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Wireless Powered OFDMA-MEC Networks with Hybrid Active-Passive Communications

Liqin Shi, Xiaoli Chu, Haijian Sun and Guangyue Lu

Abstract—**In this article, we propose a novel system model for a wireless powered mobile edge computing (MEC) network, where the Internet-of-Things (IoT) nodes perform partial offloading to the MEC server via hybrid backscatter communication (BackCom) and active radio (AR) following an OFDMA protocol, and maximize the system computation bits (SCB). For the case of the system having more subchannels than IoT nodes, we formulate the SCB maximization problem that requires the joint optimisation of the transmit power and time, subchannel allocation, computation frequency and time of the MEC server, as well as the IoT nodes' BackCom time and reflection coefficients, transmit power and time for AR-based offloading, local computing time and frequencies, subject to the MEC server's computation capacity and the quality-of-service (QoS) and energy-causality constraints of each IoT node. By applying the proof by contradiction and time sharing relaxation, we transform the formulated problem into a convex one and then solve it by using the existing convex tools. For the case of the system having less subchannels than IoT nodes, we propose a dynamic subchannel allocation scheme that allows each IoT node to choose one task-offloading mode from three modes: HAPR, BackCom only, and AR only, while ensuring that no more than one IoT node occupies a subchannel at any time. The SCB are maximized by first determining the subchannel allocation and mode selection of each IoT node and then optimising the remaining resource allocation for the MEC server and all IoT nodes under the obtained subchannel assignment and mode selection. Simulations validate the superior performance of the proposed schemes over several benchmark schemes from the SCB perspective.**

Index Terms—**Backscatter, hybrid active-passive communications, computation offloading, OFDMA.**

I. Introduction

THE Internet of Things (IoT) is expected to provide intelligent services by deploying massive IoT devices to collect data from the environment and timely processing the collected data. In practice, limited by the production cost, most IoT devices are energy-constrained and with a limited computation capacity. To overcome this problem, wireless powered mobile edge computing (WPMEC), which allows IoT nodes to harvest energy from a dedicated energy source (DES) and offload computation tasks to a nearby MEC server, has been proposed.

In WPMEC, computation tasks can be offloaded from IoT nodes to MEC servers via active radio (AR), passive radio (PR), or hybrid active-passive radio (HAPR). In AR [1], [2], an IoT node needs to generate carrier signals to carry the offloaded data to a nearby MEC server, which requires power-consuming active components, e.g., oscillator and power amplifier, equipped at the IoT node. Considering AR employed at each user, the sum power minimization problem for a MEC network with multiple unmanned aerial vehicles (UAVs) was studied in [3] and the total energy consumption was minimized for a non-orthogonal multiple access (NOMA) based MEC network in [4]. In PR [5], [6], a.k.a., backscatter communication (BackCom)[1], the IoT node modulates an incident signal to carry its offloaded data and reflects the modulated signal to the MEC server by adjusting its antenna load impedance, thereby avoiding the use of power-consuming active components. We note that PR consumes much less energy than AR but at the cost of a lower offloading rate. PR and AR have different tradeoffs between offloading data rate and energy consumption. HAPR is the combination of AR and PR and provides an opportunity to exploit the different tradeoffs between energy consumption and offloading data rate offered by AR and PR. Thus, HAPR was recently proposed for data offloading in WPMEC [7].

In [7], the offloading time via AR and that via PR of each IoT node were jointly optimized to minimize the energy consumption of the DES under the complete offloading mode, while satisfying the minimum computation bits and energy causality per IoT node. In [8], a deep reinforcement learning (DRL) framework was developed for energy efficient HAPR based data offloading in WPMEC. The authors in [9] proposed a hierarchical multi-agent DRL to achieve the minimum energy consumption at both the DES and the MEC server for HAPR-based WPMEC. In [10], the total computation bits of all IoT nodes were maximized by jointly optimizing the time and power reflection coefficient (PRC) of each IoT node for PR-based offloading, the time and transmit power of each IoT node for AR-based offloading, and each IoT node's local computing frequency and time via convex optimization. Considering the same optimization variables as in [10], the computation energy efficiency (CEE) and the CEE fairness among IoT nodes were maximized in [11] and [12], respectively. In [13], the authors minimized the total delay for completing given computation tasks of all IoT nodes by jointly

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[1]In this paper, BackCom and PR are used interchangeably.

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optimizing the time of each IoT node for PR-based offloading and AR-based offloading, each IoT node's portions of task bits for PR/AR based offloading and local computing, etc.

The above works [7]–[13] have shown that HAPR-based WPMEC outperforms WPMEC based on AR or PR, yet all of them considered a single-carrier scenario, which will limit the achievable offloading data rate as compared with multi-carrier transmission technologies, such as orthogonal frequency division multiple access (OFDMA) [14]. Although resource allocation has been studied for OFDMA-based WP-MEC networks [15]–[17], which however have not considered HAPR.

In this article, the resource allocation for wireless powered OFDMA-MEC with HAPR is studied. Our main contributions are given below.

