Energy-Efficient Downlink Resource Allocation for Mobile Devices in Wireless Systems

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***Abstract*—Mobile users have become increasingly addicted to multimedia applications which are extremely downlink-intensive. We observed that conventional objectives, like *rate adaptive* and *margin adaptive*, adopted for radio resource allocation may lead to unnecessary energy consumption of mobile devices, which is adverse to the development of mobile multimedia applications. This paper presents an alternative objective, called *energy adaptive*, and formulates the energy-efficient downlink resource allocation problem. The objective is to minimize the total energy consumption of mobile devices for data reception while satisfying users' data rate requirements and base station's available transmit power. We prove that the target problem is $\mathcal{NP}$-hard and propose an efficient heuristic algorithm to solve the problem. The results of simulations conducted to evaluate the efficacy of the proposed algorithm agree with our observation on the conventional objectives, as well as providing some useful insights into the design of energy-efficient downlink resource allocation for wireless systems.**

***Keywords*—Downlink resource allocation, energy efficiency, mobile devices, wireless systems.**

I. Introduction

Advances in wireless communications have enabled ubiquitous personal computing and facilitated the development of various mobile services. Among those attractive services, mobile users have become increasingly addicted to multimedia applications, such as video streaming, in recent years. Mobile video traffic was anticipated to account for about 60 percent of mobile data traffic by 2017 [1]. One of the essential characteristics of multimedia applications is their asymmetric data delivery with extremely downlink-intensive traffic [2]; thus, the amount of downlink data of mobile devices is more considerable than that of uplink against such applications. Moreover, as indicated in some studies on energy consumption entities, mobile devices require significant power consumption for data reception [3, 4]. This motivates us to study energy-efficient downlink resource allocation for mobile devices in wireless systems.

The *Orthogonal Frequency Division Multiple Access* (OFDMA) technology is adopted by the fourth-generation (4G) wireless systems, e.g., LTE [5] and WiMAX [6], for downlink transmissions. The downlink resource allocation problem for power and channel in OFDMA-based networks has been extensively studied, and the objective functions considered as the performance metrics can roughly be classified into *rate adaptive* (RA) and *margin adaptive* (MA) [7]. In regard to this power and channel allocation problem, researches first paid attention to maximize the data rate for all users with a constraint on the transmit power of the base station, e.g., [7–12], referred to as the RA objective. However, data rate maximization is not beneficial for real-time multimedia data whose bit rate is generally constant and determined by the adopted compression algorithm [13]. Therefore, some researches aimed to minimize the transmit power of the base station while satisfying users' data rate requirements, e.g., [13–16]; this objective is called the MA objective. Nevertheless, the transmit power only occupies about 5 percent of the operating power consumption of a base station in general [17]. More importantly, the RA and MA objectives may increase the energy consumption of mobile devices for data reception and, thus, put further pressure on limited battery capacity of mobile devices. The reason behind the phenomenon is that both the objectives tend to scatter the radio resources allocated to the same user over different time slots, thereby causing a mobile device to stay in receive mode for a longer time and consume more energy. We will use a simple example in a subsequent section to illustrate this phenomenon in more details. Based on the above observation, the resource allocation dedicated to mobile devices in wireless systems should consider reducing the energy consumption for data reception as a primary objective.

In this paper, we introduce an alternative objective, called *energy adaptive* (EA), into downlink resource allocation in 4G wireless systems to reduce the energy consumption of mobile devices for data reception. The contributions of this paper are as follows. First, we observe an interesting phenomenon that the conventional objectives, like RA and MA, may lead to unnecessary energy consumption of mobile devices for data reception. This phenomenon appears to be adverse to the development of mobile multimedia applications. Next, we propose EA as an alternative objective and define the problem of energy-efficient downlink resource allocation. The objective is to minimize the total energy consumption of mobile devices for data reception while simultaneously satisfying the data rate requirement of every user and the available transmit power of the base station. We prove that the target problem is $\mathcal{NP}$-hard and propose an efficient heuristic algorithm to solve the problem. Finally, we conduct a series of simulations, with real video sequences encoded by H.264 with JM version 18.4 and the parameters set according to LTE [5], to evaluate the performance of the proposed algorithm. To provide further insights, we compare our algorithms with the two algorithms respectively developed for the RA objective [12] and the MA objective [16], as well as a lower bound estimated for the optimal solution. The simulation results agree with our observation on the conventional objectives, namely RA and

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MA, which may cause mobile devices to consume a significant amount of unnecessary energy, compared with EA. In addition, based on the simulation results, there is a tradeoff between the energy consumption of the base station and mobile devices. The tradeoff also explains why EA is used to term the alternative raised in this paper for resource allocation.

The remainder of this paper is organized as follows. Section II reviews some related works on radio resource allocation in OFDMA-based networks. In Section III, we describe the system model and define the problem. In Section IV, we prove the problem is $\mathcal{NP}$-hard and propose an efficient heuristic algorithm. Some simulation results and insights are discussed in Section IV. Section V concludes this work.

