Resource Allocation and Data Offloading for Energy Efficiency in Wireless Power Transfer Enabled Collaborative Mobile Clouds

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***Abstract*—The rapidly-increasing high data rate wireless networks and the fast-growing smartphone techniques are continually changing our daily behaviors and coloring our life. However, in order to fully experience the high rate broadband multimedia services, prolonging the battery life of user equipment is critical for the mobile users, especially for the smartphone users. In this work, the problem of offloading the cellular data via a collaborative mobile cloud in an energy efficient manner is investigated. The CMC is formed by a group of users interested in downloading the same content from the operator. Through Device-to-Device communications, the users inside CMC are able to cooperate during downloading procedure and offload data from Base Station for other CMC members. When considering wireless power transfer and MIMO wireless channel, an efficient algorithm is presented to address how to optimally schedule the data offloading and radio resources to obtain the energy efficiency as well as fairness among mobile users. Specifically, the proposed framework takes energy saving maximization, Quality of Service (QoS) requirement as well as user fairness into consideration. Performance evaluations demonstrate that significant energy saving gain can be achieved by the proposed data offloading scheme.**

***Index Terms*—energy efficiency; collaborative mobile clouds; data offloading; content distribution; wireless energy/power transfer; beamforming; resources allocation**

I. Introduction

Offloading cellular data to femtocells or WiFi networks might be restricted by the network deployment and it also relies on the availability of Internet access [1]. Nowadays, the information to be delivered in cellular networks can include many different types of multimedia data generated by service providers, e.g, multimedia newspapers/advertisements may contain video clips, music, and small phone games. Benefiting from the delay-tolerant nature of non-real time applications, service providers may directly offload the information to required users to reduce cellular data traffic as well as their operation costs. Therefore, in addition to infrastructure data loading, mobile data offloading through ad hoc networks, such as Device-to-Device (D2D)/ Machine-to-Machine (M2M) systems, is also a very attractive technique in the light of distributing the delay-tolerant or non-real time data to numbers of mobile terminals (MTs). In [1], the authors utilized the concept of mobile social networks and studied the user-set selection problem to minimize the mobile data traffic from content and social domains. In [2], a content distribution framework called collaborative mobile cloud (CMC) was introduced. A CMC consists of numbers of MTs that can download from the base station (BS) and share some content in a cooperative manner. Applying the mobile cloud framework, the content can be separated into several segments or chunks where BS offloads different chunks to selected MTs using the cellular channels, then the MTs exchange the received chunks via D2D communications. Therefore, only a few data streams are delivered through cellular networks instead of transmitting entire data content to each requested MT. The CMC is foreseeable to reduce the energy consumption of MTs during downloading process as it can significantly reduced the data reception time [2].

Although the use of CMC is able to reduce the energy consumption for a group of MTs when receiving common interested multimedia data, the selected offloading MTs may consume more energy during local data chunk dissemination. Therefore, due to the self-fish nature, how to stimulate and bootstrap the mobile users to join the cloud and offload data for others is of research importance. The most common thoughts on it may lay on the social benefits, such as awards or payment reduction. Meanwhile, intuitively and interestingly, the emerging simultaneous wireless information and power transfer (SWIPT) technique provides another potential solution from technological domain. As RF signal can carry both information and energy simultaneously, the induced SWIPT has gained much attention [3]. 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, so enabling SWIPT is full of possibility especially for the MTs who have difficult to obtain other energy harvesting sources such as solar and wind. In [4], the authors proposed a receiver architecture which can split the received power into two power

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streams to facility the SWIPT. In [5], different subcarrier and power allocation algorithms were proposed for the multiuser OFDM systems with SWIPT. Non-convex optimization problem was formulated with the objective to maximize the energy efficiency performance in term of $bits/Joule$. For a large scale MIMO system with SWIPT receivers, the authors of [6] presented an optimization scheme to maximize the energy efficiency of the system while satisfying the delay constraints by jointly allocating the transmission time duration and transmit power. Similarly, in the context of multiple antenna transmission with wireless power transfer, there has been some works, e.g. [7], also dedicated to the development of beamforming.

