Energy-Efficient Resource Allocation and User Scheduling for Collaborative Mobile Clouds With Hybrid Receivers

Zheng Chang, *Member, IEEE*, Jie Gong, *Member, IEEE*, Tapani Ristaniemi, *Senior Member, IEEE*, and Zhisheng Niu, *Fellow, IEEE*

***Abstract*—In this paper, we study the resource allocation and user scheduling algorithm for minimizing the energy cost of data transmission in the context of orthogonal frequency-division multiple-access (OFDMA) collaborative mobile clouds (CMCs) with simultaneous wireless information and power transfer receivers. The CMC, which consists of several collaborating mobile terminals, offers one potential solution for downlink content distribution and for energy consumption (EC) reduction. Previous work on the design of the CMC system mainly focused on cloud formulation or energy efficiency (EE) investigation, whereas how to allocate the radio resource and schedule user transmission has not gotten much attention. With the objective of minimizing system EC, an optimization problem that jointly considers subchannel assignment, power allocation, and user scheduling has been presented. We propose different algorithms to address the formulated problem based on the convex optimization technique. Simulation results demonstrate that the proposed user scheduling and resource allocation algorithms can achieve significant EE performance.**

***Index Terms*—Collaborative mobile clouds (CMCs), content distribution, green communications, power allocation, resource allocation, subchannel allocation, user cooperation, user scheduling.**

I. Introduction

A. Background

ADVANCED wireless communication systems bring to end users new high-speed services and features that have never been expected in the past. Nevertheless, the dramatic growth in Internet traffic and the growing pervasive use of mobile technologies continually and significantly increase CO_2 emissions in the future, unless new energy-efficient mechanisms can be investigated. Nowadays, the energy crisis and global warming problems are requiring much research on energy efficiency (EE). In the information and communications technology industry, which is becoming one of the major consumers of global energy consumption (EC), researchers have investigated various approaches for energy saving. On the other hand, the conventional wireless networks are energy constrained in the sense that the network elements, such as mobile phones, are equipped with batteries. The battery capacity has improved at relatively slow speed during the last decades, which creates the bottleneck in prolonging the lifetime of the networks. Meanwhile, the rise of online services significantly increases the demand for high-data-rate transmissions, hence straining the current network and drawing down the battery voltage of mobile devices much faster than before. All these issues have resulted in increased interest in energy-efficient research to reduce the energy requirements for wireless communications, thus, contributing not only to goals for sustainable development but also to the profitability of the telecommunications industry and user experience improvement. So-called green communications, including the design of energy-efficient communication infrastructures, protocols, devices, and services, become inevitable trends for the evolution of future networks. In this paper, we are also aiming at proposing novel approaches to reduce the network energy cost, particularly from the terminal aspect.

B. Related Work

Conventional studies on energy-constrained networks usually focused on designing the energy saving scheme proposals. Recently, the energy harvesting (EH) technique received considerable attention due to its capability of realizing self-maintenance in wireless networks. Meanwhile, research studies on EH have mainly concentrated on the transmitter side [1]. That is, for a cellular network, the recent work mainly focused on the development of base stations (BSs) to utilize the harvested energy rather than mobile nodes (see, e.g., [2] and [3]). Although there are many EH resources, such as solar, wind, and tide, they are usually either location dependent or weather dependent. Thus, for indoor users who cannot access solar or wind, EH becomes a luxury or even impossible. These

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Z. Chang and T. Ristaniemi are with the Department of Mathematical Information Technology, University of Jyväskylä, 40014 Jyväskylä, Finland (e-mail: zheng.chang@jyu.fi; tapani.ristaniemi@jyu.fi).

J. Gong is with the School of Data and Computer Science, Sun Yat-sen University, Guangzhou 510006, China (e-mail: gongj26@mail.sysu.edu.cn).

Z. Niu is with the Tsinghua National Laboratory for Information Science and Technology, Department of Electronic Engineering, Tsinghua University, Beijing 100084, China (e-mail: niuzhs@tsinghua.edu.cn).

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constraints motivate the wireless power transfer technology for the terminals, which enables the radio receiver to capture the radio frequency (RF) radiation and convert it into a direct current voltage [4].

As RF signal can carry both information and energy simultaneously, the induced simultaneous wireless information and power transfer (SWIPT) has gained much attention [5], [6]. Through SWIPT, the receiver not only can receive data from the transmitter but also can recycle the transmit power to prolong the battery lifetime. Nowadays, electromagnetic wave is almost everywhere and all around people's lives; hence, enabling SWIPT is full of possibilities in future wireless networks. In [4] and [5], the fundamental trade-offs between wireless information and power transfer were studied with the assumption that the receiver can simultaneously receive information and harvest energy from the RF signal. Zhang and Ho in [7] and Zhou *et al.* in [8] proposed a receiver architecture that can split the received power into two power streams to facilitate SWIPT. The same authors [7], [8] also investigated the rate-energy regions for a SWIPT receiver in a two-user peer-to-peer scenario. Liu *et al.* in [9] focused on the optimization problem of power control and scheduling for a SWIPT receiver. The optimal information decoding (ID) and EH mode switching was then derived. The work in [10] studied the outage probability of a cooperative EH relay network with multiple transmission pairs. In [11] and [12], different subcarrier and power allocation algorithms were proposed for the multiuser orthogonal frequency-division multiplexing systems with SWIPT. A nonconvex optimization problem was formulated with the objective of maximizing the EE performance in terms of bits per joule. For a large-scale multiple-input–multiple-output system with SWIPT receivers, Chen *et al.* in [13] presented an optimization scheme to maximize the EE of the system while satisfying the delay constraints by jointly allocating the transmission time duration and transmit power.

Meanwhile, multimedia services, such as news download (e.g., breaking news), multimedia multicasting (e.g., live sport events or videos), or content distribution (e.g., device configuration files/pictures), are facing increasing popularity in daily life. Hence, how to efficiently provide those services for various users also attracts much interest. One of the potential solutions for content distribution in mobile networks is to design a cooperative content distribution architecture named collaborative mobile cloud (CMC) where the users can share some content and information cooperatively through device-to-device (D2D) or machine-to-machine (M2M) communications [14]. In addition, CMC is foreseeable to reduce the EC of mobile terminals (MTs) as well [16]. Different from the concepts of cloud computing and cloud radio access network where a centralized entity with rich computational resources executes the computing or data processing tasks instead of the MT [17], [18], CMC is formed by a number of MTs that can process data in a distributed and cooperative manner. In the CMC, the MTs can actively use two wireless interfaces: one to communicate with the BS over long-range (LR) wireless technology [such as Long-Term Evolution (LTE)] and another to cooperate with other MTs over a short-range (SR) communication link (such as wireless local area network/ad hoc) [15]. In the traditional service, each MT has to download the whole content on its own, which leads to significant EC, particularly if the LR data rate is low. In the CMC system, several MTs can form a coalition, and each MT receives parts of required information data from BS. Then, they exchange the received data with others [16]. In such a case, each MT only needs to download parts of the data, and consequently, the receiving time can be significantly reduced. Although information exchange over SR introduces new transmission overhead, the EC can still be significantly decreased as the SR is generally more efficient in terms of data rate [19].

As SWIPT enables the traditional information receiver to harvest energy from transmission signal, a CMC formed by a group of SWIPT receivers is expected to improve energy saving performance. Moreover, other than the EE benefits in the technology domain, enabling wireless power transfer also brings novel insights in the cloud formulation. It can be found that the user who is selected for data transmission may consume more energy when transmitting data. Although it can obtain energy savings in the long term, the selfish nature of the user may prevent the user from being selected. Therefore, using wireless power transfer is, indeed, one catalyst for the users to join the cloud as additional energy can be obtained from the BS. Previous work on the design of CMC mainly focused on cloud formulation or EE investigations; how to allocate the limited radio resources, such as subchannels or transmit power, lacks attention. However, as the future wireless network is orthogonal frequency-division multiple access (OFDMA) based, an efficient and practical radio resource allocation scheme is critical. Intuitively, there are two ways for delivering data between the BS and CMC. One way is that the BS can transmit different packets to different MTs in a parallel way. In this case, more channel bandwidths are needed as the BS is transmitting to different MTs with different data simultaneously. The other way is that the BS can transmit to the MTs in a sequence. For each data segment, one MT is selected as the receiver for the BS and the transmitter for other MTs. As such, channel bandwidth can be effectively utilized. In this paper, we focus on the latter case. By pushing toward resource allocation for CMC with SWIPT receivers, there are some obstacles that need more attention.

- How to schedule the proper MT to receive from the BS and transmit to other MTs is essential. As CMC is expected to be an energy-efficient content distribution system, the MTs being selected should be able to minimize the overall system energy cost.
- How to properly assign the subchannels for transmission between the BS and CMC and the transmission inside CMC should also be concentrated on. Moreover, power allocation schemes for both the BS and MTs need to be investigated so that the transmit power consumption can be minimized.
- The ID and EH functionalities of receivers make the problem even more complicated. At each scheduling time, which MT should be selected so that the harvested energy can be maximized while the receive EC can be minimized? In addition, since, eventually, a better channel condition and higher transmit power of the BS can bring more energy for harvesting, which set of subchannnels

and how much transmit power should be used so that the sum of consumed energy and harvested energy can be minimized call for contiguous consideration.