II. Related Works

Radio resource allocation has been considered as one of the most important issues in OFDMA-based wireless networks [18]. In recent years, many researchers have developed effective algorithms to allocate limited radio resources (i.e., power and channel) with the purpose of optimizing various objective functions as system performance metrics, especially RA and MA.

The RA objective attempts to maximize the total data rate of all users under a given transmit power constraint of their base station, e.g., [8–10]. In particular, Jang et al. [8] proved that the data rate in *one single symbol* can be maximized when each subcarrier is assigned to only one user with the best channel gain for that subcarrier and the transmit power is distributed over the subcarriers by a *water-filling policy*. However, users with poor channel gains (e.g., those far away from the base station) may suffer from starvation. To achieve the fairness of data rates among users, some studies considered the proportional rate constraint [7] or individual rate constraint [11]. For example, Biagioni et al. [12] considered multiple symbols for each resource allocation and adopted the max-min data rate of users as a variant objective function.

On the other hand, because the data rate requirements of some applications (e.g., video streaming) are fixed, Wong et al. [13] raised the MA objective to minimize the total transmit power of the base station while satisfying every user's data rate requirement. In [13], a subcarrier allocation algorithm with a lower bound on the total transmit power was proposed. This led to the launch of several studies on the resource allocation problem with the MA objective and a number of heuristic algorithms, e.g., [14–16]. However, the resource allocation algorithms with the RA or the MA objective do not consider the battery capacity of mobile devices and tend to increase the energy consumption of mobile devices for data reception.

Recently, some studies aimed to minimize the downlink energy consumption of mobile devices in OFDMA systems. The energy consumed by a device is proportional to the number of symbols it receives. In [19], assuming that mobile devices have been allocated in specific subchannels, a heuristic algorithm was proposed to determine the allocation of symbols so as to minimize the total number of symbols received by all mobile devices. In [20], Chu et al. proposed an optimal algorithm when the user requirements only allow some fixed combinations such that the requirements can always be partitioned into several sets, each of which can be satisfied by exactly one symbol. In our previous work [21], we proposed approximation algorithms for energy-efficient video multicast in OFDMA-based wireless networks. However, the above algorithms do not consider the phenomenon that a user may have different channel gains on different subchannels. Therefore, how to allocate the available transmit power of the base station among the subchannels is not addressed, which is an essential issue of the EA objective in minimizing the downlink energy consumption while satisfying every user's data rate requirement.

III. System Model and Problem Formulation

A. System Model

The OFDMA-based multi-carrier technology has been widely adopted by 4G wireless networks for downlink transmissions. In 4G wireless systems, data is transmitted in the OFDMA frame structure. A frame consists of *slots* in the time domain and *subchannels* in the frequency domain, as shown in Fig. 1. A slot comprises one or several *symbols*, and a subchannel consists of several *subcarriers*. Because the fast fading effect may not be the same for different subchannels, a user may have different levels of channel gains on different subchannels [11]. We assume that a base station can collect the information about the channel gain either by the measurement reports of users or by the estimation of the base station itself [11].

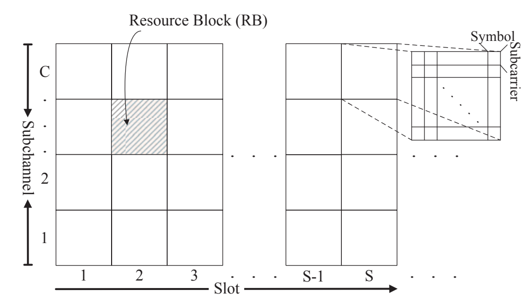

Fig. 1. The OFDMA frame structure.

In the OFDMA frame structure, a combination of a slot and a subchannel, referred to as a *resource block (RB)*, is the basic unit for resource allocation. For resource allocation, the base station has to determine which RB should be allocated to which user, referred to as *RB allocation*. In addition to RB allocation, the base station needs to determine the power level of each RB so that the data rate requirement of the corresponding user can be satisfied, referred to as *power allocation*. Based on *Shannon capacity* [22], a higher power level allocated in the RB with a higher channel gain leads to a higher data rate. Notice that the available power of a base station is limited. Once the power level of an RB is determined, the receiving power of a transceiver can be deemed a constant [23]; consequently, the energy consumption required to receive data depends on the amount of reception time and is proportional to the number of slots the device needs to receive [19–21]. If a mobile device can receive its data in a shorter time, it can have a longer time for power saving [6, 20]. As a result, an appropriate resource allocation, power and RB allocation, can reduce the energy consumption of mobile devices for data reception.

B. Problem Formulation

In this paper, we study joint power and RB allocation for downlink transmissions in 4G wireless systems. The objective is to minimize the total energy consumption of mobile devices for receiving downlink data, provided that the data rate requirement of every user is satisfied and the available power of a base station is limited. For the sake of brevity, we omit "$\forall$" when the meaning is clear from the context.