In this work, our aim is to study the resource allocation and data offloading scheme for the Wireless power transfer enabled Collaborative Mobile Cloud (WeCMC) with the objective to maximize the energy efficiency of the considered system. In a traditional service, each MT has to download the whole content on its own, which leads to the significant energy consumption of the batteries, especially if the cellular data rates are relatively low that results in a long receive time. In the WeCMC system, several selected MTs can offload the data and during offloading process while other MTs can harvest energy from received signal. Previous work on the related subject mainly focused on the user-set formulation or energy efficiency investigations [8] [9], how to allocate the limited radio resources such as frequency subchannels or transmit power lacks of concerns. Moreover, how to select users to offload data and how to design the beamformer in the context of multiple antenna transmitter also need to be investigated. In this work, we are going to address these problems. Comparing with previous existed works, the main contributions of this work can be summarized: 1) As WeCMC is expected as an energy efficient content distribution system, the selected MTs should be able to minimize the overall system energy cost and maximize the harvested energy from wireless power transfer. Therefore, one aim of this work is to propose user scheduling scheme that can obtain the energy consumption minimization; 2) In addition, we also focus on the algorithm that can properly assign the subchannels for the transmission between BS and WeCMC, and the transmission inside WeCMC should also be concentrated. Moreover, beamformer design for multiple antenna BS and power allocation for MTs need to be investigated so that the transmit power consumption can be minimized.

II. WeCMC System Description

In our considered system, it is assumed that N_{MT} MTs locating close are interested in the same content, e.g., multimedia, TV, movie, news etc. The MTs are able to decode information and harvest energy from the received radio signals. Due to the hardware limitation, MT can not decode information and harvest energy at the same time. We consider a MISO channel model so that the BS is equipped with $N_T > 1$ antennas and all MTs are equipped with a single antenna. Moreover, there are N subchannels in the system. We assume the channel follows quasi-static block fading and BS can accurately obtain the channel status by the feedback from the MTs.

To concentrate on the data offloading and resource allocation proposals, we do not assume any particular type of wireless power transfer receivers. The considered MT in this work consists of an energy harvesting unit for power transfer and a conventional signal processing core unit for data offloading and decoding, respectively. Moreover, for the conventional signal processing, we separate receiver architecture into RF unit and baseband unit. In the following section, the energy consumption models will be given. Before we introduce the energy consumption models, several indicators are defined. First the user selection indicator ρ_k is defined as follows,

$$\rho_k = \begin{cases} 1, & \text{if } k \text{ is chosen for receiving from BS,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

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

$$\beta_{s,i} = \begin{cases} 1, & \text{if subchannel } i \text{ is used for downlink,} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

and

$$\beta_j = \begin{cases} 1, & \text{if subchannel } j \text{ is assigned to deliver data in CMC} \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

A. Data Offloading Receiver (DOR)

In this work, we assume that the linear precoding at the BS. Moreover, we consider the receivers have both data offloading (DO) and energy harvesting (EH) functionalities but can only perform one due to hardware limitation. In the following, we refer the receivers perform DO functionality as the data offloading receivers (DORs) and energy harvesting MTs as energy harvesting receivers (EHRs).

For the cellular link, it is assumed MTs require same data from a multiple antenna BS. Therefore, it is more efficient to use multicasting as the transmission mechanism and to consider the channel as MISO multicasting channel. Without loss of generality, we consider the DOR with dedicated information beam. For the selected DOR k, the data rate of cellular link can be expressed as

$$R^c_{s,k,i} = \log_2\left(1 + \frac{p^{c_{tx}}_{s,i}|\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}_i|^2}{\sigma^2_z}\right). \tag{4}$$

where $p^{c_{tx}}_{s,i}$ is the multicasting power of BS on subchannel i. Without loss of generality, we consider information signal has unit variance. We also assume a quasi-static fading channel where $\mathbf{h_{s,k,i}} \in \mathbb{C}^{N_T \times 1}$ is the channel coefficient from BS to MT k on subchannel i. The additive Gaussian noise follows $\mathcal{N}(0, \sigma^2_z)$. It is worth noticing that $\mathbf{h_{s,k,i}}$ represents the path loss, slow and fast fading effects. $\boldsymbol{\omega}_i$ is the information beamforming vector for DOR k on subchannel i.