C. Contributions

Some of the previous works on designing the energy-efficient content distribution platform usually concentrated on platform formulation [19], [20], [23]. The authors in this line of work studied the group or coalition formulation problem where several groups can be formulated, and each group can select one user as the head for receiving data from the BS [19], [20]. Yaacoub *et al.* in [20] also proposed a scheduling algorithm for the LR to select proper resources to carry out the downlink transmission. It is worth noting that the considered system model can be applied to vehicular networks, as well as for data download, storage, and sharing. In the vehicular networks, the proposed roadside units are deployed to assist in data download and sharing [21], [22]. Different from other previous works, we address the user scheduling and resource allocation problem for both LR and SR other than cloud formulation for the considered system. Moreover, this work is also the first in this area, attempting to provide resource allocation solutions to wireless-power-transfer-inspired mobile cloud platforms. To utilize the channel bandwidth, during the BS data delivery process, one dedicated receiver, which is denoted as ID MT (IMT), will receive the assigned data and the other MTs, which are denoted as EH MTs (EMTs), will harvest energy from the signal. As such, the transmission of the system is in a sequence, and no extra bandwidth other than the conventional multicasting is required. After receiving from the BS, the IMT will share the data to other EMTs of the previous stage. Solving the formulated problem is challenging due to the aforementioned obstacles. To address the formulated problem, different nonlinear programming methods are applied. Initial results of this work have been published in [24], whereas in this work, we tackle challenges on this subject in a more in-depth way and provide fundamental analysis. The main contribution over previous existing works is threefold.

- We first model the EC of the overall transmission process when considering baseband circuit EC, RF transmit and receive EC, and harvested energy.
- Then, we focus on the algorithm design aspect and propose a joint power allocation, subchannel allocation, and user scheduling scheme with the objective of optimizing the EC performance of CMC with SWIPT.
- By using nonlinear fractional programming optimization techniques and iterative algorithm design, we address the formulated user scheduling and resource allocation problem. Simulation results are presented to illustrate the energy saving gain of the proposed scheme.

The rest of this paper is organized as follows. Section II describes the CMC system model. In Section III, EC models of ID and EH receivers as well as CMC are presented. In Section IV, we formulate the optimization problem and introduce a resource allocation and user scheduling solution. We demonstrate the benefits of our proposed algorithm in Section V through simulation study and, finally, conclude this work in Section VI.

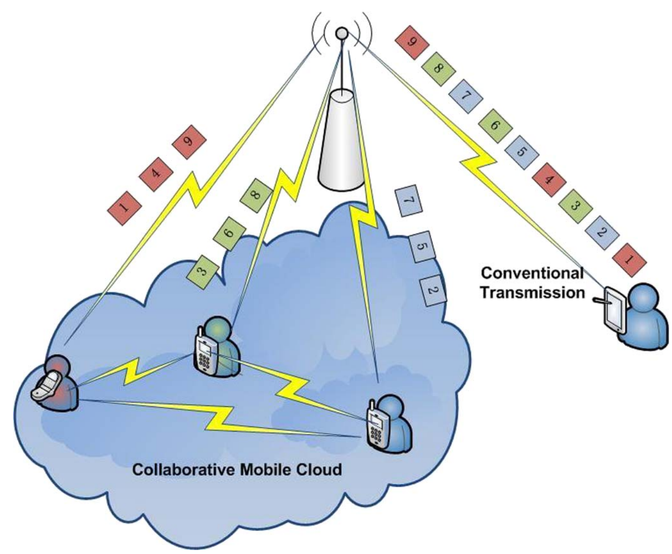


Fig. 1. Collaborative mobile cloud.

II. System Model

In our considered OFDMA system, it is assumed that K MTs located geographically close are interested in downloading the same content from a BS by using one LR wireless technology (e.g., Universal Mobile Telecommunications System/High Speed Packet Access, Worldwide Interoperability for Microwave Access, or LTE). In the CMC system, an MT first receives parts of the data and then shares them with other MTs through SR transmission via D2D/M2M connections [16]. As D2D/M2M connections are able to offer better data rate than LR, then the receive time durations of other MTs on an SR link can be reduced when receiving a certain amount of data. The MTs are able to decode information and harvest energy from the received radio signals. All transceivers are equipped with a single antenna. Moreover, we assume that the channel follows quasi-static block fading and that the channel state information (CSI) can be accurately obtained by the feedback from the receivers. Our proposed scheme can be extended to the case that the CSI cannot be perfectly obtained by the BS. While the focus will be, in turn, on examining the CSI imperfection effect, it can be also noticed that the feedback transmission from the MTs to the BS may induce additional EC. We consider that the feedback can be realized through the standard feedback mechanisms and channels. Correspondingly, the EC on feedback channels is assumed to be constant and does not bring additional influence on the presented system and schemes. Therefore, to concentrate on the radio resource allocation scheme in the downlink, in this work, we will not take into consideration the EC on the feedback, CSI delivery, or channel training frame.

The transmission process of CMC is shown in Fig. 1, comparing with the conventional transmission, e.g., unicasting/multicasting. In Fig. 1, the CMC consists of three MTs. To simply present the concept of the CMC, we divide the overall data stream into nine segments. In a conventional setup, the communication interface of an MT (e.g., standalone MT) has to remain active for the whole reception duration. This results in high EC due to the required RF and baseband processing

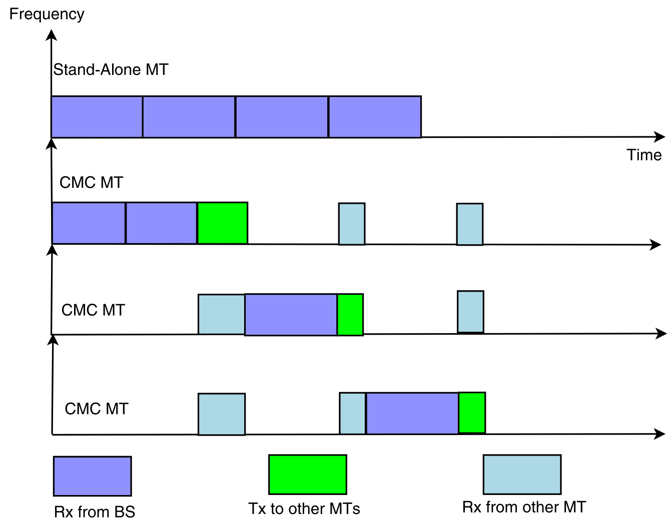


Fig. 2. Transmission procedure.

during data reception. In the CMC, the BS can distribute various and exclusive segments of data (three segments in the figure) to different MTs, and MTs can then exchange/share the received parts with other coalition members by utilizing the SR transmission among MTs. Thus, the reception duration can be seriously reduced compared with the conventional transmission given that SR has a better data rate than LR because of, e.g., its better channel condition. The time sequence of the transmission process is shown in Fig. 2, where how the transmission duration can be reduced can be found. However, to share the received data, additional communication overheads are induced, such as the transmit power of the SR transmitter and transmit/receive durations. Consequently, the inherent EE performance calls for a careful algorithm design [25].

To focus on the resource allocation algorithm design and isolate it from the specific hardware implementation details, we do not assume a particular type of EH receiver. In this paper, we focus on the receivers that consist of an EH unit and a conventional signal processing core unit for EH and ID, respectively. In addition, for the conventional signal processing, we separate receiver architecture into two parts, namely, RF unit and baseband unit. In the following section, the EC model of the considered system is presented.

III. Energy Consumption Model

A. Channel Model

We consider an OFDMA system where a BS services K mobile receivers. In particular, each receiver is able to decode information and harvest energy from the received radio signals. At first, the BS transmits data to MT k. Thus, letting x be the transmitted data from the BS, the received data on subchannel i at MT k can be modeled as

$$y_1 = \sqrt{P^{L_{\rm tx}}_{s,k,i} L_{s,k} H_{s,k,i}}\, x + z_{s,k,i} \tag{1}$$

where $P^{L_{\rm tx}}_{s,k,i}$ and $H_{s,k,i}$ are the transmit power and channel fading gain on subchannel i from the BS to MT k, respectively. $L_{s,k}$ represents the path loss from the BS to MT k. $z_{s,k,i}$ is the Gaussian additive noise with zero mean and variance σ_z^2.

After receiving from the BS, MT k is able to deliver the data to other MTs. For interdevice multicasting among MTs inside the CMC, the received signal at subchannel j can be modeled as

$$y_2 = \sqrt{P^{S_{\rm tx}}_{k,j} L_k H_{k,j}}\, x + z_{k,j} \tag{2}$$

where $P^{S_{\rm tx}}_{k,j}$ is the multicast transmit power of MT k on subchannel j, and L_k and $H_{k,j}$ are the path loss and the channel gain from k to the MT with the worst channel condition, respectively.

B. EH Receiver

In practice, the model of an EH receiver depends on its specific implementation. For example, electromagnetic induction and electromagnetic radiation are able to transfer wireless power, and the receiver is able to recycle the wireless power from radio signal [5]. Nevertheless, the associated hardware circuit in the receivers and the corresponding EH efficiency can be different. Moreover, the signal used for decoding the modulated information cannot be used for harvesting energy due to hardware limitations [7]. In this paper, we do not go into the details of any particular type of EH receiver, and the general EH receiver model is used, e.g., that in [8], [10], and [11].

We denote $P^H_{s,n,i}$ as the harvested power on subchannel i by EMT n. Then, we have [8]

$$P^H_{s,n,i} = \vartheta_n P^{L_{\rm tx}}_{s,n,i} L_{s,n} H_{s,n,i} \tag{3}$$

where we assume the conversion efficiency $0 < \vartheta_n \leq 1$.

C. ID Receiver

For the data rate on LR $R^L_{s,k,i}$, the maximum achievable data rate in bits per second per hertz from the BS to MT k on subchannel i is given as

$$R^L_{s,k,i} = \log_2\left(1 + \frac{P^{L_{\rm tx}}_{s,k,i} L_{s,k} H_{s,k,i}}{\sigma_z^2}\right). \tag{4}$$

In the CMC, the IMT k needs to multicast its received data to other CMC members such that the data rate on subchannel j of the SR link can be expressed as

$$R^S_{k,j} = \log_2\left(1 + \frac{P^{S_{\rm tx}}_{k,j} L_k H_{k,j}}{\sigma_z^2}\right) \tag{5}$$

where we also assume that the noise levels on LR and SR are of the same kind for simplicity.