For each resource allocation, we consider a set of frames with $S \cdot C$ available RBs to be allocated to N admitted users, where S is the number of slots and C is the number of subchannels. The bandwidth of a subchannel is denoted as B. The channel gains of a user on different subchannels may be different; the channel gain of user n on subchannel c is denoted as $g_{(n,c)}$. Every user can have a preferred data rate requirement; the data rate requirement of user n is denoted as R_n. The available power of the base station is limited and denoted as P_{BS}. Let $p_{(n,s,c)}$ denote the power level of the RB comprised of slot s and subchannel c allocated to user n. Based on Shannon capacity, if the RB comprised of slot s and subchannel c is allocated to user u and allocated with power level $p_{(n,s,c)}$, the user can obtain a data rate of $\frac{B}{S} \cdot \log_2(1 + g_{(n,c)} \frac{p_{(n,s,c)}}{\sigma})$ [12]. Moreover, we define $\chi_{(n,s,c)}$ as an indicator function, which is 1 if the RB comprised of slot s and subchannel c is allocated to user n, and 0 otherwise. If any RB in slot s is allocated to user n, the mobile device of the user has to consume an amount of energy, denoted as J_n (its value depends on the device capability), to receive data during the time slot. A resource allocation is *feasible* if all the following constraints are satisfied.

Resource constraints: Equation (1) ensures that each RB can only be allocated to a user at a time.

$$\sum_{n=1}^{N} \chi_{(n,s,c)} \leq 1, \forall\ s, c \tag{1}$$

Requirement constraint: Equation (2) states that every user must be satisfied with the data rate the user obtains.

$$\sum_{s=1}^{S} \sum_{c=1}^{C} \frac{B}{S} \cdot \log_2(1 + g_{(n,c)} \frac{p_{(n,s,c)}}{\sigma}) \cdot \chi_{(n,s,c)} \geq R_n, \forall\ n \tag{2}$$

Available transmit power constraint: The total transmit power cannot exceed the available power of the base station.

$$\sum_{n=1}^{N} \sum_{c=1}^{C} p_{(n,s,c)} \leq P_{BS},\ \forall\ s \tag{3}$$

We now define the target problem formally as follows.

The Energy-Efficient Downlink Resource Allocation Problem

Input instance: Consider $S \cdot C$ available RBs to be allocated to N users. The bandwidth of a subchannel is B. User n has a channel gain $g_{(n,c)}$ on subchannel c and a data rate requirement R_n. The base station has available power P_{BS}. The noise power is σ. The device of user n consumes J_n energy for data reception during a slot.

Objective: Our objective is to find a feasible resource allocation, comprised of a power allocation $p_{(n,s,c)}$ and an RB allocation $\chi_{(n,s,c)}$, such that the total energy consumption of all the devices is minimized. The objective function is expressed by

$$\texttt{Minimize} \quad \sum_{n=1}^{N} J_n \times \sum_{s=1}^{S} \left(\bigvee_{c=1}^{C} \chi_{(n,s,c)} \right),$$

TABLE I. SUMMARY OF NOTATIONS

N	The number of users
S	The number of available slots
C	The number of available subchannels
B	The bandwidth of a subchannel
P_{BS}	The available power of the base station
σ	The noise power
R_n	The data rate required by user n
J_n	The energy consumption of the mobile device of user n for data reception during a slot
$g_{(n,c)}$	The channel gain of user n on subchannel c
$p_{(n,s,c)}$	The power level allocated to the RB comprised of slot s and subchannel c for user n
$\chi_{(n,s,c)}$	An indicator function, which is 1 if the RB comprised of slot s and subchannel c is allocated to user n, and 0 otherwise

subject to constraints (1)-(3), where $\bigvee_{c=1}^{C}\ \chi_{(n,s,c)}$ indicates whether user n needs to receive data during slot s, and $\sum_{s=1}^{S}(\bigvee_{c=1}^{C}\ \chi_{(n,s,c)})$ represents the number of slots during which user n needs to receive data. Table I summarizes the notations used in the problem formulation.

C. An Illustrative Example

We use an example, as shown in Fig. 2, to explain our observation on the impact of different resource allocation strategies (i.e., with different objectives) on the energy consumption of mobile devices for data reception. Consider four users (i.e., $N = 4$). The numbers of slots and subchannels are set respectively as 3 and 4 (i.e., $S = 3$ and $C = 4$). The bandwidth of a subchannel is set at 180KHz (i.e., $B = 180\text{K}$). The channel gains of each user on the four subchannels are set as some permutation of 0.4, 0.3, 0.2, and 0.1. The data rate requirement of each user is set at 60Kbps (i.e., $R_n = 60\text{K}$, $\forall\ n$). The available power of the base station is set at 5W (i.e., $P_{BS} = 5$). The noise power is set at 1W (i.e., $\sigma = 1$). Each mobile device consumes 320μJ for data reception during a slot (i.e., $J_n = 320\mu$, $\forall\ n$). Then, the base station determines the power and RB allocation under the RA, MA, and EA objectives, respectively.