- We study the system computation bits (SCB) maximization for a wireless powered OFDMA-MEC network with HAPR, thereby filling a gap in the existing works on HAPR-based WPMEC. Specifically, we propose a novel system model, where each IoT node harvests energy from the energy signals emitted by the MEC server and uses its harvested energy to offload part of its tasks to the MEC server via HAPR and perform local computation of the remaining tasks. Accordingly, each transmission block duration is divided into five phases: the energy harvesting (EH) phase, the BackCom phase, the AR phase, the task execution phase, and the downloading phase. Letting K denote the total number of IoT nodes and C denote the total number of subchannels in the system, we maximize the SCB for the two cases of $K \leq C$ and $C < K \leq 2C$.
- For the case of $K \leq C$, following the OFDMA protocol (i.e., each subchannel is assigned to no more than one IoT node), we formulate a SCB maximization problem that jointly optimizes the energy transmission time, transmit power, subchannel allocation, computation frequency and time of the MEC server, as well as the IoT nodes' BackCom time and reflection coefficients, transmit power and time for AR-based offloading, and local computing time and frequencies, subject to the constraints on the quality-of-service (QoS), energy causality, latency, computation capacity, and maximum transmit power. Since the formulated problem is a non-convex mixed-integer programming problem, which is difficult to solve directly, we transform it into a convex one by means of proof by contradiction and time-sharing relaxation, and then solve it by using convex optimisation tools.
- For the case of $C < K \leq 2C$, where the number of IoT nodes is larger than that of subchannels, we propose a dynamic subchannel allocation scheme that allows each IoT node to choose one task-offloading mode from three modes: HAPR, BackCom only (i.e., stay quiet in the AR phase), and AR only (i.e., stay quiet in the BackCom phase). Hence, a subchannel can be shared by an IoT node performing BackCom only and another IoT node performing AR only because they occupy it at different time in a transmission block. With the offloading mode selection indicators included as additional optimization variables, the formulated SCB maximization problem becomes more complicated than that in the case of $K \leq C$, and cannot be solved by using existing methods. To solve it, we first obtain the suboptimal solutions of the subchannel assignment and mode selection for each IoT node by leveraging the relevant constraints of the formulated problem, and then obtain the optimal values of the other variables by solving the problem under the obtained subchannel assignment and mode selection of all IoT nodes.
- The superiority of the proposed schemes over several benchmark schemes in terms of the SCB is verified through simulations. Besides, the proposed scheme for the case of $C < K \leq 2C$ will enable more IoT nodes than conventionally allowed by the limited number of subchannels to offload tasks in a wireless powered OFDMA-MEC network.

Fig. 1. The wireless powered OFDMA-MEC network with HAPR and its frame structure.

II. System Model

As depicted in Fig. 1, this article considers a wireless powered OFDMA-MEC network, where K single-antenna IoT nodes communicate with an MEC server via HAPR. The whole system bandwidth is denoted by B MHz and divided into C orthogonal subchannels of equal bandwidth. Each IoT node operates in the half-duplex (HD) mode while the MEC server operates in the full-duplex (FD) mode so that the MEC server can receive the tasks backscattered by the IoT nodes when it broadcasts the energy signals. Each IoT node is equipped with a rechargeable battery. In order to prolong the IoT nodes' operation time, each IoT node only utilizes the harvested energy to support task offloading and/or local computing. Note that at the beginning of a transmission block, each IoT node may use the energy already stored in its battery to support its local computation and the consumed battery energy will be compensated by harvesting energy from the energy signals of the MEC server. Each IoT node employs the partial offloading scheme [1], [2], [5] and can choose to offload part of its tasks to the MEC server while computing the remaining tasks locally. To support tasks offloading and local computation, all the IoT nodes have four separate circuits that are the EH circuit, the computing circuit, the BackCom circuit and the AR circuit. Specifically, each IoT node harvests energy from the energy signals emitted by the MEC server, offloads some of its tasks to the MEC server via HAPR, and executes its remaining tasks locally. Following [1], [2], [5], [6], [12], [13], we suppose that all the devices in the considered system are time synchronized. All channels are modeled as quasi-static fading, namely channel state information (CSI) remains static within a transmission block but may change between adjacent transmission blocks. Assume that the MEC server has perfect CSI at the beginning of a transmission block. In what follows, we discuss how the CSI of all links can be obtained by the MEC server in practice. Firstly, the MEC server broadcasts a pilot signal to the K IoT nodes. When the IoT nodes receive the pilot signal, they take turns to reflect the received pilot signal to the MEC server. Then the MEC server can perform least-square estimation to obtain the product of the forward channel gain and the backward channel gain, which are equal due to the channel reciprocity, and hence the MEC server can obtain the forward channel gain from the MEC server to each IoT node by taking square root of the product.