D. Tx and Rx EC of CMC

As we know, the EC can be modeled as a linear function containing the power consumption and the time duration.

Therefore, the EC for receiving data size S_T from the BS can be expressed as

$$E_{s,k,i}^{L_{\rm rx}} = \left(P_{s,k,i}^{L_{\rm rx}} + P_E\right) T_{s,k,i}^{L_{\rm rx}} = \frac{\left(P_{s,k,i}^{L_{\rm rx}} + P_E\right) S_T}{R_{s,k,i}^L} = \frac{(P_{\rm rx} + P_E) S_T}{R_{s,k,i}^L} \quad (6)$$

where $P_{s,k,i}^{L_{\rm rx}}$ is the RF power consumption of k for receiving from the BS on subchannel i, and P_E is the electronic circuit power consumption of the baseband associated with transmission bandwidth. The nonlinear effect of the power amplifier is ignored. In this paper, the EC refers to that when receiving and sending data on a certain subchannel; hence, the baseband power consumption is considered together with RF Tx/Rx power consumption. $T_{s,k,i}^{L_{\rm rx}} = S_T/R_{s,k,i}^L$ is the required time for receiving data S_T on LR subchannel i. Furthermore, we can assume that the receive RF power consumption is the same for both LR and SR links and is equal to $P_{\rm rx}$. After receiving from the BS, MT k is going to transmit its received data to other required MTs. There are two conventional ways to deliver data inside the CMC, namely, unicasting and multicasting. We have discussed the EE of using both schemes in [25], where multicasting is shown to be superior in terms of EE performance over unicasting. Hence, in this work, we invoke only multicasting as the transmission strategy inside the CMC.

When multicasting is used, an IMT only needs to broadcast its data to other MTs in the CMC once with the data rate that can reach the MT with the worst channel condition. Thus, the transmit EC of the IMT is given as

$$E_{k,j}^{S_{\rm tx}} = \left(P_{k,j}^{S_{\rm tx}} + P_E\right) T_{k,j}^{S_{\rm tx}} = \frac{\left(P_{k,j}^{S_{\rm tx}} + P_E\right) S_T}{R_{k,j}^S}. \quad (7)$$

Therefore, the total EC of the CMC when using MT k as the IMT can be expressed as follows:

$$E_{k,i,j} = E_{s,k,i}^{L_{\rm rx}} + E_{k,j}^{S_{\rm tx}} + \sum_{n,n\neq k}^{K} E_{n,j}^{S_{\rm rx}}. \quad (8)$$

$E_{k,i,j}$ is the EC of IMT k when assigning subchannel i for receiving from the BS and subchannel j for broadcasting its received data. $E_{n,j}^{S_{\rm rx}}$ is the EC of each EMT when receiving from the IMT on subchannel j, and it can be expressed as

$$E_{n,j}^{S_{\rm rx}} = \left(P_{n,j}^{S_{\rm rx}} + P_E\right) T_{k,j}^{S_{\rm rx}} = \frac{\left(P_{n,j}^{S_{\rm rx}} + P_E\right) S_T}{R_{k,j}^S} = \frac{(P_{\rm rx} + P_E) S_T}{R_{k,j}^S}. \quad (9)$$

E. Energy Consumption of Base Station

The EC of the BS is given as

$$E_s^{L_{\rm tx}} = \left(P_{s,k,i}^{L_{\rm tx}} + P_B\right) T_{s,k,i}^{L_{\rm rx}} = \frac{\left(P_{s,k,i}^{L_{\rm tx}} + P_B\right) S_T}{R_{s,k,i}^L} \quad (10)$$

where P_B is the BS baseband operating power consumption.

IV. Resource Allocation and User Scheduling

A. Problem Formulation

In the previous section, we presented the EC model of the CMC with hybrid ID-EH receivers in each scheduling time slot. Here, the considered problem will be formulated as a joint optimization of subchannel allocation, power allocation, and user scheduling with the objective of minimizing the EC during each transmission time of sending data S_T.

To minimize the EC of a CMC, at first, one MT inside the CMC will be selected as the IMT, and other MTs will be considered as EH receivers. Then, the BS transmits the data to the IMT on the selected subchannel i with data rate $R_{s,k,i}^L$. Then, the IMT will act as a relay and forwards the received data to other MTs on the selected subchannel j with multicast data rate $R_{k,j}^S$. In this paper, we tackle the problem when one subchannel is used for the LR link and one is used for the SR link. However, the work can be applied to multiple-subchannel problems as well.

To this end, taking harvested energy into consideration, for each data segment transmission, we can formulate the optimization objective as

$$\mathcal{E}(\boldsymbol{\rho}, \boldsymbol{\omega}, \mathbf{P}) = \sum_{k=1}^{K}\sum_{i=1}^{N} \rho_k \omega_{s,k,i} E_s^{L_{\rm tx}} + \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} \omega_{s,k,i}\omega_{k,j}\rho_k E_{k,i,j} - \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{n,n\neq k} \omega_{s,k,i}\rho_k Q_{s,n,i} \quad (11)$$

where N is the number of available subchannels, and K is the total number of MTs inside the CMC. $\mathbf{P}$ is the power allocation policy. $\boldsymbol{\rho} = \{\rho_k\}\,\forall\, k$, and $\boldsymbol{\omega} = \{\omega_{s,k,i}, \omega_{k,j}\}\,\forall\, k,i,j$ are the user selection and subchannel allocation indicators. In this paper, there is no constraint on whether i and j can be the same since no interference will be occurred. $Q_{s,n,i}$ is the harvest energy, and obversely, $Q_{s,n,i} = P_{s,n,i}^H S_T/R_{s,k,i}^L$. Note that mathematically, $\mathcal{E}(\boldsymbol{\rho}, \boldsymbol{\omega}, \mathbf{P})$ can take the negative value. However, the case where $\mathcal{E}(\boldsymbol{\rho}, \boldsymbol{\omega}, \mathbf{P})$ is positive always holds for a practical system. The defined binary variable ρ_k is the indicator whether MT k is selected as the IMT, that is

$$\rho_k = \begin{cases} 1, & \text{if } k \text{ is chosen as IMT for receiving from BS} \\ 0, & \text{otherwise.} \end{cases} \quad (12)$$

In addition, we also define ω as the indicator whether a certain subchannel is assigned to MT k, e.g.,

$$\omega_{s,k,i} = \begin{cases} 1, & \text{if subchannel } i \text{ is used by } k \text{ for downlink} \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

$$\omega_{k,j} = \begin{cases} 1, & \text{if subchannel } j \text{ is assigned to } k \text{ to deliver data} \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

Therefore, the user selection and resource allocation optimization problem can be formulated as

$$\min_{\boldsymbol{\rho},\boldsymbol{\omega},\mathbf{P}} \mathcal{E}(\boldsymbol{\rho},\boldsymbol{\omega},\mathbf{P}) \tag{15}$$

s.t.

$$\begin{aligned}
&C1: \sum_{k=1}^{K}\rho_k = 1\\
&C2: \sum_{k=1}^{K}\omega_{s,k,i} = 1, \sum_{k=1}^{K}\omega_{k,j} = 1\\
&C3: R^{L}_{s,k,i} \geq R_{L,\min}\\
&C4: R^{S}_{k,j} \geq R_{S,\min}\\
&C5: \sum_{k=1}^{K}\sum_{i=1}^{N}\rho_k\omega_{s,k,i}P^{L_{\text{tx}}}_{s,k,i} \leq P_{s,\max}\\
&C6: \sum_{k=1}^{K}\sum_{j=1}^{N}\rho_k\omega_{k,j}P^{S_{\text{tx}}}_{k,j} \leq P_{k,\max}.
\end{aligned} \tag{16}$$

Here, the optimization problem (15) is formulated with several constraints. The first constraint C1 is to ensure that only one user is selected for receiving data from the BS in a scheduled slot. C2 ensures that the subchannels allocated to MT k are unique. $R_{L,\min}$ in C3 and $R_{S,\min}$ in C4 are the required data rates for LR and SR, respectively. C5 and C6 ensure that the power allocation of the BS and the IMT should not be higher than the maximum allowed transmit power.

It is worth noting that (15) with (16) is combinatorial in nature with a nonconvex structure. In general, there is no standard approach for solving such nonconvex optimization problems, and such integer programming problem is recognized as NP-hard. In the extreme case, an exhaustive search or branch-and-bound method is needed to obtain the global optimal solution that requires high computational complexity even for small K and N. To make the problem tractable, we transform the objective function and approximate the transformed objective function to simplify the problem.

B. Power and Subchannel Allocation Scheme

Theorem 1: The objective function (15) is a quasi-convex function w.r.t. to the power allocation variables $P^{L_{\text{tx}}}_{s,k,i}$ and $P^{S_{\text{tx}}}_{k,j}$, respectively.

The proof of **Theorem 1** can be found in Appendix A. Thus, as a result, the unique global optimal solutions for $P^{L_{\text{tx}}}_{s,k,i}$ and $P^{S_{\text{tx}}}_{k,j}$ exist, and the optimal point can be obtained by using the bisection method [26]. We can also apply the nonlinear fractional programming method to solve the formulated problem [27] of power allocation and subchannel allocation in the following.