Then for the selected K DORs, the data rate can be expressed as

$$R_{s,i}^{c} = \min_{k \in \mathcal{K}} \left\{ \log_2 \left(1 + \frac{\sum_i^N \beta_{s,i} \rho_k p_{s,i}^{c_{tx}} |\mathbf{h}_{s,k,i}^H \boldsymbol{\omega}_i|^2}{\sigma_z^2} \right) \right\}. \quad (5)$$

After receiving from BS, the DORs will distribute the data to other MTs through multicasting in a D2D manner. Therefore, the data rate of D2D link on subchannel j is

$$R_{\mathcal{K},j}^{d} = \log_2 \left(1 + \frac{\sum_j^N \sum_{k \in \mathcal{K}} \rho_k \beta_j p_{k,j}^{d_{tx}} |h_{k,j}|^2}{\sigma_z^2} \right). \quad (6)$$

where $p_{k,j}^{d_{tx}}$ is the multicasting power of DOR k on subchannel j and $h_{k,j}$ is the worst channel gain from DOR to other MTs. In addition, we also assume the noise of both links are of the same kind.

B. Energy Harvesting Receiver (EHR)

In practice, electromagnetic induction and electromagnetic radiation are able to transfer wireless power, and the receiver is able to recycle the wireless power from radio signal [3]. Nevertheless, due to the fact that the associated hardware circuit in the receivers might differ, so the corresponding EH efficiency can be different as well. Besides, the signal used for decoding the modulated information cannot be used for harvesting energy due to hardware limitations [4]. In the case of EH users, no baseband processing is needed to harvest the carried energy through beamforming vectors [4]. Based on the law of energy conservation, the harvested energy is proportional to the total received power. So denoting the conversion efficiency $0 < \vartheta_k \leq 1$, the energy harvested of a EHR n on subchannel i is given by

$$P_{s,n,i}^{EH} = \sum_i^N \beta_{s,i} \vartheta_n p_{s,i}^{c_{tx}} |\mathbf{h}_{s,n,i} \omega_i|^2, \quad (7)$$

C. Energy Consumption Model

1) Energy Consumption of BS: The energy consumption of the BS is given as

$$E_s^{c_{tx}} = (\varepsilon p_{s,i}^{c_{tx}} + p_b) T_{s,i}^{c} = \frac{(\varepsilon p_{s,i}^{c_{tx}} + p_b) S_T}{R_{s,i}^{c}}, \quad (8)$$

where p_b is the BS baseband operating power consumption and the power consumption on antennas. S_T is the amount of data to be transmitted. ε stands for the nonlinearity effect of power amplifier.

2) Tx and Rx Energy Consumption of CMC: The energy consumption for receiving data size S_T from BS can be expressed as

$$\begin{aligned} E_{s,k,i}^{c_{rx}} = (p_{s,k,i}^{c_{rx}} + p_e) T_{s,k,i}^{c_{rx}} &= \frac{(p_{s,k,i}^{c_{rx}} + p_e) S_T}{R_{s,i}^{c}} \\ &= \frac{(p_{rx} + p_e) S_T}{R_{s,i}^{c}}, \end{aligned} \quad (9)$$