Fig. 2(a) shows an optimal solution for the resource allocation problem with the RA objective. In order to maximize the data rate, the base station always allocates each RB to the user with the highest channel gain. As a result, each RB is allocated to a user with channel gain 0.4; moreover, each RB is allocated equally with 1.25W, since the available transmission power is 5W. Consequently, each device needs to receive data in three slots, and the total energy consumption for data reception is $320\mu \times 3 \times 4 = 3840\mu$J. Fig. 2(b) shows an optimal solution for the MA objective. To minimize the transmit power, the base station also tries to allocate each RB to a user with the highest channel gain 0.4; however, it allocates only 0.65W to each RB so that all the user requirements can at least be satisfied. In this example, the four devices consume 3840μJ as well. With the EA objective, as shown in Fig. 2(c), the base station tends to allocate RBs in the same slot to each user. As a result, some RBs are allocated to users with channel gain 0.4, while some RBs allocated to users with channel gain 0.3; moreover, 1.59W and 0.75W are allocated to the RBs associated respectively with channel gain 0.4 and 0.3. Based on the allocation, each user can be satisfied with a data rate of $\frac{180\text{K}}{3} \log_2(1 + 0.4 \times 1.59) + \frac{180\text{K}}{3} \log_2(1 + 0.3 \times 0.75) = 60.1$Kbps, and the total transmit power in a slot is $2 \times (1.59 + 0.75) = 4.68$W, which is less than the available power. Importantly, the total energy consumption for data reception is only $320\mu \times 4 = 1280\mu$J.

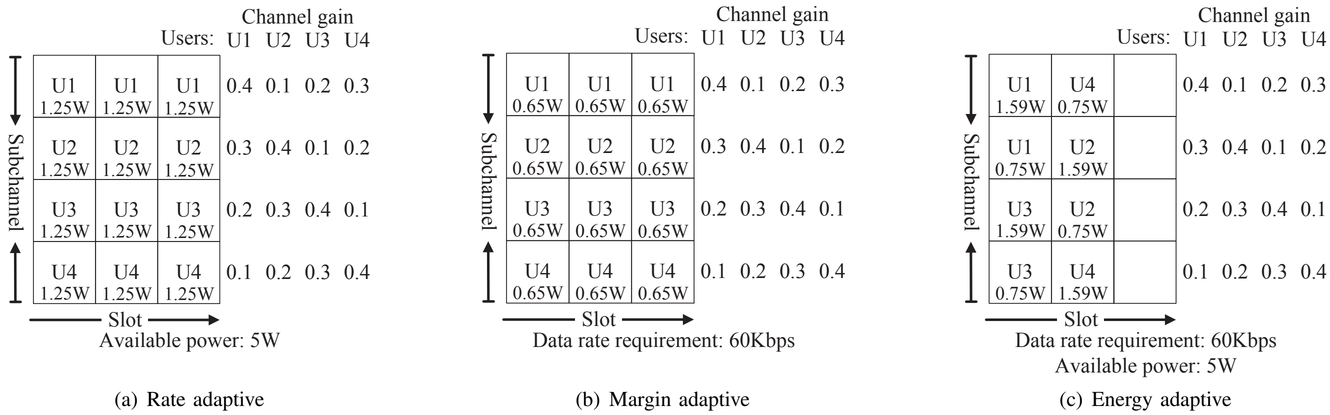

Fig. 2. An illustrative example for the resource allocation problem with different objectives.

Comparing Fig. 2(b) and Fig. 2(c), we observe an interesting phenomenon that, in order to save the transmit power of the base station, each mobile device will stay in receive mode for a longer time and consume more energy to achieve the required data rate.

IV. Energy-Efficient Downlink Resource Allocation

In this section, we prove that the problem is $\mathcal{NP}$-hard by a reduction from the *partition problem*, which is known to be $\mathcal{NP}$-complete [24], and present an efficient algorithm to derive effective resource allocation.

A. Problem Hardness

Theorem 1. The energy-efficient downlink resource allocation problem is $\mathcal{NP}$-hard.

Proof*:* The input instance of the partition problem is a set of m integers, $A = \{a_1, a_2, \ldots, a_m\}$. The output is YES if and only if A can be partitioned into two subsets Z and $A \backslash Z$ with the same sum, i.e., $\sum_{a_i \in Z} a_i = \sum_{a_i \notin Z} a_i = \frac{1}{2} \sum_{a_i \in A} a_i$.