1) Problem Transformation: First, given that the user scheduling is done, i.e., $\rho_k = 1$, we can reform the objective function $\mathcal{E}(\boldsymbol{\rho},\boldsymbol{\omega},\mathbf{P})$ as a function of $\{\boldsymbol{\omega},\mathbf{P}\}$. Substituting (3), (8), and (10) into (11), we can arrive at (17), shown at bottom of the page, where $P_c = P_B + P_{\text{rx}} + P_E$. One may notice that obtaining the power allocation policy involves solving $\mathcal{E}(\boldsymbol{\omega},\mathbf{P})$, which can be expressed as

$$\mathcal{E}(\boldsymbol{\omega},\mathbf{P}) = \mathcal{E}_{\text{LR}}\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right) + \mathcal{E}_{\text{SR}}\left(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j}\right) \tag{18}$$

where $\mathcal{E}_{\text{LR}}(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}) = U_1(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i})/R_1(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i})$, and $\mathcal{E}_{\text{SR}}(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j}) = U_2(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j})/R_2(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j})$. From (18), one can observe that the power allocation schemes for the BS and the scheduled MT are separated. In other words, we can obtain optimal power allocation by addressing $\mathcal{E}_{\text{LR}}(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i})$ and $\mathcal{E}_{\text{SR}}(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j})$ individually when user scheduling is done. We can see that both $\mathcal{E}_{\text{LR}}(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i})$ and $\mathcal{E}_{\text{SR}}(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j})$ are quasi-convex functions w.r.t. power allocation variables. For the sake of presentation simplicity, we introduce a method for solving $\mathcal{E}_{\text{LR}}(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i})$, which is derived from nonlinear fractional programming [27].

The global optimal solution q^*_{LR} can be expressed as

$$q^*_{\text{LR}} = \mathcal{E}_{\text{LR}}\left(\omega^*_{s,k,i}, P^{L*}_{s,k,i}\right) = \min_{\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}} \frac{U_1\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right)}{R_1\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right)}. \tag{19}$$

Theorem 2: The optimal solution q^*_{LR} can be obtained if and only if

$$\min_{\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}} U_1\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right) - q^*_{\text{LR}} R_1\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right) = 0. \tag{20}$$

Theorem 2 gives a necessary and sufficient condition w.r.t. optimal power allocation. The proof can be found in Appendix B. Particularly, for the considered optimization problem with an

$$\mathcal{E}(\boldsymbol{\omega},\mathbf{P}) = \frac{\overbrace{S_T\left(\sum_{i=1}^{N}\omega_{s,k,i}P^{L_{\text{tx}}}_{s,k,i} + P_c - \sum_{i=1}^{N}\sum_{n,n\neq k}\omega_{s,k,i}\vartheta_n P^{L_{\text{tx}}}_{s,k,i}L_{s,n}H_{s,n,i}\right)}^{U_1\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right)}}{\underbrace{\sum_{i=1}^{N}\omega_{s,k,i}R^{L}_{s,k,i}}_{R_1\left(\omega_{s,k,i}, P^{L_{\text{tx}}}_{s,k,i}\right)}} + \frac{\overbrace{S_T\sum_{j=1}^{N}\omega_{k,j}\left(P^{S_{\text{tx}}}_{k,j} + (K-1)P_{\text{rx}} + KP_E\right)}^{U_2\left(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j}\right)}}{\underbrace{\sum_{j=1}^{N}\omega_{k,j}R^{S}_{k,j}}_{R_2\left(\omega_{k,j}, P^{S_{\text{tx}}}_{k,j}\right)}} \tag{17}$$

objective function in fractional form, there exists an equivalent optimization problem with an objective function in subtractive form, i.e., $U_1(\omega_{s,k,i}, P^{L_{\rm tx}}_{s,k,i}) - q^*_{\rm LR} R_1(\omega_{s,k,i}, P^{L_{\rm tx}}_{s,k,i})$, and both formulations result in the same power allocations. To achieve the optimal $q^*_{\rm LR}$, the iterative algorithm with guaranteed convergence in [27] can be applied. The proof is given in Appendix C, and the iterative algorithm is given in Algorithm 1.

Algorithm 1 Iterative Algorithm for Obtaining $q^*_{\rm LR}$

1: Set maximum tolerance δ;
2: **while** (!Convergence) **do**
3: Solve the problem (21) for a given $q_{\rm LR}$ and obtain subchannel and power allocation $\{\boldsymbol{\omega}', \boldsymbol{P}'\}$;
4: **if** $U_1(\boldsymbol{\omega}', \boldsymbol{P}') - q_{\rm LR} R_1(\boldsymbol{\omega}', \boldsymbol{P}') \leq \delta$ **then**
5: Convergence = true;
6: **return** $\{\boldsymbol{\omega}^*, \boldsymbol{P}^*\} = \{\boldsymbol{\omega}', \boldsymbol{P}'\}$ and obtain $q^*_{\rm LR}$ by (19);
7: **else**
8: Convergence = false;
9: **return** Obtain $q_{\rm LR} = U_1(\boldsymbol{\omega}', \boldsymbol{P}')/R_1(\boldsymbol{\omega}', \boldsymbol{P}')$;
10: **end if**
11: **end while**

During the iteration, to achieve $q^*_{\rm LR}$, we need to address the following problem with $q_{\rm LR}$:

$$\min_{\omega_{s,k,i}, P^{L_{\rm tx}}_{s,k,i}} U_1\left(\omega_{s,k,i}, P^{L_{\rm tx}}_{s,k,i}\right) - q_{\rm LR} R_1\left(\omega_{s,k,i}, P^{L_{\rm tx}}_{s,k,i}\right) \quad (21)$$

s.t.

$$\sum_{k=1}^{K} \omega_{s,k,i} = 1$$
$$R^L_{s,k,i} \geq R_{L,\min}$$
$$\sum_{i=1}^{N} \omega_{s,k,i} P^{L_{\rm tx}}_{s,k,i} \leq P_{s,\max}. \quad (22)$$

Basically, such a problem is a nonconvex optimization problem due to the involved integer programming. Tackling the mix convex and combinatorial optimization problem requires prohibitively high complexity w.r.t. K and N. Another solution that can balance computational complexity and optimality can be obtained when addressing such problem in the dual domain. For the formulated optimization problem, as the convexity does not hold (e.g., mixed integer programming), addressing it in the dual domain may result in a duality gap between the primal and dual problem. As discussed and proved in [28], in the considered multicarrier systems, the duality gap of such a nonconvex resource allocation problem that satisfies the time-sharing condition is negligible, as the number of subcarriers becomes sufficiently large, e.g., 64. To address the problem, we relax $\omega_{s,k,i}$ to be [0, 1] instead of a Boolean. Then, $\omega_{s,k,i}$ can be interpreted as a time-sharing factor for utilizing the subchannel. As one can see, the optimization problem obviously is able to satisfy the time-sharing condition, it can be solved by using the dual method, and the solution is asymptotically optimal [28]. The same procedure can be used for achieving $\omega^*_{k,j}$ and $P^{S_{\rm tx}*}_{k,j}$.

2) Dual-Problem Formulation and Decomposition: Here, we solve the resource allocation optimization problem of an LR link by solving its dual for a given value of $q_{\rm LR}$. Given that the subchannel allocation is done, the Lagrangian function of the primal problem (21) can be given as

$$\mathcal{L}(\mathbf{P}, \mu, \theta) = U_1\left(P^{L_{\rm tx}}_{s,k,i}\right) - q_{\rm LR} R_1\left(P^{L_{\rm tx}}_{s,k,i}\right) - \mu\left(R^L_{s,k,i} - R_{L,\min}\right) - \theta\left(P_{s,\max} - P^{L_{\rm tx}}_{s,k,i}\right) \quad (23)$$

where μ, θ are the Lagrange multipliers associated with different constraints. Therefore, the dual problem is

$$\max_{\mu,\theta} \min_{\mathbf{P}} \mathcal{L}(\mathbf{P}, \mu, \theta). \quad (24)$$

By using Lagrange dual decomposition, the dual problem (24) can be decomposed into two layers, i.e., minimization of (23), which is the inner problem, and maximization of (24), which is the outer problem. The dual problem can be solved by addressing both problems iteratively, where, in each iteration, the optimal power allocation and subchannel allocation can be obtained by using the Karush–Kuhn–Tucker (KKT) conditions for a fixed set of Lagrange multipliers, and the outer problem is solved using the (sub)gradient method [29].

Using convex optimization techniques and applying the KKT conditions, the closed-form optimal power allocation on subcarrier i for user k for a given $q_{\rm LR}$ can be obtained as

$$P^{L_{\rm tx}*}_{s,k,i} = \left[\frac{q_{\rm LR} + \mu}{ln2\Omega_n} - \frac{1}{\Gamma_n}\right]^+ \quad (25)$$

where $\Omega_n = S_T(1 - \sum_{n\neq k}^{K} \vartheta_n L_{s,n} H_{s,n,i}) - \mu$, and $\Gamma_n = (L_{s,n} H_{s,n,i})/\sigma_z$. Meanwhile, to obtain the optimal subchannel allocation $\omega^*_{s,k,i}$, we take the derivative of the subproblem w.r.t. $\omega_{s,k,i}$, which yields

$$\Theta_i = \frac{\partial \mathcal{L}(\boldsymbol{\omega}, \mu, \theta)}{\partial \omega_{s,k,i}} = \Psi \quad (26)$$

where

$$\Psi = S_T\left(P^{L_{\rm tx}}_{s,k,i} + P_{\rm rx} + P_E - \sum_{n\neq k} \vartheta_k P^{L_{\rm tx}}_{s,k,i} L_{s,n} H_{s,n,i}\right) - (q_{\rm LR} + \mu) + \left(1 + \log_2\left(1 + \frac{P^{L_{\rm tx}}_{s,k,i} L_{s,k} H_{s,k,i}}{\sigma_z^2}\right) - \frac{P^{L_{\rm tx}}_{s,k,i} L_{s,k} H_{s,k,i}/\ln 2\sigma_z^2}{1 + P^{L_{\rm tx}}_{s,k,i} L_{s,k} H_{s,k,i}/\sigma_z^2}\right). \quad (27)$$

Thus, the subchannel allocation is given by

$$\omega^*_{s,k,i} = \begin{cases} 1, & \text{if } i = \arg\max_d \Theta_d \\ 0, & \text{otherwise.} \end{cases} \quad (28)$$

Moreover, the subgradient method with guaranteed convergence can be used to address the Lagrange multiplier, which leads to [30]

$$\mu^{l+1} = \mu^l + \epsilon_\mu \left(R_{L,\min} - R^L_{s,k,i}\right) \tag{29}$$

$$\theta^{l+1} = \mu^l + \epsilon_\theta \left(P^{L_{\rm tx}}_{s,k,i} - P_{s,\max}\right) \tag{30}$$

where θ^{l+1} and μ^{l+1} are the values of θ and μ at $l+1$ iterations. ϵ_θ and ϵ_μ are the corresponding step sizes. Since problem (21) is a convex optimization problem, it is guaranteed that the iteration between the outer and inner problems converges to the primal optimal solution of (21).