Let T denote the transmission block duration, which is divided into five phases, as shown in Fig. 1. In the EH phase, the MEC server broadcasts energy signals via C downlink subchannels and each IoT node works in the EH mode on its allocated subchannel. Let $\tau_{\rm e}$ and $h_{c,k}$ ($c \in \mathcal{C} = \{1, 2, ..., C\}$, $k \in \mathcal{K} = \{1, 2, ..., K\}$) denote the EH time and the channel gain between the k-th IoT node and the MEC server on the c-th subchannel, respectively, then the harvested energy of the k-th IoT node in the EH phase is given as

$$E_k^{\rm h} = \eta \tau_{\rm e} \sum_{c=1}^{C} \alpha_{c,k} P_{c,k}^{\rm e} h_{c,k}, \tag{1}$$

where $P_{c,k}^{\rm e}$ is the transmit power of the MEC server to the k-th IoT node on the c-th subchannel within the EH phase, η $(0 \le \eta \le 1)$ is the efficiency of energy conversion for the EH circuit, $\alpha_{c,k} \in \{0, 1\}$ is the subchannel allocation indicator with $\alpha_{c,k} = 1$ indicating that subchannel c is allocated to the IoT node k and $\alpha_{c,k} = 0$ otherwise. Note that the linear EH model is assumed here for analytical tractability and this work can been extended to a scenario with a non-linear EH model by using the approach adopted in [2] or [10].

In the BackCom phase, the MEC server broadcasts predefined carrier signals and each IoT node offloads its tasks to the MEC server by backscattering the received signals on its allocated subchannel. Thereby, in this phase, the offloaded task bits from the k-th IoT node is written as[2]

$$R_k^{\rm b} = \sum_{c=1}^{C} \alpha_{c,k} \tau_{\rm b} W \log_2 \left(1 + \frac{\xi \beta_{c,k} P_{c,k} h_{c,k}^2}{W \sigma^2}\right), \tag{2}$$

where $\tau_{\rm b}$, $\beta_{c,k}$ $(0 \le \beta_{c,k} \le 1)$, $P_{c,k}$, and $W = \frac{B}{C}$ denote the time duration of the BackCom phase, the PRC of the k-th IoT node on the c-th subchannel [18], the transmit power from the MEC server to the k-th IoT node on the c-th subchannel in the BackCom phase, and the bandwidth of each subchannel, respectively, ξ expresses the performance gap between the BackCom and the AR [12], [13], and σ^2 is the noise power spectral density.

The IoT nodes can harvest energy while backscattering energy signals for task offloading, and the k-th IoT node's energy harvested during BackCom phase is given as

$$E_k^{\rm b} = \eta \tau_{\rm b} \sum_{c=1}^{C} \alpha_{c,k} \left(1 - \beta_{c,k}\right) P_{c,k} h_{c,k}. \tag{3}$$

The total harvested energy at the k-th IoT node during the above two phases can be given as

$$\begin{aligned} E_k^{\rm tot} &= E_k^{\rm h} + E_k^{\rm b} \\ &= \eta \sum_{c=1}^{C} \alpha_{c,k} h_{c,k} \left(\tau_{\rm e} P_{c,k}^{\rm e} + \tau_{\rm b} P_{c,k} - \tau_{\rm b} \beta_{c,k} P_{c,k}\right). \end{aligned} \tag{4}$$

In the AR phase, the MEC server stops broadcasting energy signals and all IoT nodes transmit their tasks following the OFDMA protocol. Let $p_{c,k}$ denote the transmit power of the k-th IoT node on the c-th subchannel, then in this phase, the task bits offloaded by the k-th IoT node are determined as

$$R_k^{\rm a} = \sum_{c=1}^{C} \alpha_{c,k} \tau_{\rm a} W \log_2 \left(1 + \frac{p_{c,k} h_{c,k}}{W \sigma^2}\right), \tag{5}$$

where $\tau_{\rm a}$ represents the time duration of the AR phase.

Accordingly, at the end of the AR phase, the total task bits received at the MEC server can be written as

$$\begin{aligned} R_{\rm off} &= \sum_{k=1}^{K} \left(R_k^{\rm b} + R_k^{\rm a}\right) \\ &= \sum_{k=1}^{K} \sum_{c=1}^{C} \alpha_{c,k} W \Bigg(\tau_{\rm b} \log_2 \left(1 + \frac{\xi \beta_{c,k} P_{c,k} h_{c,k}^2}{W \sigma^2}\right) \\ &\quad + \tau_{\rm a} \log_2 \left(1 + \frac{p_{c,k} h_{c,k}}{W \sigma^2}\right)\Bigg). \end{aligned} \tag{6}$$

In the task execution phase, the MEC server computes the received task bits while all IoT nodes stop performing task offloading. In particular, let $f_{\rm c}$ and $\tau_{\rm c}$ denote the MEC server's computing frequency and time, respectively, then the maximum amount of bits that can be computed by the MEC server in this phase is given by $R_{\rm m} = \frac{f_{\rm c} \tau_{\rm c}}{C_{\rm cpu}}$, where $C_{\rm cpu}$ is the MEC server's required number of CPU cycles when computing

[2]Note that when the MEC server receives the backscattered signals from the IoT nodes, it still broadcasts energy signals. This means the self-interference (SI) at the MEC server exists and is cancelled in (2) since the MEC server knows both the CSI of all channels and the transmitted energy signals, and the successive interference cancellation (SIC) can be done at the MEC server to remove SI.

one bit. Note that if $R_{\rm off} > R_{\rm m}$, not all the received task bits can be computed at the MEC server. Hence, the actual amount of bits computed by the MEC server in this phase is given as

$$R_{\rm c} = \min\{R_{\rm off}, R_{\rm m}\}. \tag{7}$$

In the downloading phase, the MEC server broadcasts the obtained computation results to the corresponding IoT nodes. Since the computation results are usually just a few bits, the time for broadcasting computation results is negligible in this article [1], [2], [5], [15], [19].

