is $1.1565 \times 10^{-8} W/Hz$.

Firstly, we consider that all the users are delay-tolerant users and none of them have minimum data rate constraint. Fig.2 shows that the best particle slowly converges to an optimal point when the iteration index gets larger and finally to the best power allocation solution P, which results in the highest

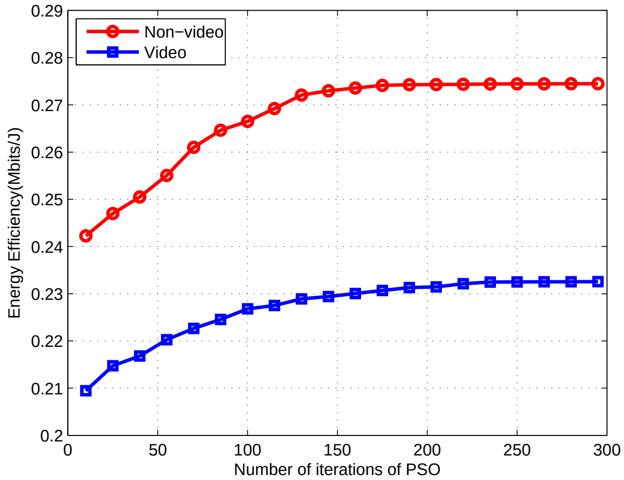

Fig. 3: EE vs. number of iterations for different population size

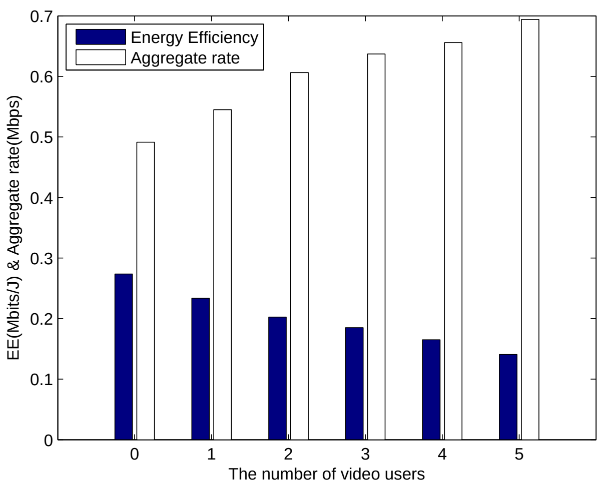

Fig. 4: EE vs. Throughput for different number of video users

general EE. Compared with the WFPA proposed in [12], our CPSO-based power allocation algorithm can converge much faster. However, both of them have greatly improvement at EE compared with EEPA. The simulation results show that the CPSOPA proposed in this paper is fit for an energy-efficient power allocation.

Subsequently, we consider a distinctive case, where all users are video delay-sensitive users and it's not easy to solve the problem with WFPA for minimum data rate constraint has to be satisfied. As shown in Fig.3, the optimal EE decrease by approximate 40%, compared with non-video case. For the purpose of satisfying the video users' minimum data rate, extravagant power should be transmitted, as a result, the EE at the base station will be definitely decreasing.

Fig.4 shows the influence of the number of video users on the EE and aggregate data rate, respectively. As more users added into the video-user group, the aggregate data rate increase at the expense of the degradation of the EE. For more video users need to guarantee their minimum-data-rate QoS, more transmission power will be transmitted, which is less energy-efficient. Therefore, the aggregate rate has increased, while the EE has decreased, which means that the EE and minimum-data-rate QoS can't be simultaneously improved.

V. Conclusion

In this paper, we have studied energy-efficient power allocation problem in downlink of a single cell OFDMA network, which carries multimedia data to users with various QoS requirements. Firstly, we formulate the EE optimization problem as the maximization of the EE with QoS considered. Subsequently, we introduce the easy-operated CPSO into our power allocation and propose a CPSOPA algorithm. Simulation results show that CPSOPA algorithm can converge faster than WFPA, and both of them have significant EE improvement compared with EPPA. Furthermore, in practical wireless networks, the minimum-data-rate QoS and EE can't be simultaneously improved. To guarantee the video users' QoS, extravagant power will be transmitted, the aggregate data rate increase at the expense of the degradation of EE.

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