Given an instance $\langle A \rangle$ of the partition problem, we explain how to construct an instance $\langle N, S, C, B, R_n, J_n, P_{BS}, \sigma, g_{(n,c)} \rangle$ of our problem in polynomial time such that A can be evenly partitioned if and only if there exists a resource allocation whose total energy consumption is not more than 2. The construction is as follows. Consider two users (i.e., $N = 2$). The numbers of available slots and subchannels are respectively set as $S = 1$ and $C = m$. The bandwidth of a subchannel is set as $B = 1$. Each user has to obtain a data rate of $R_n = \frac{m}{2} \sum_{a_i \in A} a_i$, $\forall 1 \leq n \leq 2$, and the energy required to receive data during one slot is set as $J_n = 1$, $\forall 1 \leq n \leq 2$. Let the available power of the base station be $P_{BS} = m$ and the noise power be $\sigma = 1$. The channel gain of each user on subchannel c is set as $g_{(n,c)} = 2^{m a_c} - 1$, $\forall\ 1 \leq c \leq m$, $1 \leq n \leq 2$.

To complete the proof, we show that two partitioned subsets can be used to derive a resource allocation whose total energy consumption is not more than 2, and vice versa. We allocate the available power m equally to the m subchannels, so that the RB comprised of slot s and subchannel c can provide user n with a data rate of $\frac{B}{S} \log_2(1 + g_{(n,c)} \cdot \frac{p_{(n,s,c)}}{\sigma}) = m a_c$. Consequently, each integer a_c corresponds to the data rate provided by an RB, and each subset corresponds to the RBs allocated to a user. Two evenly partitioned subsets imply that both the users can be satisfied with the data rates provided by the RBs in the only one slot. Thus, the total energy consumption is 2. On the other hand, if the total energy consumption is no more than 2, the two users must be satisfied with the RBs in the only one slot. It implies that the set can be evenly partitioned by assigning the corresponding integers into the corresponding subset. The existence of a polynomial-time algorithm for the partition problem implies the same for ours, which completes the proof. ■

B. Algorithm Description

In this section, we propose an efficient algorithm, for the energy-efficient downlink resource allocation problem. The proposed algorithm relies on two well-known power allocation strategies, namely *equal power allocation* [8] and *water-filling power allocation* [9]. The equal power strategy allocates the available power equally to all the subchannels [8], while the water-filling strategy can achieve the maximum data rate given that the available power is allocated to some designated subchannels in one single slot [8, 9, 25]. However, an algorithm that implementing the water-filling strategy requires much higher computational complexity than that implementing the equal power strategy. In Algorithm 1 for power allocation, we devise a selection mechanism between the equal power strategy and the water-filling strategy against each slot. Moreover, for RB allocation, we allocate RBs in column-major order to each user so as to reduce the energy consumption for data reception.

The proposed algorithm, as shown in Algorithm 1, starts with the initialization of some parameters. A power allocation function $p_{(n,s,c)}$ is used to record the power allocated to the RB comprised of slot s and subchannel c for user n, and is initialized as 0, $\forall\ n, s, c$ (Line 1). An indicator function $\chi_{(n,s,c)}$ registers if the RB comprised of slot s and subchannel c is allocated to user n, and is also initialized as 0, $\forall\ n, s, c$ (Line 2). A variable φ initialized as 0 is used to count the current number of allocated RBs (Line 3), and a variable $\hat{s}$ initialized as 1 is employed to index the currently used slot (Line 4). Then, the algorithm allocates available resources to every user until the corresponding requirement is satisfied (Lines 5-21). For each user $\hat{n}$, it computes the respective data rates that can be provided by a slot with equal power allocation and water-filling power allocation, denoted as $r_{\hat{n}}^E$ and $r_{\hat{n}}^W$, where $r_{\hat{n}}^W \geq r_{\hat{n}}^E$ (Lines 6-7). The water-filling strategy is selected if both of the following two conditions are met: 1) none of the

Algorithm 1

Input: S, C, B, N, R_n, J_n, P_{BS}, $g_{(n,c)}$, σ
Output: $p_{(n,s,c)}, \chi_{(n,s,c)}$
1: $p_{(n,s,c)} \leftarrow 0, \forall\ n, s, c$
2: $\chi_{(n,s,c)} \leftarrow 0, \forall\ n, s, c$
3: $\varphi \leftarrow 0$
4: $\hat{s} \leftarrow 1$
5: **for** $\hat{n} = 1$ to N **do**
6: $r^E_{\hat{n}} \leftarrow \sum_{c=1}^{C} \frac{B}{S} \log_2(1 + g_{(\hat{n},c)} \cdot \frac{P_{BS}}{\sigma C})$
7: $r^W_{\hat{n}} \leftarrow \sum_{c=1}^{C} \frac{B}{S} \log_2(1+g_{(\hat{n},c)} \cdot \frac{p^*_{(\hat{n},\hat{s},c,)}}{\sigma})$, where $p^*_{(\hat{n},\hat{s},c)}$, $\forall\ c$, are computed by a water-filling algorithm
8: **while** $R_{\hat{n}} > 0$ **do**
9: **if** $\chi_{(n,\hat{s},c)} = 0, \forall n, c$ and $R_{\hat{n}} - r^E_{\hat{n}} > 0$ **then**
10: $\varphi \leftarrow \varphi + C$
11: $\hat{s} \leftarrow \lceil \frac{\varphi}{C} \rceil$
12: $R_{\hat{n}} \leftarrow R_{\hat{n}} - r^W_{\hat{n}}$
13: $\chi_{(\hat{n},\hat{s},c)} \leftarrow 1, \forall c$
14: $p_{(\hat{n},\hat{s},c)} \leftarrow p^*_{(\hat{n},\hat{s},c)}, \forall c$
15: **else**
16: $\varphi \leftarrow \varphi + 1$
17: $\hat{s} \leftarrow \lceil \frac{\varphi}{C} \rceil$
18: $\hat{c} \leftarrow \arg\max_c \{g_{(\hat{n},c)} |\ \chi_{(n,\hat{s},c)} = 0, \forall n\}$
19: $R_{\hat{n}} \leftarrow R_{\hat{n}} - \frac{B}{S} \log_2(1 + g_{(\hat{n},\hat{c})} \cdot \frac{P_{BS}}{\sigma C})$
20: $\chi_{(\hat{n},\hat{s},\hat{c})} \leftarrow 1$
21: $p_{(\hat{n},\hat{s},\hat{c})} \leftarrow \frac{P_{BS}}{C}$
22: **return** $p_{(n,s,c)}$ and $\chi_{(n,s,c)}$, $\forall\ n, s, c$