Each IoT node can perform local computing at any time during a transmission block as long as its battery contains sufficient energy, since the computing circuit is separate from the EH circuit and the BackCom circuit. Let τ_k and f_k represent the computing time and frequency of the k-th IoT node, respectively, then the amount of bits computed by the k-th IoT node in each transmission block is given as

$$R_k^{\rm loc} = \frac{\tau_k f_k}{C_{{\rm cpu},k}}, \tag{8}$$

where $C_{{\rm cpu},k}$ denotes the k-th IoT node's required number of CPU cycles when computing one bit.

The energy consumption of the k-th IoT node when performing local computation is given as [19]

$$E_k^{\rm cos} = \varepsilon_k f_k^3 \tau_k, \tag{9}$$

where ε_k expresses the effective capacitance coefficient (ECC) from the processor's chip at the k-th IoT node.

III. SCB Maximization for $K \le C$

Here, we maximize the SCB for the case of $K \le C$, i.e., the number of subchannels is no less than the number of IoT nodes. In particular, we assume that each subchannel is assigned to no more than one IoT node, i.e., $\sum_{k=1}^{K} \alpha_{c,k} \le 1, \forall c$, and formulate a SCB maximization problem that requires the joint optimisation of the EH time, transmit power, subchannel allocation, computation frequency and time of the MEC server, and the IoT nodes' BackCom time and reflection coefficients, transmit power and time for AR-based offloading, computing time and frequencies, subject to the constraints on the QoS, energy causality, latency, computation capacity and maximum transmit power.

A. Problem Formulation

The SCB consist of two parts: the computation bits achieved by all IoT nodes through local computing and the computation bits at the MEC server. According to (7) and (8), we can calculate the SCB as

$$C_{\rm tot} = R_{\rm c} + \sum_{k=1}^{K} R_k^{\rm loc}. \tag{10}$$

The QoS constraint requires that the total computation bits of each IoT node are not less than its minimum required computation bits. Let $C_{{\rm min},k}$ denote the minimum required computation bits of the k-th IoT node. We introduce the auxiliary variables $\{\lambda_k\}_{k=1}^{K}$ ($0 \le \lambda_k \le 1, \forall k \in \mathcal{K}$) to denote the portion of $C_{{\rm min},k}$ that are executed at the MEC server. Then, the QoS constraint for the k-th IoT node can be expressed as

$$R_k^{\rm b} + R_k^{\rm a} \ge \lambda_k C_{{\rm min},k}, \forall k, \tag{11}$$

$$\sum\nolimits_{k=1}^{K} \lambda_k C_{{\rm min},k} \le R_{\rm m}, \tag{12}$$

$$R_k^{\rm loc} \ge (1-\lambda_k) C_{{\rm min},k}, \forall k, \tag{13}$$

where (11) and (12) assure that at least $\lambda_k C_{{\rm min},k}$ task bits can be offloaded from the k-th IoT node and executed at the MEC server, and (13) assures that at least $(1-\lambda_k) C_{{\rm min},k}$ task bits can be executed by the k-th IoT node locally.

The energy-causality constraint requires that each IoT node only uses its harvested energy to perform task offloading and computing. That is, the total energy consumption for task offloading and computing at each IoT node should not exceed its harvested energy in the whole transmission block. Following [6], [20], [21], we suppose that the power consumption of BackCom at the k-th IoT node is fixed at $P_{{\rm b},k}$. Based on (9), the energy-causality constraint of the k-th IoT node can be expressed as

$$\sum_{c=1}^{C} \alpha_{c,k} \left(P_{{\rm b},k}\tau_{\rm b} + p_{c,k}\tau_{\rm a}\right) + \varepsilon_k f_k^3 \tau_k \le E_k^{\rm tot}, \forall k. \tag{14}$$

For the MEC server's transmit power constraints in the EH and BackCom phases, we have

$$0 \le \sum\nolimits_{k=1}^{K} \sum\nolimits_{c=1}^{C} \alpha_{c,k} P_{c,k}^{\rm e} \le P_{\rm max}, \tag{15}$$

$$0 \le \sum\nolimits_{k=1}^{K} \sum\nolimits_{c=1}^{C} \alpha_{c,k} P_{c,k} \le P_{\rm max}, \tag{16}$$

where $P_{\rm max}$ is the maximum allowed transmit power of the MEC server.