where $p_{s,k,i}^{c_{rx}}$ is the RF power consumption of k for receiving from BS on subchannel i and p_e is the electronic circuit power consumption of baseband associated with transmission bandwidth. In this work, the energy consumption refers to the one when receiving and sending data on certain subchannel, so the baseband power consumption is considered together with RF Tx/Rx power consumption. $T_{s,k,i}^{c_{rx}} = \frac{S_T}{R_{s,i}^{c}}$ is the required time for receiving data S_T on cellular subchannel i. Further we can assume the receive RF power consumption are the same for both cellular and D2D links, and equals to p_{rx}. After receiving from the BS, DOR k is going to transmit its offloaded data to other MTs. There are two conventional ways to deliver data inside WeCMC, which are unicasting and multicasting. We have discussed the energy efficiency of using both two schemes in [10] and the multicasting shown the superior energy efficiency performance over unicasting. So in this work, we only invoke multicasting as the transmission strategy inside WeCMC.

When multicasting is used, a DOR only needs to broadcast its data to other MTs in CMC once with the data rate that can reach the MT with the worst channel condition. Accordingly, the D2D communication within the WeCMC can be modeled as a virtual MISO channel as well when multiple MTs are selected. Thus, the transmit energy consumption is given as

$$E_{k,j}^{d_{tx}} = (\varepsilon p_{k,j}^{d_{tx}} + p_e) T_{\mathcal{K},j}^{S_{tx}} = \frac{(\varepsilon p_{k,j}^{d_{tx}} + p_e) S_T}{R_{\mathcal{K},j}^{d}}. \quad (10)$$

Therefore, the total energy consumption of WeCMC when using MTs in $\mathcal{K}$ as the DORs can be expressed as follows:

$$E_{\mathcal{K},i,j} = \sum_{k \in \mathcal{K}} \rho_k (\sum_{i=1}^{N} \beta_{s,i} E_{s,k,i}^{c_{rx}} + \sum_{j=1}^{N} \beta_j E_{k,j}^{d_{tx}}) + \sum_{n, n \notin \mathcal{K}}^{N_{MT}} \sum_{j=1}^{N} \beta_j E_{n,j}^{d_{rx}}. \quad (11)$$

$E_{\mathcal{K},i,j}$ is the energy consumption of DORs in $\mathcal{K}$ when assigning subchannel i for receiving from BS and subchannel j for broadcasting its received data. $E_{n,j}^{d_{rx}}$ is the energy consumption of each EHR when receiving from DOR on subchannel j, and it can be expressed as

$$E_{n,j}^{S_{rx}} = (p_{n,j}^{d_{rx}} + p_e) T_{k,j}^{d_{rx}} = \frac{(p_{rx} + p_e) S_T}{R_{\mathcal{K},j}^{d}}. \quad (12)$$

III. Problem Formulation

Intuitively, longer transmission time of cellular link can increase the time for wireless power transfer, but at the cost of higher transmit and receive energy consumption. Therefore, to minimize the energy consumption for a fix amount of data, we will formulate a joint optimization problem of user set selection, beamformer design, subchannel and power allocation for each transmission interval. For each data segment transmission, we can formulate the optimization objective as

$$\mathcal{E}(\boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\omega}, \mathbf{P}) = E_s^{c_{tx}} + E_{\mathcal{K},i,j} - \sum_{n, n \notin \mathcal{K}} Q_{s,n,i}, \quad (13)$$

K is the total number of DORs, which is $K = |\mathcal{K}|$. $\mathbf{P}$ is the power allocation policies. $\boldsymbol{\rho} = \{\rho_k\}, \forall k$ and $\boldsymbol{\beta} = \{\beta_{s,i}, \beta_j\}, \forall i, j$ are the user selection and subchannel allocation indicators. $\boldsymbol{\omega}$ is the beamformer design policy. The $Q_{s,n,i}$ is the harvest energy and obversely $Q_{s,n,i} = P^H_{s,n,i} S_T / R^c_{s,i}$. Note that mathematically $\mathcal{E}$ can take the negative value, while in practise $\mathcal{E}$ is always positive. In addition, we have $T^c_{s,i} = S_T / R^c_{s,i}$ and $T^{S_{tx}}_{\mathcal{K},j} = T^{S_{rx}}_{\mathcal{K},j} = S_T / R^d_{\mathcal{K},j}$. Therefore, the optimization problem can be formulated as

$$\min_{\boldsymbol{\rho},\boldsymbol{\beta},\boldsymbol{\omega},\mathbf{P}} \mathcal{E}(\boldsymbol{\rho},\boldsymbol{\beta},\boldsymbol{\omega},\mathbf{P}), \tag{14}$$

s.t.