subchannels in the currently used slot $\hat{s}$ has been allocated to any user, i.e., $\chi_{(n,\hat{s},c)} = 0, \forall n, c$, and 2) the remaining requirement of user $\hat{n}$ cannot be satisfied by a slot with equal power allocation, i.e., $R_{\hat{n}} - r^E_{\hat{n}} > 0$. If the water-filling strategy is selected (Line 9), the number of allocated slots φ is increased by C and the index of the currently used slot $\hat{s}$ is updated accordingly (Lines 10-11). Thus, user $\hat{n}$ can obtain a data rate of $r^W_{\hat{n}}$ in the slot (Line 12). The RB allocation function $\chi_{(\hat{n},\hat{s},c)}$ is set as 1, $\forall c$, to indicate that all the RBs in the slot are allocated to the user, and the power allocation function $p_{(\hat{n},\hat{s},c)}$, $\forall c$, is set according to water-filling power allocation (Lines 13-14).

In contrast, the algorithm selects the equal power strategy and allocates the RBs in the current slot $\hat{s}$ one by one (Line 15). As a result, φ is increased by 1 and $\hat{s}$ is updated accordingly (Lines 16-17). To provide a data rate as high as possible, the algorithm finds an unused subchannel $\hat{c}$ with the highest channel gain for user $\hat{n}$ (Lines 18). The RB comprised of $\hat{s}$ and $\hat{c}$ is allocated to user $\hat{n}$, so the user can obtain a data rate of $\frac{B}{S} \log_2(1+g_{(\hat{n},\hat{c})} \cdot \frac{P_{BS}}{\sigma C})$ (Line 19). The RB allocation function $\chi_{(\hat{n},\hat{s},\hat{c})}$ is set as 1 to indicate that the RB has been allocated, and the power allocation function $p_{(\hat{n},\hat{s},\hat{c})}$ is set as $\frac{P_{BS}}{C}$ (Lines 20-21). Finally, the RB and power allocation functions are returned (Line 22).

Theorem 2. The time complexity of Algorithm 1 is $O(N\omega + NSC^2)$, where ω is the running time of the adopted water-filling algorithm.

Proof*:* The initialization process requires $O(NSC)$ time. For each user $\hat{n}$, the two data rates, $r^E_{\hat{n}}$ and $r^W_{\hat{n}}$, are computed only once and can be done in $O(C)$ and $O(C + \omega)$ time, respectively. Thus, computing the counterparts for the N users takes $O(NC + N\omega)$ time. The time complexity in the **while** loop is obviously dominated by the time required to check if $\chi_{(n,\hat{s},c)} = 0,\ \forall\ n, c$, i.e., $O(NC)$. Since at least one RB will be allocated for each loop and there are at most $S \cdot C$ RBs, the **while** loop takes at most $O(NSC^2)$ time throughout the algorithm. Thus, the time complexity of Algorithm 1 is $O(N\omega + NSC^2)$. ■

V. Performance Evaluation

A. Simulation Setup

We developed a simulation model using C++ programs to evaluate the performance of the proposed algorithm. The parameter settings used in the simulation model were based on the LTE specification for a 10MHz spectrum [5]. The number of available slots was set at 40, and each slot time was 0.5ms. The number of available subchannels was set at 50, and the bandwidth of a subchannel was 180KHz. The network consisted of one base station and some mobile users, each of which was placed randomly in the coverage area of the base station at a distance between 100 to 300 meters from the base station. We investigated the impact of the available transmit power of the base station varying from 10 to 20W [17], as well as the impact of the number of users varying from 5 to 40. The power consumption of each device in receive mode was assigned randomly at 620mW [3] or 1400mW [4] to consider heterogeneous mobile devices. Accordingly, the amount of energy consumed by a device to receive data during one slot was 310μJ or 700μJ. Path loss, shadowing, and multipath fading were taken into consideration in the simulation model. We adopted the *log-distance path loss model* with propagation loss exponent of 3 for urban areas and a reference distance of 100 meters. The shadowing follows a *log-normal distribution* with zero mean and standard deviation of 8dB. Moreover, the subchannels were assumed to suffer from *multipath Rayleigh fading*.