To summarize the iterative algorithm between inner and master problems, the multiplier updates can be interpreted as the pricing adjustment [31]. Particularly, if the demand of the radio resources exceeds the supply, then the gradient method will raise the prices via adjusting the Lagrange multipliers in the next iteration; otherwise, it will reduce the shadow prices until it is not out of limits. By combining the gradient updates and the subchannel allocation criterion, only one subchannel is eventually selected, although time sharing is considered for solving the transformed problem in (21). The details of the subchannel and power allocation algorithm are presented in Algorithm 2.

Algorithm 2 Subchannel and Power Allocation

1: Initialize $q_{\rm LR}, P^{L_{\rm tx}}_{s,k,i}$ and dual variables;
2: **while** (!Convergence) **do**
3: Solve the problem (28) for a given $q_{\rm LR}$ and obtain subchannel allocation;
4: Solve the problem (25) and obtain power allocation;
5: Update dual variables according to (29) and (30);
6: **end while**
7: **return** Obtain subchannel and power allocation policies.

We have presented the scheme on how to address the minimization of $\mathcal{E}_{\rm LR}(\omega_{s,k,i}, P^{L_{\rm tx}}_{s,k,i})$. The same procedure can be applied to obtain the optimal solution of minimizing $\mathcal{E}_{\rm SR}(\omega_{k,j}, P^{S_{\rm tx}}_{k,j})$. Then, we are able to obtain the solution set of (15) when considering optimal k is selected.

C. User Scheduling Scheme

For the user scheduling problem, the goal is to select one MT to act as the IMT when the BS is transmitting a data segment and as the data transmitter when delivering data to other MTs after receiving from the BS. Therefore, with the assumption that subchannel and power allocations have been done, we are aiming at finding an MT that can achieve the best EE performance considering both LR and SR links. When subchannel and power allocations are done, the objective function (15) can be reformed as

$$\min \mathcal{E}(\boldsymbol{\rho}) = \frac{U_1(\boldsymbol{\rho})}{R_1(\boldsymbol{\rho})} + \frac{U_2(\boldsymbol{\rho})}{R_2(\boldsymbol{\rho})} \tag{31}$$

where

$$U_1(\boldsymbol{\rho}) = \sum_{k=1}^{K} \rho_k S_T \Bigg(P^{L_{\rm tx}}_{s,k,i} + P_B + P_{\rm rx} + P_E - \sum_{n,n\neq k} \vartheta_n P^{L_{\rm tx}}_{s,k,i} L_{s,n} H_{s,n,i} \Bigg) \tag{32}$$

$$U_2(\boldsymbol{\rho}) = \sum_{k=1}^{K} \rho_k S_T \left(P^{S_{\rm tx}}_{k,j} + P_{\rm rx} + 2P_E \right) \tag{33}$$

$$R_1(\boldsymbol{\rho}) = \sum_{k=1}^{K} \rho_k R^L_{s,k,i} \tag{34}$$

$$R_2(\boldsymbol{\rho}) = \sum_{k=1}^{K} \rho_k R^S_{k,j}. \tag{35}$$

The reformed problem (31) also subjects to constraints in (16). Consequently, we can obtain the user scheduling criteria as

$$\rho^*_k = \begin{cases} 1, & \text{if } k = \arg\min_a \Phi_a \\ 0, & \text{otherwise} \end{cases} \tag{36}$$

where

$$\Phi_a = \frac{U_1(\rho_a)}{R_1(\rho_a)} + \frac{U_2(\rho_a)}{R_2(\rho_a)}. \tag{37}$$

D. Solution Description

The proposed solution involves two subproblems, namely, resource (subchannel and power) allocation and user scheduling, and they are hierarchically interconnected. Convergence is guaranteed since in the sublayer, the two transferred problems are linear for the user scheduling indicator and convex for the resource allocation indicator, respectively. The solution is illustrated in Algorithm 3.

Algorithm 3 Solution Description

1: Initialize $q_{\rm LR}, q_{\rm SR}, \boldsymbol{\rho}$ and small positive real number δ;
2: **while** (!Convergence) **do**
3: Update dual variables according to (29) and (30);
4: Obtain subchannel and power allocation policies $\{\boldsymbol{\omega}', \boldsymbol{P}'\}$ according to Algorithm 2 for a given $q_{\rm LR}, q_{\rm SR}$ and $\boldsymbol{\rho}$;
5: Update the $\boldsymbol{\rho}$;
6: **if** $U_{1/2}(\boldsymbol{\omega}', \boldsymbol{P}') - q_{\rm LR/SR} R_{1/2}(\boldsymbol{\omega}', \boldsymbol{P}') \le \delta$ **then**
7: Convergence = true;
8: **return** $\{\boldsymbol{\omega}^*, \boldsymbol{P}^*\} = \{\boldsymbol{\omega}', \boldsymbol{P}'\}$ and obtain $q^*_{\rm LR}$ and $q^*_{\rm SR}$;
9: **else**
10: Convergence = false;
11: **return** Obtain $q_{\rm LR/SR} = U_{1/2}(\boldsymbol{\omega}', \boldsymbol{P}')/R_{1/2}(\boldsymbol{\omega}', \boldsymbol{P}')$;
12: **end if**
13: **end while**
14: **return** Obtain user scheduling and resource allocation solutions.

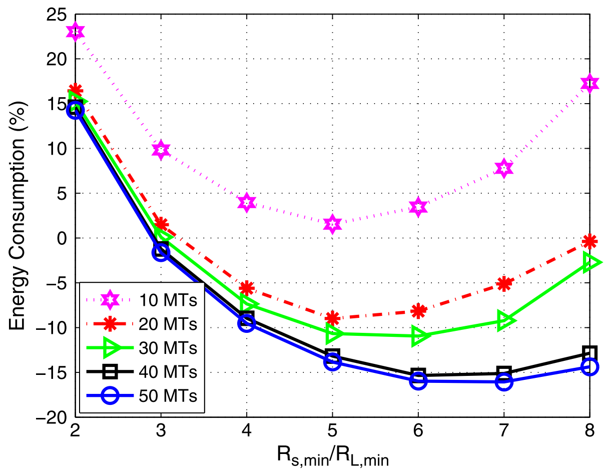


Fig. 3. User EC of CMC.

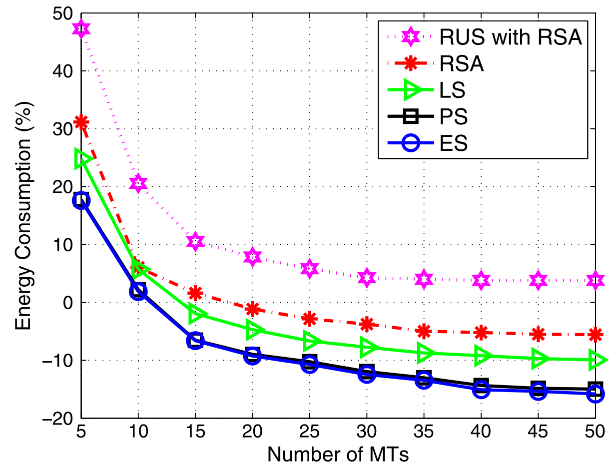


Fig. 4. User EC with EH.

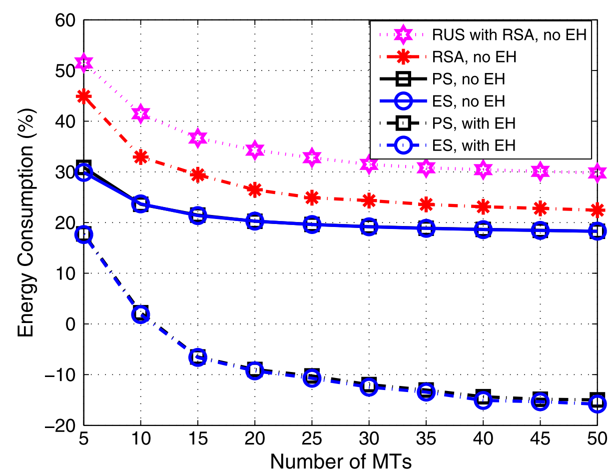


Fig. 5. User EC with/without EH.

V. Simulation Results

A. Simulation Setting

We present the performance evaluation in this section. For the LR transmission link, the Stanford University SUI-3 channel model is used and modified to include multipath effects [32] with a central frequency of 2 GHz. We use the 3-tap channel, and signal fading follows a Rician distribution. We choose the number of subchannels N to be 64; hence, the duality gap can be ignored [28]. Flat quasi-static fading channels are adopted; hence, the channel coefficients are assumed to be constant during a complete data transmission and can vary from one to another independently. For the SR transmission link, the path loss follows the IEEE 802.11ac standards with 5-GHz central frequency. We consider that the frequency bandwidths on both LR and SR are equal; hence, no extra frequency band is needed. The noise variance is assumed 1 for simplicity. Although the baseband power values P_E and P_B are not constant in general and their values depend on the features of circuit design, it is out of the scope of this work, and we assume they are fixed according to [16]. The conversion efficiency is assumed as $\vartheta_k = 0.5\ \forall\, k$ for simplicity. To illustrate the energy saving performance, we compare our resource allocation scheme with pure multicast transmission, that is, the reference EC is that when the BS uses multicast to deliver all data to every MT as the "conventional transmission," as shown in Fig. 1. In the user location setup, we consider that the BS is about 500 m from MTs and that MTs are randomly located in a 50 × 50 m^2 square.