Using (10)-(16), we arrive the following SCB maximization problem, i.e,

$$\begin{aligned}
\mathbf{P_0}:\ & \max_{\mathcal{V}} \quad C_{\rm tot} \\
\text{s.t.}\ & {\rm C1}: (11)-(13), \\
& {\rm C2}: (14), \\
& {\rm C3}: 0 \le f_{\rm c} \le f_{\rm max}, 0 \le f_k \le f_k^{\rm max},\ \forall k, \\
& {\rm C4}: \tau_{\rm e} + \tau_{\rm b} + \tau_{\rm a} + \tau_{\rm c} \le T, \tau_{\rm e}, \tau_{\rm b}, \tau_{\rm a}, \tau_{\rm c} \ge 0, \\
& {\rm C5}: 0 \le \tau_k \le T,\ \forall k, \\
& {\rm C6}: (15), (16), P_{c,k}^{\rm e} \ge 0, P_{c,k} \ge 0, \forall k, \forall c, \\
& {\rm C7}: 0 \le \beta_{c,k} \le 1, \forall k, \forall c, \\
& {\rm C8}: 0 \le \lambda_k \le 1, \forall k, \\
& {\rm C9}: \textstyle\sum_{k=1}^{K} \alpha_{c,k} \le 1, \alpha_{c,k} \in \{0,1\}, \forall k, \forall c,
\end{aligned}$$

where $\mathcal{V} = \big\{\tau_{\rm e}, \tau_{\rm b}, \tau_{\rm a}, \tau_{\rm c}, \{\tau_k\}, \{P_{c,k}^{\rm e}\}, \{P_{c,k}\}, \{\alpha_{c,k}\}, \{\beta_{c,k}\}, \{p_{c,k}\}, \{f_k\}, f_{\rm c}, \{\lambda_k\}\big\}$ denotes the set of the optimization variables, $f_k^{\rm max}$ and $f_{\rm max}$ are the maximum allowed computing frequencies for the k-th IoT node and the MEC server, respectively.

In $\mathbf{P_0}$, C1 and C2 are the QoS and energy-causality constraints for all IoT nodes. C3 limits the maximum allowed computation frequencies of the MEC server and IoT nodes. C4 and C5 guarantee that all the time allocation is within one transmission block T. C6 sets the maximum allowed total transmit power of the MEC server in the EH and BackCom phases. C7 and C8 are the constraints on the PRC of each IoT node and λ_k, $\forall k$, respectively. C9 ensures that each subchannel is allocated to at most one IoT node during each transmission block.

It is obvious that $\mathbf{P_0}$ is non-convex. This is because the subchannel allocation indicator $\alpha_{c,k}$ is a binary integer and there exist several coupling relationships among multiple optimization variables except for $\alpha_{c,k}$, i.e., $P^{\rm e}_{c,k}$ and $\tau_{\rm e}$, $P_{c,k}$, $\beta_{c,k}$ and $\tau_{\rm b}$, $p_{c,k}$ and $\tau_{\rm a}$, f_k and τ_k, etc, in the objective function and constraints. Therefore, $\mathbf{P_0}$ is generally hard to solve.

B. Solution

In this subsection, we first simplify $\mathbf{P_0}$ to make it more tractable and then transform it into a convex problem. To reduce the complexity of $\mathbf{P_0}$ caused by $R_{\rm c}$ as given in (7), we introduce a slack variable $\Delta = R_{\rm c} = \min\{R_{\rm off}, R_{\rm m}\}$, substitute it into the objective function of $\mathbf{P_0}$ and obtain

$$
\begin{aligned}
\mathbf{P_1}:\ & \max_{\mathcal{V},\Delta} \quad \Delta + \textstyle\sum_{k=1}^{K} R_k^{\rm loc} \\
\text{s.t. }& \text{C1} - \text{C9}, \\
& \text{C10}: \textstyle\sum_{k=1}^{K}\left(R_k^{\rm b} + R_k^{\rm a}\right) \geq \Delta, \\
& \text{C11}: R_{\rm m} \geq \Delta.
\end{aligned}
$$

According to (2) and (5), both $R_k^{\rm b}$ and $R_k^{\rm a}$ contain a sum of log functions, making C1 and C10 rather complicated. Hence, we simplify the expressions of $R_k^{\rm b}$ and $R_k^{\rm a}$ by removing the sum of log functions. Since each subchannel is assigned to no more than one IoT node, $R_k^{\rm b}$ and $R_k^{\rm a}$ can be equivalently rewritten as

$$
R_k^{\rm b} = \tau_{\rm b} W \log_2\left(1 + \frac{\xi \sum_{c=1}^{C} \alpha_{c,k}\beta_{c,k}P_{c,k}h_{c,k}^2}{W\sigma^2}\right), \quad (17)
$$

$$
R_k^{\rm a} = \tau_{\rm a} W \log_2\left(1 + \frac{\sum_{c=1}^{C} \alpha_{c,k}p_{c,k}h_{c,k}}{W\sigma^2}\right). \quad (18)
$$

Next, we introduce the following proposition to deal with the coupled relationships between f_k and τ_k, as well as between $f_{\rm c}$ and $\tau_{\rm c}$ in $\mathbf{P_1}$, and obtain the k-th IoT node's optimal computing time, denoted by τ_k^*, and the MEC server's optimal computation frequency, denoted by $f_{\rm c}^*$.

Proposition 1: The amount of bits computed by the considered network is maximized when the MEC server executes all the received task bits with its maximum allowed computing frequency and each IoT node executes tasks locally during the whole transmission block, i.e., $f_{\rm c}^* = f_{\max}$ and $\tau_k^* = T$, $\forall k \in \mathcal{K}$.