TABLE II. Data rate of each video sequence encoded by H.264

Video sequence	Data rate requirement
Akiyo	10.82Kbps
Grandma	11.77Kbps
Container	14.47Kbps
Hall monitor	22.08Kbps
News	36.58Kbps

We used five standard video test sequences with QCIF resolution, namely Akiyo, Grandma, Container, Hall Monitor, and News, all of which can be downloaded from [26]. Each user randomly selected a test sequence. The video sequences were encoded by H.264 with JM, version 18.4, and the IBBP encoding structure was used for each video sequence. The QP value of each I, P, and B frame was set at 34. The other encoding parameters were set as the default values of H.264 with JM, version 18.4. The data rate of each video sequence is listed in Table II.

We compared the proposed algorithm, denoted as *EA*, with two algorithms. The first algorithm was developed for the RA objective [12], denoted as RA. The second algorithm, denoted as *MA*, was proposed in [16]. The performance metrics were the amounts of energy respectively consumed by mobile devices and by the base station, as well as the summation of the two amounts. In addition to the three algorithms, a lower bound estimated for the optimal solution for the target problem, denoted as *OPT-LB* and expressed by

$$\sum_{n=1}^{N} J_n \times \left\lceil \frac{R_n}{r_n^W} \right\rceil,$$

was adopted as a baseline for comparison. Notice that the lower bound was taken due to the extremely high computational complexity of a brute-force approach, as shown in Fig. 3(a). The derived simulation result is the average of the output values of 1000 independent runs. The average running time required by each of the three algorithms per run is shown in Fig. 3(b).

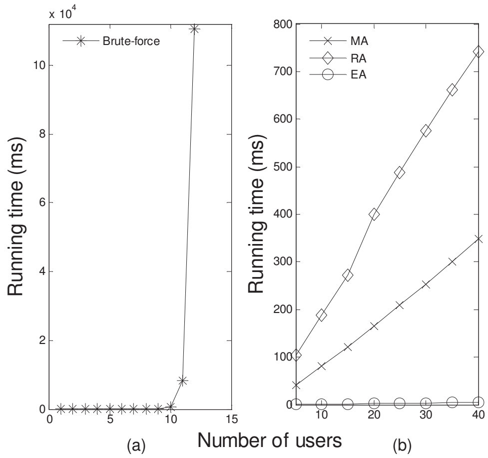

Fig. 3. Average running time required by each algorithm per run.

B. Simulation Results

Fig. 4(a) shows the impact of the available transmit power of the base station on the energy consumption of mobile devices. As what we can see in the figure, the energy consumption of mobile devices decreases as the available power increases under *EA* and *OPT-LB*. The result was as expected because an RB allocated with larger power can provide a higher data rate. As a result, each user's requirement can be satisfied with fewer RBs and thus fewer slots under *EA* and *OPT-LB*. In contrast, the available power does not have a significant impact on the energy consumption of mobile devices under *RA* and *MA*. It implies that both *RA* and *MA* do not leverage the available power to reduce the energy consumption of mobile devices. The simulation results show that mobile devices under *RA* and *MA* consume 13 to 27 times more energy than under *EA*. Moreover, the energy consumption of mobile devices under *EA* is close to that under *OPT-LB*.

Although giving the base station higher available transmit power is more helpful in reducing the energy consumption of mobile devices, we are interested in the energy consumption of the base station under different objective functions as well. As shown in Fig. 4(b), the energy consumption of the base station increases as the available power of the base station increases under *EA* and *RA*, and the increase is more apparent under *RA* than under *EA*. This is because *RA* attempts to exhaust the available power over all the slots to improve the data rate, while *EA* uses as few slots as possible to satisfy users' data rate requirements. The simulation results show that the base station under *EA* consumes 1.9 to 2.2 times more energy than under *MA*. Comparing Fig. 4(a) with Fig. 4(b), we observed an interesting tradeoff between the energy consumption of the base station and the energy consumption of the mobile devices. That is, if the base station attempts to save the transmit power, then mobile devices may consume more energy for data reception, and vice versa. This tradeoff also explains why we use *energy adaptive* to represent the new concept raised in this work for resource allocation. More importantly, when the total energy consumption of the mobile devices and the base station is considered, *EA* is still more energy efficient than *MA* by 3.6 times, as shown in Fig. 4(c).