B. Performance Evaluation

In the following figures, the EC performance of the proposed scheme is examined. First, the energy saving performance of CMC is examined in Fig. 3, where only the EC of MTs is shown. For each scheduling interval, the EC ratio is obtained by normalizing the presented system with a conventional multicasting scheme, i.e.,

$$\mathrm{EC} = \frac{E_{k,i,j} - \sum_{n,n\neq k}^{K} Q_{s,n,i}}{\sum_{k}^{K} E_{s,k,i}^{L_{\mathrm{rx}}}} \times 100\%. \tag{38}$$

In Fig. 3, we fix the $R_{L,\min} = 1$ b/s/Hz and vary the value of $R_{S,\min}$ to illustrate the energy saving benefits of CMC and the effectiveness of advocating the SR for CMC. It can be observed that, at first, when $R_{S,\min}$ increases, the EC of CMC is decreased because the time durations for transmitting and receiving are reduced, and as a result, so is the consumed energy. Since a higher data rate requires higher transmit power consumption, at a certain level, the EC is increased. For example, for the case that there are ten MTs inside the CMC, the best option for obtaining maximized energy saving is $R_{S,\min}/R_{L,\min} = 5$. The negative value on the y-axis in Fig. 3 implies that the harvested energy at MTs is higher than the consumed energy, which means that the SWIPT is appreciated for the MTs facing EC problems. Moreover, one can find that the CMC consisting of more MTs can improve the energy saving potential.

In Figs. 4 and 5, we assume $R_{S,\min}/R_{L,\min} = 5$ and present the EC performance of all MTs in a CMC to show the effectiveness of the proposed scheme (PS) for the CMC. We compare our PS with the following reference benchmarks:

- the simulation results when random subchannel allocation (RSA) is used instead of the proposed one;

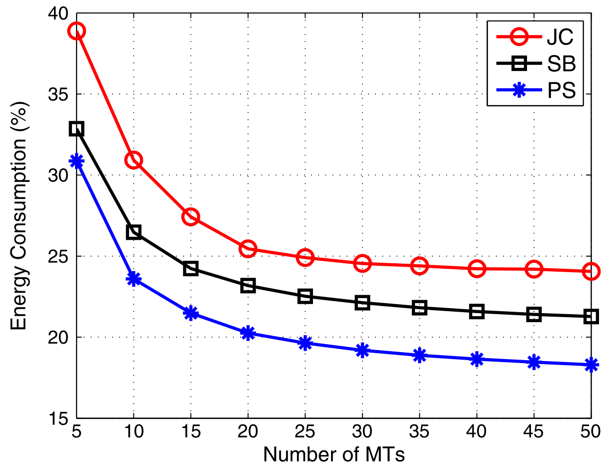


Fig. 6. Comparison of user EC performance.

- the simulation results when the random user scheduling (RUS) together with RSA is also considered;
- the results obtained by exhaustive searching of IMT and subchannels.

To see the wireless power transfer impact, we plot the performance of using SWIPT in Fig. 4. Moreover, to illustrate the impact of the time-sharing conditions on addressing the formulated problem, we present the performance when assuming the number of subchannels N to be 8 (LS) in Fig. 4. In addition, the comparison of the performance with SWIPT and without SWIPT is shown in Fig. 5. In general, we can see that the CMC is able to reduce the EC in both cases. The energy saving is at least 50%. Even for the cases without EH, the energy saving for the MTs can be up to 80%. When the MTs are able to harvest energy from the RF signal, the EC performance is improved further. We can also observe that when $N = 8$, the system performance is worse than the proposed one, which also confirms that the time-sharing condition is important for addressing the formulated problem [28]. In Fig. 5, one can see that enabling wireless power transfer is able to improve the EC performance up to 30%, which evidences the significance of the SWIPT technique. In Fig. 6, we compare our proposed scheme with the algorithms presented in [33] and [34]. We refer to that in [33] as "JC," where a user selection scheme is proposed with the joint consideration of user's energy, LR data rate, distance to other users, and mobility. The select best was modified from that proposed in [34], of which the target is to select the user with the best channel condition to the BS. In Fig. 6, it can be found that the proposed scheme has superior energy saving performance over the others and that the JC algorithm has the worst energy saving gain because the proposed user selection algorithm focuses more on the energy saving criteria, and the proposed resource allocation scheme can further improve the system performance. To summarize the observations, Figs. 4 and 5 demonstrate that:

- the use of CMC is able to reach a promising energy saving gain when comparing with traditional multicasting transmission;
- the PS has supervisor performance over RSA, which induces that carefully designing the resource allocation scheme for CMC is necessary;

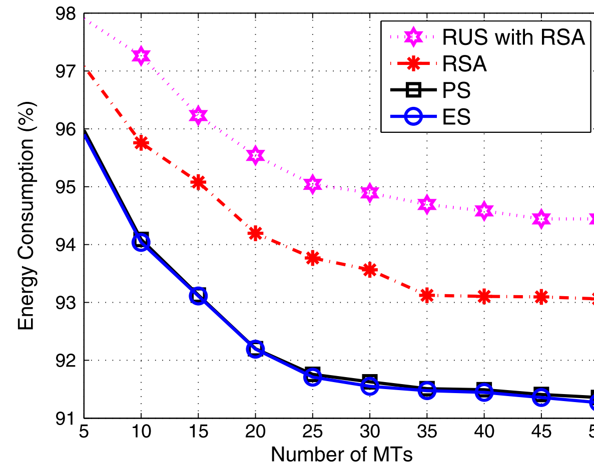


Fig. 7. System EC with both BS and user EC.

- by recycling energy from RF signal, the EC performance can be improved; and
- the performance of our proposed scheme is very close to the optimal one.

In Fig. 7, the EC of the overall system, including both BS and MTs, is presented. We compare the system performance of PS with that of RSA and that of RUS and RSA. The EC ratio is obtained by the EC of the proposed scheme normalized by that when multicasting is invoked, i.e.,

$$\mathrm{EC} = \frac{E_s^{L_{\mathrm{tx}}} + E_{k,i,j} - \sum_{n,n\neq k}^{K} Q_{s,n,i}}{\sum_k^K E_{s,k,i}^{L_{\mathrm{rx}}} + E_{s,\mathrm{tra}}^{L_{\mathrm{tx}}}} \times 100\% \tag{39}$$

where $E_{s,\mathrm{tra}}^{L_{\mathrm{tx}}}$ is the traditional multicasting transmit EC for a single data segment. When jointly considering the EC of the BS and MTs, the energy saving is up to 9% compared with multicasting transmission. This is mainly due to the fact that energy saving of the BS is fairly lower than that of MTs and the EC of the BS dominates in the overall system EC. Thus, the proposed scheme has less impact on the EC performance of the BS.

VI. Conclusion

In this paper, we have investigated the problem of resource allocation and user scheduling for OFDMA networks with CMCs. By assuming that the mobile cloud contains numbers of hybrid ID and EH user equipment devices, we proposed an algorithm that can noticeably obtain EE performance. The joint optimization problem was solved by addressing two subproblems, including opportunistic selection of the ID receiver and subchannel and power allocations with the objective of minimizing the EC. Simulation results illustrated the performance gains of the proposed resource allocation and user scheduling schemes compared with the other baseline schemes, which unveiled the potential gain of using wireless power transfer for the MTs. The presented results demonstrate the following: 1) The CMC system is able to reduce the EC of the system, particularly at the MT side during the receiving process; 2) the proposed resource allocation and user scheduling algorithms are able to reduce the total transmit EC and improve the EE performance;

3) the wireless power transfer is able to further improve the energy saving performance of MTs. Therefore, properly invoking the wireless power transfer provides a promising solution for future EC problems.

As one future direction, the work could be extended to the cloud formulation problem whereby resource allocation and multiple-CMC formulation can be jointly studied. Another extension of this work is to investigate the trade-off between EE and user fairness in the future since user fairness is also an important factor in the user cooperation schemes. Social and user fairness factors will be considered when allocating the radio resource and scheduling users for data assignment so that fairness among the CMCs is guaranteed.

Appendix A
Proof of Theorem 1

Recall the EC model, i.e.,

$$\begin{cases} E_s^{L_{\text{tx}}} = \frac{(P_{s,k,i}^{L_{\text{tx}}}+P_B)S_T}{R_{s,k,i}^L} \\ E_{k,i,j} = \frac{(P_{\text{rx}}+P_E)S_T}{R_{s,k,i}^L} + \frac{(P_{k,j}^{S_{\text{tx}}}+P_E)S_T}{R_{k,j}^S} + \frac{(P_{\text{rx}}+P_E)S_T}{R_{k,j}^S} \\ Q_{s,n,i} = \frac{\vartheta_n P_{s,k,i}^{L_{\text{tx}}} L_{s,n} H_{s,n,i} S_T}{R_{s,k,i}^L}. \end{cases} \tag{40}$$