Proof. The detailed process of this proof can be found in Appendix A. ■

Substituting $f_{\rm c} = f_{\max}$, $\tau_k = T$, (17) and (18) into $\mathbf{P_1}$, the following optimization problem can be obtained, given by,

$$
\begin{aligned}
\mathbf{P}_2:\ & \max_{\mathcal{V}',\Delta} \quad \Delta + \textstyle\sum_{k=1}^{K} \frac{f_k T}{C_{{\rm cpu},k}} \\
\text{s.t. }& \text{C1}': \tau_{\rm b} W\log_2\left(1 + \frac{\xi \sum_{c=1}^{C} \alpha_{c,k}\beta_{c,k}P_{c,k}h_{c,k}^2}{W\sigma^2}\right) \\
& \qquad + \tau_{\rm a} W\log_2\left(1 + \frac{\sum_{c=1}^{C}\alpha_{c,k}p_{c,k}h_{c,k}}{W\sigma^2}\right) \geq \lambda_k C_{\min,k}, \forall k, \\
& \qquad \textstyle\sum_{k=1}^{K} \lambda_k C_{\min,k} \leq \frac{f_{\max}\tau_{\rm c}}{C_{\rm cpu}}, \\
& \qquad \frac{f_k T}{C_{{\rm cpu},k}} \geq (1-\lambda_k)\, C_{\min,k}, \forall k, \\
& \text{C2}': \sum_{c=1}^{C} \alpha_{c,k}\left(P_{{\rm b},k}\tau_{\rm b} + p_{c,k}\tau_{\rm a}\right) + \varepsilon_k f_k^3 T \leq E_k^{\rm tot}, \forall k, \\
& \text{C3}': 0 \leq f_k \leq f_k^{\max},\ \forall k, \\
& \text{C4}, \text{C6}-\text{C9}, \\
& \text{C10}': \textstyle\sum_{k=1}^{K} \tau_{\rm b} W\log_2\left(1 + \frac{\xi \sum_{c=1}^{C}\alpha_{c,k}\beta_{c,k}P_{c,k}h_{c,k}^2}{W\sigma^2}\right) \\
& \qquad + \tau_{\rm a} W\log_2\left(1 + \frac{\sum_{c=1}^{C}\alpha_{c,k}p_{c,k}h_{c,k}}{W\sigma^2}\right) \geq \Delta, \\
& \text{C11}': \frac{f_{\max}\tau_{\rm c}}{C_{\rm cpu}} \geq \Delta,
\end{aligned}
$$

where $\mathcal{V}' = \{\tau_{\rm e}, \tau_{\rm b}, \tau_{\rm a}, \tau_{\rm c}, \{P^{\rm e}_{c,k}\}, \{P_{c,k}\}, \{\alpha_{c,k}\}, \{\beta_{c,k}\}, \{p_{c,k}\}, \{f_k\}, \{\lambda_k\}\}$.

It can be observed that $\mathbf{P_2}$ is still a mixed integer programming problem, which is hard to solve, e.g., the traditional Brute-force method suffers from a high computational complexity. In order to solve $\mathbf{P_2}$ with a lower computation complexity, we relax the binary subchannel allocation indicator $\alpha_{c,k}$ to be a continuous real variable in the range $[0, 1]$ [5], [22]–[24], which can be regarded as a time-sharing factor for the k-th IoT node on the c-th subchannel. As a result, more than one IoT nodes can share the same subchannel by occupying different time/OFDM symbols.

Although the time-sharing relaxation avoids integer optimization variables, $\mathbf{P_2}$ is still non-convex due to the coupled relationships among several variables. To address this problem, the auxiliary variables, $x_{c,k} = \alpha_{c,k}\beta_{c,k}P_{c,k}\tau_{\rm b}$, $y_{c,k} = \alpha_{c,k}P_{c,k}\tau_{\rm b}$, $z_{c,k} = \alpha_{c,k}p_{c,k}\tau_{\rm a}$, $a_{c,k} = \tau_{\rm b}\alpha_{c,k}$ and $b_{c,k} = \tau_{\rm e}P^{\rm e}_{c,k}\alpha_{c,k}$, are introduced to replace the variables $\beta_{c,k} = \frac{x_{c,k}}{y_{c,k}}$, $P_{c,k} = \frac{y_{c,k}}{a_{c,k}}$, $p_{c,k} = \frac{z_{c,k}\tau_{\rm b}}{a_{c,k}\tau_{\rm a}}$, $\alpha_{c,k} = \frac{a_{c,k}}{\tau_{\rm b}}$ and