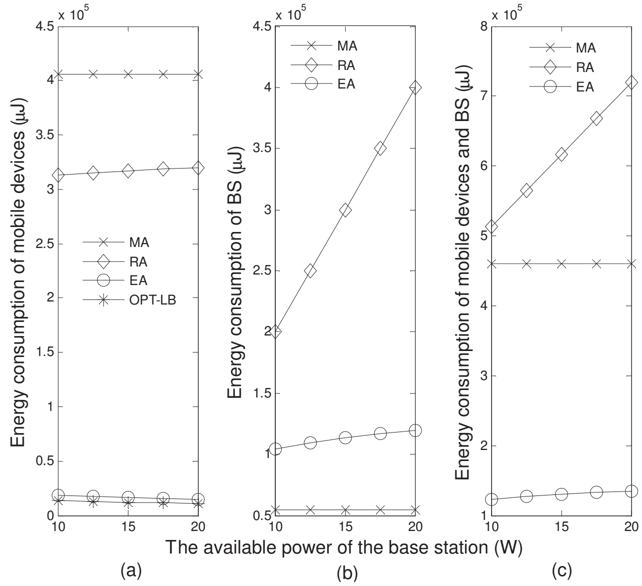

Fig. 4. Impacts of the available transmit power on the energy consumption of (a) the mobile devices, (b) the base station, and (c) the mobile devices and the base station for downlink data transmissions under 20 users.

Fig. 5(a) shows the impact of the number of users on the energy consumption of the mobile devices. In the figure, the energy consumption of the mobile devices increases as the number of users increases under all the algorithms. The reason for *EA* is that, as the number of users increases, the total amount of data rate requirements increases. The more the RBs allocated to satisfy the data rate requirements, the more the total energy the mobile devices consume. The phenomenon is more evident under *RA* and *MA*, because they usually scatter the RBs allocated to the same user over different slots, and the total energy consumption increases, in general, proportionally to the number of users. The simulation results show that the mobile devices under *RA* and *MA* consume 14 to 26 times more energy than under *EA*, and the energy consumption of the mobile devices under *EA* is close to that under *OPT-LB*. The result is similar to that in Fig. 4(a) and also demonstrates that both *RA* and *MA* require more energy consumption for mobile devices to receive data.

As shown in Fig. 5(b), the energy consumption of the base station increases when the number of users increases under *MA* and *EA*. This is because more users have more data rate requirements and the base station has to consume more energy to transmit adequate RBs to satisfy their requirements. In contrast, the number of users does not have a significant impact on the energy consumption of the base station under *RA*, because *RA* always tries to maximize the data rate regardless of user requirements. The simulation results show that the base station under *EA* consumes 1.8 to 2.4 times more energy than under *MA*. As shown in Fig. 4(c), however, *EA* is still more energy efficient than *MA* by 2.8 times, when the total energy consumption of the mobile devices and the base station is considered.

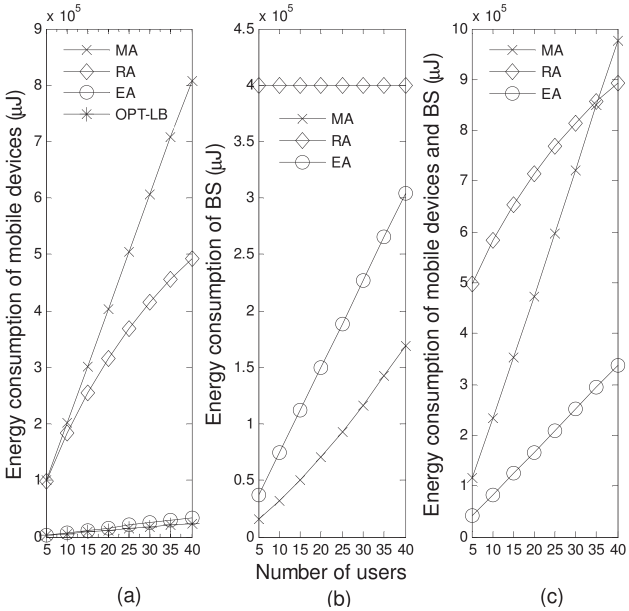

Fig. 5. Impacts of the number of users on the energy consumption of (a) the mobile devices, (b) the base station, and (c) the mobile devices and the base station under 20W available transmit power.

VI. Conclusion

In this paper, we present an alternative objective, named energy adaptive (EA), for downlink resource allocation in 4G wireless networks. The objective is to minimize the total energy consumption of mobile devices when they enjoy multimedia services with fixed data rates like video streaming. Based on the EA objective, we model the energy-efficient downlink resource allocation problem with two respective constraints to satisfy users' data rate requirements and limit the base station's transmit power. We prove that the problem is $\mathcal{NP}$-hard and propose an efficient algorithm. For performance evaluation, we conduct extensive simulations based on real video sequences, and the results demonstrate that the proposed algorithm is very effective in reducing energy consumption of mobile devices, compared with a lower bound estimated for the optimal solution. In addition, the simulation results conducted to compare the EA objective with the RA objective and the MA objective provide useful insights into energy-efficient resource allocation for 4G wireless systems.

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