To facilitate the following analysis, we assume that subchannels i and j are allocated to scheduled MT k optimally for the transmission process, i.e., $\rho_k = \omega_{s,k,i} = \omega_{k,j} = 1$. Substituting (40) into (11), we can arrive at the following equation:

$$\begin{aligned} \mathcal{E}(\mathbf{P}) &= \frac{\left(P_{s,k,i}^{L_{\text{tx}}} + P_B\right) S_T}{R_{s,k,i}^L} + \frac{(P_{\text{rx}} + P_E)S_T}{R_{s,k,i}^L} \\ &\quad + \frac{\left(P_{k,j}^{S_{\text{tx}}} + P_E\right) S_T}{R_{k,j}^S} \frac{(P_{\text{rx}} + P_E)S_T}{R_{k,j}^S} \\ &\quad - \frac{\sum_{n,n\neq k} \vartheta_n P_{s,k,i}^{L_{\text{tx}}} L_{s,n} H_{s,n,i} S_T}{R_{s,k,i}^L} \\ &= \frac{P_{s,k,i}^{L_{\text{tx}}} - \sum_{n,n\neq k} \vartheta_n P_{s,k,i}^{L_{\text{tx}}} L_{s,n} H_{s,n,i} + C_1}{R_{s,k,i}^L} \\ &\quad + \frac{\left(P_{k,j}^{S_{\text{tx}}} + C_2\right)}{R_{k,j}^S} \end{aligned} \tag{41}$$

where $C_1 = P_B + P_{\text{rx}} + P_E$ and $C_2 = P_{\text{rx}} + 2P_E$ are constant for the considered model [16]. For the sake of simplicity, we use $S_T = 1$. Note that the power allocation policy $\mathbf{P}$ is $\mathbf{P} = \{P_{s,k,i}^{L_{\text{tx}}}, P_{k,j}^{S_{\text{tx}}}\}$. We can see that $R_{s,k,i}^L$ and $R_{k,j}^S$ are concave functions w.r.t. to the power allocation $P_{s,k,i}^{L_{\text{tx}}}$ and $P_{k,j}^{S_{\text{tx}}}$, respectively. Thus, the objective function is strictly a quasi-convex function w.r.t. $P_{s,k,i}^{L_{\text{tx}}}$ and $P_{k,j}^{S_{\text{tx}}}$, respectively [26]. Furthermore, we can prove that the objective function is first monotonically nonincrease and then monotonically nondecrease. The proof can be easily obtained by $(\partial\mathcal{E}(\mathbf{P})/\partial\mathbf{P})|_{\mathbf{P}\to 0} \leq 0$ and $(\partial\mathcal{E}(\mathbf{P})/\partial\mathbf{P})|_{\mathbf{P}\to\infty} > 0$.

Appendix B
Proof of Theorem 2

Similar to the previous proof, we assume that subchannels i and j are allocated to scheduled MT k optimally for the transmission process, i.e., $\rho_k = \omega_{s,k,i} = \omega_{k,j} = 1$. Suppose $\mathcal{P}$ is the solution set and let P_0 be a solution of (19), then we have

$$q_0 = \frac{U_1(P_0)}{R_1(P_0)} \leq \frac{U_1(P)}{R_1(P)} \;\forall\, P \in \mathcal{P}. \tag{42}$$

Consequently, we can arrive at the following equation:

$$U_1(P) - q_0 R_1(P) \geq 0 \;\forall\; P \in \mathcal{P} \tag{43}$$

$$U_1(P_0) - q_0 R_1(P_0) = 0 \;\forall\, P \in \mathcal{P}. \tag{44}$$

From (43), we see that $\min\{U_1(P) - q_0 R_1(P) | P \in \mathcal{P}\} = 0$. From (44), we observe that the minimum value is taken when $P = P_0$. Therefore, the necessary condition can be proved.

To prove the sufficient condition, let P_0 be a solution of (20), then we have

$$U_1(P) - q_0 R_1(P) \geq U_1(P_0) - q_0 R_1^L(P_0) = 0 \;\forall\, P \in \mathcal{P}. \tag{45}$$

Hence

$$U_1(P) - q_0 R_1^L(P) \geq 0 \;\forall\, P \in \mathcal{P} \tag{46}$$

$$U_1(P_0) - q_0 R_1^L(P_0) = 0 \;\forall\, P \in \mathcal{P}. \tag{47}$$

From (46), we have $U_1(P)/R_1^L(P) \geq q_0$, where q_0 is the minimum of (19). From (47), we have $U_1(P_0)/R_1^L(P_0) = q_0$, where P_0 is a solution of (19).

Appendix C
Proof of Convergence of Algorithm 1

A similar procedure, as shown in [27], can be applied to prove the convergence of Algorithm 1. For simplicity, assuming that

$$f(q') = \min_{\boldsymbol{\omega},\boldsymbol{P}} U_1(\boldsymbol{\omega},\boldsymbol{P}) - q' R_1(\boldsymbol{\omega},\boldsymbol{P}) \tag{48}$$

where $\boldsymbol{\omega} = \{\omega_{s,k,i}\}$, and $\boldsymbol{P} = \{P_{s,k,i}^{L_{\text{tx}}}\}$. Then, assuming $q^{\backprime} > q'$ and considering two optimal resource allocation policies, $\{\boldsymbol{\omega}^{\backprime}, \boldsymbol{P}^{\backprime}\}$ and $\{\boldsymbol{\omega}', \boldsymbol{P}'\}$ for $f(q^{\backprime})$ and $f(q')$, respectively, we have

$$\begin{aligned} f(q^{\backprime}) &= \min_{\boldsymbol{\omega},\boldsymbol{P}} U_1(\boldsymbol{\omega},\boldsymbol{P}) - q^{\backprime} R_1(\boldsymbol{\omega},\boldsymbol{P}) \\ &= U_1(\boldsymbol{\omega}^{\backprime},\boldsymbol{P}^{\backprime}) - q^{\backprime} R_1(\boldsymbol{\omega}^{\backprime},\boldsymbol{P}^{\backprime}) \\ &< U_1(\boldsymbol{\omega}',\boldsymbol{P}') - q^{\backprime} R_1(\boldsymbol{\omega}',\boldsymbol{P}') \\ &\leq U_1(\boldsymbol{\omega}',\boldsymbol{P}') - q' R_1(\boldsymbol{\omega}',\boldsymbol{P}') \\ &= f(q'). \end{aligned} \tag{49}$$

Therefore, we can see that $f(q)$ is a strong monotonically decreasing function, i.e., $f(q^{\backprime}) < f(q')$, if $q^{\backprime} > q'$. Suppose

$\{\boldsymbol{\omega}^l, \boldsymbol{P}^l\}$ is the optimal resource allocation policies in the lth iteration and $q^l \neq q^*$ and $q^{l+1} \neq q^*$. We can observe that $q^l > 0$ and $q^{l+1} > 0$. Since in Algorithm 1, we obtain $q^{l+1} = U_1(\boldsymbol{\omega}^l, \boldsymbol{P}^l)/R_1(\boldsymbol{\omega}^l, \boldsymbol{P}^l)$. Thus, one can arrive at the following equation:

$$\begin{aligned} f(q^l) &= U_1(\boldsymbol{\omega}^l, \boldsymbol{P}^l) - q^l R_1(\boldsymbol{\omega}^l, \boldsymbol{P}^l) \\ &= R_1(\boldsymbol{\omega}^l, \boldsymbol{P}^n)(q^{l+1} - q^l). \end{aligned} \tag{50}$$

As $f(q^l) > 0$ and $R_1(\boldsymbol{\omega}^l, \boldsymbol{P}^l)$, we have $q^{l+1} > q^l$. Therefore, we can see that as long as the number of iterations is large enough, $F(q^l) \to 0$ and $F(q^l)$ satisfy the optimality condition as presented in **Theorem 2**. To this end, the convergence of Algorithm 1 can be proved.

REFERENCES

[1] J. Yang and S. Ulukus, "Optimal packet scheduling in an energy harvesting communication system," *IEEE Trans. Commun.*, vol. 60, no. 1, pp. 220–230, Jan. 2012.

[2] C. K. Ho and R. Zhang, "Optimal energy allocation for wireless communications with energy harvesting constraints," *IEEE Trans. Signal Proc.*, vol. 60, no. 9, pp. 4808–4818, Sep. 2012.

[3] J. Gong, S. Zhou, and Z. Niu, "Optimal power allocation for energy harvesting and power grid coexisting wireless communication systems," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 3040–3049, Jul. 2013.

[4] L. R. Varshney, "Transporting information and energy simultaneously," in *Proc. IEEE ISIT*, Toronto, ON, Canada, Jul. 2008, pp. 1612–1616.

[5] P. Grover and A. Sahai, "Shannon meets tesla: Wireless information and power transfer," in *Proc. IEEE ISIT*, Austin, TX, USA, Jun. 2010, pp. 2363–2367.

[6] K. Huang and E. Larsson, "Simultaneous information and power transfer for broadband wireless systems," *IEEE Trans. Signal Proc.*, vol. 61, no. 23, pp. 5972–5986, Dec. 2013.

[7] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, May 2013.

[8] X. Zhou, R. Zhang, and C.-K. Ho, "Wireless information and power transfer: Architecture design and rate–energy tradeoff," in *Proc. GLOBECOM*, Anaheim, CA, USA, Dec. 2012, pp. 3982–3987.

[9] L. Liu, R. Zhang, and K.-C. Chua, "Wireless information transfer with opportunistic energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 288–300, Jan. 2013.

[10] Z. Ding and H. V. Poor, "Cooperative energy harvesting networks with spatially random users," *IEEE Signal Process. Lett.*, vol. 20, no. 12, pp. 1211–1214, Dec. 2013.

[11] D. W. K. Ng, E. Lo, and R. Schober, "Energy-efficient resource allocation in multiuser OFDM systems with wireless information and power transfer," in *Proc. IEEE WCNC*, Shanghai, China, Apr. 2013, pp. 3823–3828.

[12] D. W. K. Ng, E. Lo, and R. Schober, "Wireless information and power transfer: Energy efficiency optimization in OFDMA systems," *IEEE Trans. Wireless Commun.*, vol. 12, no. 12, pp. 6352–6370, Dec. 2013.

[13] X. Chen, X. Wang, and X. Chen, "Energy-efficient optimization for wireless information and power transfer in large-scale MIMO systems employing energy beamforming," *IEEE Wireless Commun. Lett.*, vol. 2, no. 6, pp. 667–670, Dec. 2013.

[14] M. V. Pederson and F. H. P. Fitzek, "Mobile clouds: The new content distribution platform," *Proc. IEEE*, vol. 100, pp. 1400–1403, May 2012.

[15] L. Al-Kanj, Z. Dawy, and E. Yaacoub, "Energy-aware cooperative content distribution over wireless networks: Design alternatives and implementation aspects," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 4, pp. 1736–1760, Dec. 2013.