$P^{\mathrm{e}}_{c,k}=\frac{b_{c,k}\tau_{\mathrm{b}}}{a_{c,k}\tau_{\mathrm{e}}}$, in $\mathbf{P}_2$ and we obtain

$$
\begin{aligned}
\mathbf{P}_3:\ &\max_{\mathcal{V}'',\Delta}\quad \Delta+\sum\nolimits_{k=1}^{K}\frac{f_kT}{C_{\mathrm{cpu},k}}\\
\text{s.t. }&\mathrm{C1}'':\tau_{\mathrm{b}}W\log_2\left(1+\frac{\xi\sum_{c=1}^{C}x_{c,k}h^2_{c,k}}{\tau_{\mathrm{b}}W\sigma^2}\right)\\
&\quad+\tau_{\mathrm{a}}W\log_2\left(1+\frac{\sum_{c=1}^{C}z_{c,k}h_{c,k}}{\tau_{\mathrm{a}}W\sigma^2}\right)\geq\lambda_kC_{\min,k},\forall k,\\
&\quad\sum\nolimits_{k=1}^{K}\lambda_kC_{\min,k}\leq\frac{f_{\max}\tau_{\mathrm{c}}}{C_{\mathrm{cpu}}},\\
&\quad\frac{f_kT}{C_{\mathrm{cpu},k}}\geq(1-\lambda_k)\,C_{\min,k},\forall k,\\
&\mathrm{C2}'':\sum_{c=1}^{C}\left(P_{\mathrm{b},k}a_{c,k}+z_{c,k}\right)+\varepsilon_kf_k^3T\\
&\quad\leq\eta\sum_{c=1}^{C}h_{c,k}\left(b_{c,k}+y_{c,k}-x_{c,k}\right),\forall k,\\
&\mathrm{C3}',\mathrm{C4},\mathrm{C8},\mathrm{C11}',\\
&\mathrm{C6}':0\leq\sum\nolimits_{k=1}^{K}\sum\nolimits_{c=1}^{C}b_{c,k}\leq\tau_{\mathrm{e}}P_{\max},\\
&\quad 0\leq\sum\nolimits_{k=1}^{K}\sum\nolimits_{c=1}^{C}y_{c,k}\leq\tau_{\mathrm{b}}P_{\max},\\
&\mathrm{C7}':0\leq x_{c,k}\leq y_{c,k},\forall k,\forall c,\\
&\mathrm{C9}':\sum\nolimits_{k=1}^{K}a_{c,k}\leq\tau_{\mathrm{b}},0\leq a_{c,k}\leq\tau_{\mathrm{b}},\forall k,\forall c,\\
&\mathrm{C10}'':\sum\nolimits_{k=1}^{K}\tau_{\mathrm{b}}W\log_2\left(1+\frac{\xi\sum_{c=1}^{C}x_{c,k}h^2_{c,k}}{\tau_{\mathrm{b}}W\sigma^2}\right)\\
&\quad+\tau_{\mathrm{a}}W\log_2\left(1+\frac{\sum_{c=1}^{C}z_{c,k}h_{c,k}}{\tau_{\mathrm{a}}W\sigma^2}\right)\geq\Delta,
\end{aligned}
$$

where $\mathcal{V}''=\{\tau_{\mathrm{e}},\tau_{\mathrm{b}},\tau_{\mathrm{a}},\tau_{\mathrm{c}},\{b_{c,k}\},\{y_{c,k}\},\{a_{c,k}\},\{x_{c,k}\},\{z_{c,k}\},\{f_k\},\{\lambda_k\}\}$.

Proposition 2: $\mathbf{P}_3$ is convex and can be efficiently solved by means of the existing convex tools.

Proof. The detailed process of this proof can be found in Appendix B. ■

IV. SCB Maximization for $C<K\leq 2C$

In this section, we maximize the SCB for the case of $C<K\leq 2C$, i.e., the number of IoT nodes is larger than that of subchannels. In this case, it is not possible to allow each IoT node to occupy a distinct subchannel for the duration of a transmission block. To address this problem, we propose a dynamic subchannel allocation scheme, where some IoT nodes perform HAPR, some IoT nodes perform BackCom only (i.e., stay quiet in the AR phase), while the other IoT nodes perform AR only (i.e., stay quiet in the BackCom phase) in a transmission block. Hence, a subchannel can be shared by an IoT node performing BackCom only and another IoT node performing AR only because they occupy it at different time in a transmission block.

In order to characterize the dynamic subchannel allocation of all IoT nodes, we let $\alpha^{\mathrm{h}}_{c,k}=1$ denote the allocation of the c-th subchannel to the k-th IoT node for the HAPR mode, otherwise $\alpha^{\mathrm{h}}_{c,k}=0$; let $\alpha^{\mathrm{b}}_{c,k}=1$ denote the allocation of the c-th subchannel to the k-th IoT node for the pure BackCom mode, otherwise $\alpha^{\mathrm{b}}_{c,k}=0$; and let $\alpha^{\mathrm{a}}_{c,k}=1$ denote the allocation of the c-th subchannel to the k-th IoT node for the pure AR mode, otherwise $\alpha^{\mathrm{a}}_{c,k}=0$. Accordingly, we have $\sum_{c=1}^{C}\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}+\alpha^{\mathrm{a}}_{c,k}\leq 1$ to ensure that the k-th IoT node is allocated with at most one subchannel and one mode. For the c-th subchannel, both $\sum_{k=1}^{K}\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\leq 1$ and $\sum_{k=1}^{K}\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{a}}_{c,k}\leq 1$ should be satisfied to avoid the co-channel interference. Accordingly, the task bits offloaded by the k-th IoT node in a transmission block are determined as