$$\begin{aligned} &C1: \sum_{k=1}^{K} \omega_{s,i} = 1, \sum_{k=1}^{K} \omega_j = 1, \\ &C2: R^c_{s,i} \geq R_{c,min}, R^d_{\mathcal{K},j} \geq R_{d,min}, \\ &C3: p^{c_{tx}}_{s,i} \leq p_{s,max}, p^{d_{tx}}_{k,j} \leq p_{k,max}, \end{aligned} \tag{15}$$

The several constraints of the optimization problem (14) are to ensure that the solution is feasible.

It is worth noticing that (14) with constraints in (15) is a non-convex problem. Addressing such a integer programming non-convex optimization problem is recognized as NP-hard. An exhaustive search is needed to obtain the global optimum which has a high computational cost, even for small N_{MT} and N. In order to make the problem tractable, we transform the objective function and approximate the transformed objective function in order to simplify the problem.

IV. Energy Efficiency Optimization of WeCMC

A. Subchannel Allocation and Power Allocation

1) Problem Transformation: First given that the DORs are selected, we can reform the objective $\mathcal{E}$ as a function of $\{\boldsymbol{\beta}, \boldsymbol{\omega}, \mathbf{P}\}$. Substituting (7), (8) and (11) into (13), (16) can be obtained where $p_c = p_b + p_{rx} + p_e$. One may notice that obtaining power allocation policy involves solving $\mathcal{E}(\boldsymbol{\beta}, \boldsymbol{\omega}, \mathbf{P})$, which is

$$\mathcal{E}(\boldsymbol{\beta},\boldsymbol{\omega},\mathbf{P}) = \mathcal{E}_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) + \mathcal{E}_d(\boldsymbol{\beta}_d,\mathbf{P}_d), \tag{17}$$

where $\mathcal{E}_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) = \frac{U_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)}{R_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)}$ and $\mathcal{E}_d(\boldsymbol{\beta}_d,\mathbf{P}_d) = \frac{U_d(\boldsymbol{\beta}_d,\mathbf{P}_d)}{R_d(\boldsymbol{\beta}_d,\mathbf{P}_d)}$. From (17), it can be found that the beamforming design and power allocation for BS and scheduled DORs are separated. In other word, we can obtain optimal power allocation by addressing $\mathcal{E}_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)$ and $\mathcal{E}_d(\boldsymbol{\beta}_d,\mathbf{P}_d)$ individually with the assumption that the DORs are selected. One can also find that both $\mathcal{E}_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)$ and $\mathcal{E}_d(\boldsymbol{\beta}_d,\mathbf{P}_d)$ are quasi-convex functions w.r.t. power allocation variables, respectively. For the sake of presentation simplicity, we introduce a method for solving $\mathcal{E}_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)$ which is derived from nonlinear fractional programming [11].

The global optimal solution q^*_c can be expressed as

$$q^*_c = \mathcal{E}_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) = \min_{\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c} \frac{U_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)}{R_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)}. \tag{18}$$

Theorem 1. *The optimal solution q^*_c can be obtained iff*

$$\min_{\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c} U_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) - q^*_c R_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) = 0. \tag{19}$$

Theorem 1 presents the necessary and sufficient condition w.r.t. optimal power allocation and it can be proved by following a similar approach as in [11]. Particularly, for the considered optimization problem with an objective function in fractional form, there exists an equivalent optimization problem with an objective function in subtractive form, i.e., $U_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) - q^*_c R_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)$, and both formulations result in the same power allocation solutions. In order to obtain the q^*_c, the iterative algorithm with guaranteed convergence in [11] can be applied.