[16] Z. Chang and T. Ristaniemi, "Energy efficiency of collaborative OFDMA mobile cluster," in *Proc. IEEE CCNC*, Las Vegas, NV, USA, Jan. 2013, pp. 74–78.

[17] Z. Yin, F. R. Yu, S. Bu, and Z. Han, "Joint cloud and wireless networks operations in the mobile cloud computing environment with telecom operator cloud," *IEEE Trans. Wireless Commun.*, vol. 14, no. 7, pp. 4020–4033, Jul. 2015.

[18] D. Niyato, P. Wang, E. Hossain, W. Saad, and Z. Han, "Game theoretic modeling of cooperation among service providers in mobile cloud computing environments," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Paris, France, Apr. 2012, pp. 3128–3133.

[19] L. Al-Kanj, Z. Dawy, W. Saad, and E. Kutanoglu, "Energy-aware cooperative content distribution over wireless networks: Optimized and distributed approaches," *IEEE Trans. Veh. Technol*, vol. 62, no. 8, pp. 3828–3847, Aug. 2013.

[20] E. Yaacoub, Z. Dawy, S. Sharafeddine, and A. Abu-Dayya, "Joint energy-distortion aware algorithms for cooperative video streaming over LTE networks," *EURASIP/Elsevier Signal Process., Image Commun.*, vol. 28, no. 9, pp. 1114–1131, 2013.

[21] W. Saad, Z. Han, A. Hjorungnes, D. Niyato, and E. Hossain, "Coalition formation games for distributed cooperation among roadside units in vehicular networks," *IEEE Sel. Areas Commun.*, vol. 29, no. 1, pp. 48–60, Jan. 2011.

[22] T. Wang, L. Song, Z. Han, and B. Jiao, "Dynamic popular content distribution in vehicular networks using coalition formation games," *IEEE Sel. Areas Commun.*, vol. 31, no. 9, pp. 538–547, Sep. 2013.

[23] Z. Chang, T. Ristaniemi, and Z. Niu, "Energy efficient grouping and scheduling for content sharing based collaborative mobile cloud," in *Proc. IEEE ICC*, Sydney, NSW, Australia, Jun. 2014, pp. 4281–4286.

[24] Z. Chang, J. Gong, and T. Ristaniemi, "Energy efficient resource allocation for collaborative mobile cloud with hybrid receiver," in *Proc. IEEE INFOCOM Workshop*, Toronto, ON, Canada, Apr. 2014, pp. 747–752.

[25] Z. Chang and T. Ristaniemi, "Efficient use of multicast and unicast in collaborative OFDMA mobile cluster," in *Proc. VTC—Spring*, Dresden, Germany, Jun. 2013, pp. 1–5.

[26] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[27] W. Dinkelbach, "On nonlinear fractional programming," *Manage. Sci.*, vol. 13, pp. 492–498, Mar. 1967.

[28] W. Yu and R. Lui, "Dual methods for nonconvex spectrum optimization in multicarrier system," *IEEE Trans. Commun.*, vol. 54, no. 7, pp. 1310–1322, Jul. 2006.

[29] S. Boyd and A. Mutapcic, *Lecture Notes for EE364b*. Stanford, CA, USA: Standford Univ., 2006/2007.

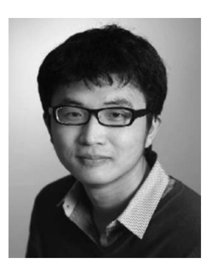
[30] Z. Chang, T. Ristaniemi, and Z. Niu, "Radio resource allocation for collaborative OFDMA relay networks with imperfect channel state information," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2824–2835, May 2014.

[31] D. W. K. Ng, E. Lo, and R. Schober, "Energy-efficient resource allocation in OFDMA systems with large numbers of base station antennas," *IEEE Trans. Wireless Commun.*, vol. 11, no. 9, pp. 3292–3304, Sep. 2012.

[32] R. Jain. (2007, Feb.), Channel Models A Tutorial v1.0.

[33] H. Bagheri, M. J. Salehi, B. H. Khalaj, and M. Katz, "An energy-efficient leader selection algorithm for cooperative mobile clouds," in *Proc. IEEE/IFIP Wireless Days*, Valencia, Spain, Nov. 2013, pp. 1–4.

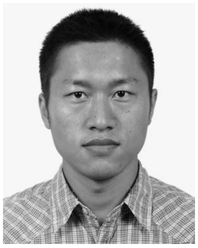
[34] B. Barua, Z. Khan, Z. Han, M. Latva-aho, and M. Katz, "On the selection of best devices for cooperative wireless content delivery," in *Proc. IEEE GLOBECOM*, Austin, TX, USA, Dec. 2014, pp. 4845–4851.



Zheng Chang (M'13) received the B.Eng. degree from Jilin University, Changchun, China, in 2007; the M.Sc. (Tech.) degree from Helsinki University of Technology (now Aalto University), Espoo, Finland, in 2009; and the Ph.D. degree from the University of Jyväskylä, Jyväskylä, Finland, in 2013.

Since 2008, he has held various research positions at Helsinki University of Technology, the University of Jyväskylä, and Magister Solutions Ltd. in Finland. From June to August in 2013, he was also a Visiting Researcher with Tsinghua University, Beijing, China, and the University of Houston, Houston, TX, USA. He is currently with the University of Jyväskylä. His research interests include signal processing, radio resource allocation, cross-layer optimizations for wireless networks, and green communications.

Dr. Chang has received awards from the Ulla Tuominen Foundation, the Nokia Foundation, and the Riitta and Jorma J. Takanen Foundation for his research.



Jie Gong (S'09–M'13) received the B.S. and Ph.D. degrees from the Department of Electronic Engineering, Tsinghua University, Beijing, China, in 2008 and 2013, respectively.

From July 2012 to January 2013, he visited the Institute of Digital Communications, University of Edinburgh, Edinburgh, U.K. During 2013–2015, he was a Postdoctoral Scholar with the Department of Electronic Engineering, Tsinghua University. He is currently an Associate Research Fellow with the School of Data and Computer Science, Sun Yat-sen University, Guangzhou, China. His research interests include cloud radio access networks, energy harvesting, and green wireless communications.

Dr. Gong coreceived the Best Paper Award from the IEEE Communications Society Asia-Pacific Board in 2013.

Tapani Ristaniemi (SM'11) received the M.Sc. degree in mathematics, the Ph.Lic. degree in applied mathematics, and the Ph.D. degree in wireless communications from the University of Jyväskylä, Jyväskylä, Finland, in 1995, 1997, and 2000, respectively.

In 2001, he was appointed as a Professor with the Department of Mathematical Information Technology, University of Jyväskylä. In 2004, he moved to the Department of Communications Engineering, Tampere University of Technology, Tampere, Finland, where he was appointed as a Professor in wireless communications. In 2006, he moved back to the University of Jyväskylä to take up his appointment as a Professor in computer science. He is an Adjunct Professor with Tampere University of Technology. In 2013, he was a Visiting Professor with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. Apart from his academic activities, he is also active in industry. In 2005, he cofounded a start-up called Magister Solutions Ltd. in Finland, which specializes in wireless system R&D for the telecom and space industries in Europe. Currently, he serves as a consultant and a Member of the Board of Directors. He has authored or coauthored over 150 publications in journals, conference proceedings, and invited sessions. His research interests include brain and communication signal processing and wireless communication systems research.

Dr. Ristaniemi served as a Guest Editor for the IEEE WIRELESS COMMUNICATIONS in 2011 and is currently an Editorial Board Member of *Wireless Networks* and the *International Journal of Communication Systems*.

Zhisheng Niu (M'98–SM'99–F'12) received the B.E. degree from Beijing Jiaotong University, Beijing, China, in 1985 and the M.E. and D.E. degrees from Toyohashi University of Technology, Toyohashi, Japan, in 1989 and 1992, respectively.

From 1992 to 1994, he was with Fujitsu Laboratories Ltd., Japan. In 1994, he joined Tsinghua University, Beijing, where he is currently a Professor with the Department of Electronic Engineering. He is also a Guest Chair Professor with Shandong University, Jinan, China. His major research interests include queueing theory, traffic engineering, mobile Internet, radio resource management of wireless networks, and green communication and networks.

Dr. Niu has been an active volunteer for various academic societies, including the Director for Conference Publications (2010–2011) and the Director for Asia-Pacific Board (2008–2009) of the IEEE Communications Society; the Membership Development Coordinator (2009–2010) of IEEE Region 10; Councilor of the Institute of Electronics, Information, and Communication Engineers (IEICE) Japan (2009–2011); and council member of the Chinese Institute of Electronics (2006–2011). He is currently a Distinguished Lecturer (2012–2015) and the Chair of the Emerging Technology Committee (2014–2015) of the IEEE Communications Society, a Distinguished Lecturer (2014–2016) of the IEEE Vehicular Technology Society, a member of the Fellow Nomination Committee of the IEICE Communication Society (2013–2014), a standing committee member of the Chinese Institute of Communications (CIC; 2012–2016), and an Associate Editor-in-Chief of the IEEE/CIC joint publication *China Communications*. He received the Outstanding Young Researcher Award from the Natural Science Foundation of China in 2009 and the Best Paper Award from the IEEE Communications Society Asia-Pacific Board in 2013. He also coreceived Best Paper Awards from the 13th, 15th, and 19th Asia-Pacific Conference on Communication in 2007, 2009, and 2013, respectively, and the 2013 International Conference on Wireless Communications and Signal Processing, as well as the Best Student Paper Award from the 25th International Teletraffic Congress. He is currently the Chief Scientist of the National Basic Research Program ("973 Project") of China on "Fundamental Research on the Energy and Resource Optimized Hyper-Cellular Mobile Communication System" (2012–2016), which is the first national project on green communications in China. He is a Fellow of the IEICE.