During the iteration, in order to achieve q^*_c, we need to address the following problem with q_c:

$$\min_{\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c} U_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c) - q_c R_1(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c), \tag{20}$$

s.t.

$$\begin{aligned} &\sum_{k=1}^{K} \beta_{s,i} = 1, \\ &R^c_{s,i} \geq R_{c,min}, \\ &\sum_{i=1}^{N} \beta_{s,i} P^{c_{tx}}_{s,i} \leq P_{s,max}, \end{aligned} \tag{21}$$

Theorem 2. *The objective function (14) is quasi-convex function w.r.t. to the power allocation policy.*

Theorem 2 can be obtained by examining the convexity of (14) and we omit due to space limitation. Therefore, an unique global optimal solution exists. We can apply the nonlinear fractional programming method to solve the formulated problem [11] of power allocation and subchannel allocation in the followings.

Basically, such a problem still is a non-convex optimization problem due to the involved integer programming. Tackling the mix convex and combinatorial optimization problem and obtaining a global optimal solution result in a prohibitively high complexity. Another solution which can balance the computational complexity and optimality can be obtained when addressing such problem in the dual domain. As discussed in [12], in the considered multi-carrier systems the duality gap of such a non-convex resource allocation problem satisfying the time-sharing condition is negligible as the number of subcarriers becomes sufficiently large e.g., 32 or 64. Since our optimization problem satisfies the time-sharing condition, it can be solved by using the dual method and the solution is asymptotically optimal. The same idea can be used for addressing β^*_j and $P^{d_{tx}*}_{k,j}$.

2) Dual Formulation and Decomposition: We solve the power allocation problem of cellular link by solving its dual for a given value of q_c. The Lagrangian function of the primal problem (19) can be given as,

$$\mathcal{E}(\boldsymbol{\beta}_c, \boldsymbol{\omega}_c, \mathbf{P}_c) = \frac{\overbrace{S_T\left(\sum_{i=1}^{N}\beta_{s,i}p_{s,i}^{c_{tx}} + p_c - \sum_{i=1}^{N}\sum_{n,n\neq k}\beta_{s,i}\vartheta_n p_{s,i}^{c_{tx}}|\mathbf{h}_{s,n,i}\omega_i|^2\right)}^{U_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)}}{\underbrace{R_{s,i}^c}_{R_c(\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c)}} + \frac{\overbrace{S_T\sum_{j=1}^{N}\beta_j(\sum_{k}^{K}p_{k,j}^{d_{tx}} + (N_{MT}-K)p_{rx} + N_{MT}p_e)}^{U_d(\boldsymbol{\beta}_c,\mathbf{P}_c)}}{\underbrace{R_{\mathcal{K},j}^d}_{R_d(\boldsymbol{\beta}_c,\mathbf{P}_c)}}. \tag{16}$$

$$\begin{aligned}\mathcal{L}(\boldsymbol{\beta}_c, \boldsymbol{\omega}_c, \mathbf{P}_c, \lambda, \mu, \theta, \gamma) = U_c(\boldsymbol{\beta}_c, \boldsymbol{\omega}_c, \mathbf{P}_c)\\ -q_c R_c(\boldsymbol{\beta}_c, \boldsymbol{\omega}_c, \mathbf{P}_c) - \lambda(\sum_{k=1}^{K}\beta_{s,i} - 1)\\ -\mu(R_{s,i}^c - R_{c,min}) - \theta(P_{s,max} - P_{s,i}^{c_{tx}}),\end{aligned} \tag{22}$$

where λ, μ, θ are the lagrange multipliers associated with different constraints. The dual problem can be expressed as

$$\max_{\lambda,\mu,\theta}\ \min_{\boldsymbol{\beta}_c,\boldsymbol{\omega}_c,\mathbf{P}_c} \mathcal{L}(\beta_c, \boldsymbol{\omega}_c, \mathbf{P}_c, \lambda, \mu, \theta). \tag{23}$$

By using Lagrange dual decomposition, the dual problem (23) can be decomposed into two layers, minimization of (22) which is the inner problem and maximization of (23) which is the outer problem. The dual problem can be solved by addressing both problems iteratively, where in each iteration, the optimal power allocation can be obtained by using the KKT conditions for a fixed set of Lagrange multipliers, and the outer problem is solved using the (sub)gradient method. Moreover, we consider the maximum ratio transmission (MRT) strategy is used for beamformer design, which can maximize data rate on the cellular link.

Meanwhile, in order to obtain the optimal subchannel allocation, by assuming that the number of subchannel is sufficiently large (e.g., 32) we take the derivative of the subproblem w.r.t. $\beta_{s,i}$. Thus, the subchannel allocation is given by

$$\beta_{s,i}^* = \begin{cases}1, & \text{if } i = \arg\max_d \frac{d\mathcal{L}}{d\beta_{s,d}},\\ 0, & \text{otherwise.}\end{cases} \tag{24}$$

By combining the gradient updates and the subchannel allocation criterion, only one subchannel is selected eventually even though time-sharing is considered for solving the transformed problem in (20).

We have presented the scheme on how to address the minimization of $\mathcal{E}_c(\boldsymbol{\beta}_c, \boldsymbol{\omega}_c, \mathbf{P}_c)$. The same procedure can be applied to obtain the optimal solution of minimizing $\mathcal{E}_d(\boldsymbol{\beta}_d, \mathbf{P}_d)$. Then we are able to obtain the solution set of (14) when considering optimal $\mathcal{K}$ is selected.

B. User Scheduling Scheme

For the user scheduling problem, the goal is to select MTs to act as DORs when BS is transmitting data segment and as the data transmitters forming a virtual MISO when delivering data to other MTs after receiving from BS. Therefore, with the assumption that subchannel and power allocations have been done, we are aiming to find the MTs that can achieve the best energy efficiency performance considering both cellular multicasting link and D2D MISO multicasting link. When subchannel and power allocations are done, the objective function can be reformed as,

$$\min \mathcal{E}(\boldsymbol{\rho}) = \frac{U_1(\boldsymbol{\rho})}{R_1(\boldsymbol{\rho})} + \frac{U_2(\boldsymbol{\rho})}{R_2(\boldsymbol{\rho})}, \tag{25}$$

where

$$\begin{aligned}U_1(\boldsymbol{\rho}) = \rho_k S_T(p_{s,i}^{c_{tx}} + p_b + p_{rx} + p_e\\ - \sum_{n,n\notin\mathcal{K}}\vartheta_n p_{s,i}^{c_{tx}}|\boldsymbol{h}_{s,n,i}\boldsymbol{\omega}_i|^2),\end{aligned} \tag{26}$$

$$U_2(\boldsymbol{\rho}) = S_T(\sum_{k}^{K}\rho_k p_{k,j}^{d_{tx}} + (N_{MT}-K)p_{rx} + N_{MT}p_e), \tag{27}$$

$$\begin{aligned}R_1(\boldsymbol{\rho}) = R_{s,i}^c,\\ R_2(\boldsymbol{\rho}) = R_{\mathcal{K},j}^d.\end{aligned} \tag{28}$$

The reformed problem (25) also subjects to constraints in (15). Therefore, we can obtain the user scheduling criteria as,

$$\rho_k^* = \begin{cases}1, & \text{if } k = \arg\min_a \Phi_a,\\ 0, & \text{otherwise.}\end{cases} \tag{29}$$

where

$$\Phi_a = \frac{U_1(\rho_a)}{R_1(\rho_a)} + \frac{U_2(\rho_a)}{R_2(\rho_a)}. \tag{30}$$

V. Performance Evaluation

We choose the number of subchannels N to be 64, so the duality gap can be ignored [12]. The noise variance is assumed 1 for simplicity. In practise, the baseband power P_e and P_b are not constant in general and their values should depend on the circuit design. However, it is out of the scope of this work and we assume they are fixed and the values are according to [9]. The conversion efficiency is assumed as $\vartheta_k = 0.5, \forall k$ and $\varepsilon = 5$ for simplicity. To illustrate the energy saving performance, the performance is presented in term of energy consumption ratio, which is obtained by comparing the considered scheme with pure multicasting transmission,

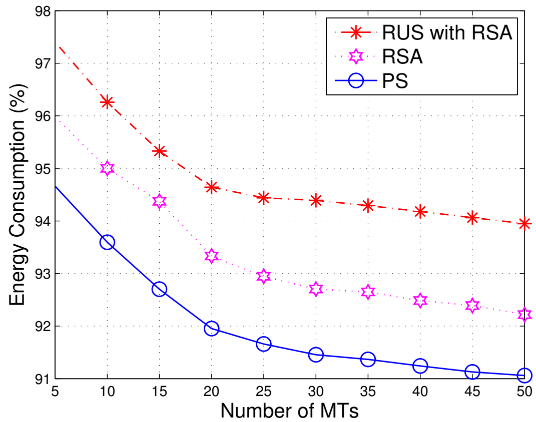

Figure 1. Energy efficiency performance of whole system

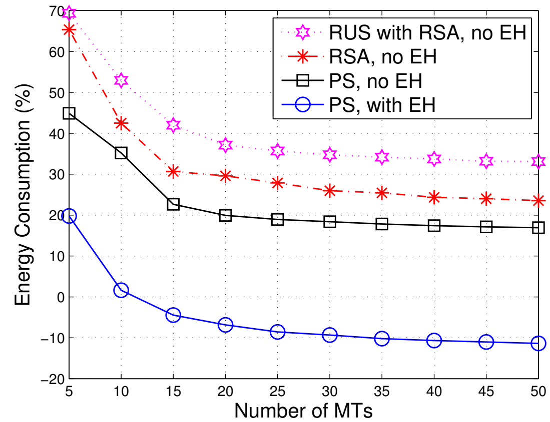

Figure 2. Energy efficiency performance of MTs

that is, the reference energy consumption is the one when BS use multicasting to deliver all data to every user. We also compare our scheme (PS) with random subchannel allocation (RSA) and random user and subchannel allocation (RUS with RSA). In Fig. 1, the energy efficiency performance of the whole system including BS and MTs is presented. As one can observe, the proposed WeCMC is able to obtain energy saving comparing with conventional multicasting scheme, though the energy saving gain is not strong (about 9%). The advantages of our presented user scheduling and subchannel allocation schemes also can be found.

As mentioned, the primer task of CMC is to save energy at the terminal side, so in Fig. 2, the energy efficiency performance is illustrated excluding the energy consumption of BS. Moreover, in order to see the wireless power transfer impact, we plot the performance with/without energy harvesting. It can be well observed that the proposed scheme can obtain the energy saving gain even without energy harvesting at MT side. In addition, the wireless power transfer feature can future improve the energy efficiency performance. In this setting, the whole group of MTs can harvest more energy than the cost,which evidences the significance of SWIPT technique.

VI. Conclusion

In this work, we investigated the problem of resource allocation for the collaborative mobile cloud with wireless power transfer. We presented a theoretical analysis on the energy consumption of MTs within the cloud. Moreover, user scheduling schemes were introduced in order to investigate when and how many users should participate for receiving from the BS in order to improve the energy efficiency. Accordingly, the subchannel and power allocation schemes are proposed with the objective to minimize the energy consumption of considered system. The simulation results demonstrated the energy saving benefits of forming the mobile cloud and also illustrated the advantages of advocating wireless power transfer for mobile cloud.

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