$$
\begin{aligned}
R^{\mathrm{D}}_k&=\sum\nolimits_{c=1}^{C}\Bigg[\left(\alpha^{\mathrm{b}}_{c,k}+\alpha^{\mathrm{h}}_{c,k}\right)\tau_{\mathrm{b}}W\log_2\left(1+\frac{\xi\beta_{c,k}P_{c,k}h^2_{c,k}}{W\sigma^2}\right)\\
&\quad+\left(\alpha^{\mathrm{a}}_{c,k}+\alpha^{\mathrm{h}}_{c,k}\right)\tau_{\mathrm{a}}W\log_2\left(1+\frac{p_{c,k}h_{c,k}}{W\sigma^2}\right)\Bigg]\\
&=\tau_{\mathrm{b}}W\log_2\left(1+\frac{\xi\sum_{c=1}^{C}\left(\alpha^{\mathrm{b}}_{c,k}+\alpha^{\mathrm{h}}_{c,k}\right)\beta_{c,k}P_{c,k}h^2_{c,k}}{W\sigma^2}\right)\\
&\quad+\tau_{\mathrm{a}}W\log_2\left(1+\frac{\sum_{c=1}^{C}\left(\alpha^{\mathrm{a}}_{c,k}+\alpha^{\mathrm{h}}_{c,k}\right)p_{c,k}h_{c,k}}{W\sigma^2}\right).
\end{aligned}\tag{19}
$$

Therefore, the SCB can be calculated as

$$
C^{\mathrm{D}}_{\mathrm{tot}}=\min\left\{\sum\nolimits_{k=1}^{K}R^{\mathrm{D}}_k,R_{\mathrm{m}}\right\}+\sum\nolimits_{k=1}^{K}R^{\mathrm{loc}}_k.\tag{20}
$$

At the end of the BackCom phase, the k-th IoT node's total harvested energy is given by

$$
\begin{aligned}
E^{\mathrm{D}}_{\mathrm{tot},k}&=\eta\sum_{c=1}^{C}h_{c,k}\Bigg[\left(\alpha^{\mathrm{a}}_{c,k}+\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\right)\left(\tau_{\mathrm{e}}P^{\mathrm{e}}_{c,k}+\tau_{\mathrm{b}}P_{c,k}\right)\\
&\quad-\left(\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\right)\tau_{\mathrm{b}}\beta_{c,k}P_{c,k}\Bigg].
\end{aligned}\tag{21}
$$

A. Problem Formulation

In this subsection, we formulate a SCB maximization problem for $C<K\leq 2C$, subject to the constraints of QoS, energy causality, and the MEC server's transmit power, as follows

$$
\begin{aligned}
\mathbf{P}_4:\ &\max_{\mathcal{V}_{\mathrm{D}}}\quad C^{\mathrm{D}}_{\mathrm{tot}}\\
\text{s.t. }&\mathrm{C12}:R^{\mathrm{D}}_k\geq\lambda_kC_{\min,k},\forall k,(12),(13),\\
&\mathrm{C13}:\sum_{c=1}^{C}\left(\left(\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\right)P_{\mathrm{b},k}\tau_{\mathrm{b}}+\left(\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{a}}_{c,k}\right)p_{c,k}\tau_{\mathrm{a}}\right)\\
&\quad+\varepsilon_kf_k^3\tau_k\leq E^{\mathrm{D}}_{\mathrm{tot},k},\forall k,\\
&\mathrm{C3}-\mathrm{C5},\mathrm{C7},\mathrm{C8},\\
&\mathrm{C14}:\sum\nolimits_{k=1}^{K}\sum\nolimits_{c=1}^{C}\left(\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\right)P^{\mathrm{e}}_{c,k}\leq P_{\max},\\
&\quad\sum\nolimits_{k=1}^{K}\sum\nolimits_{c=1}^{C}\left(\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\right)P_{c,k}\leq P_{\max},\\
&\quad P^{\mathrm{e}}_{c,k}\geq 0,P_{c,k}\geq 0,\forall k,\forall c,\\
&\mathrm{C15}:\sum\nolimits_{c=1}^{C}\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}+\alpha^{\mathrm{a}}_{c,k}\leq 1,\forall k,\\
&\mathrm{C16}:\sum\nolimits_{k=1}^{K}\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{b}}_{c,k}\leq 1,\sum\nolimits_{k=1}^{K}\alpha^{\mathrm{h}}_{c,k}+\alpha^{\mathrm{a}}_{c,k}\leq 1,\forall c,\\
&\quad\alpha^{\mathrm{h}}_{c,k},\alpha^{\mathrm{b}}_{c,k},\alpha^{\mathrm{a}}_{c,k}\in\{0,1\},\forall k,\forall c,
\end{aligned}
$$

where $\mathcal{V}_{\mathrm{D}}=\{\tau_{\mathrm{e}},\tau_{\mathrm{b}},\tau_{\mathrm{a}},\tau_{\mathrm{c}},\{\tau_k\},\{P^{\mathrm{e}}_{c,k}\},\{P_{c,k}\},\{\alpha^{\mathrm{h}}_{c,k}\},\{\alpha^{\mathrm{b}}_{c,k}\},\{\alpha^{\mathrm{a}}_{c,k}\},\{\beta_{c,k}\},\{p_{c,k}\},\{f_k\},f_{\mathrm{c}},\{\lambda_k\}\}$, C12, C13 and C14 are the constraints on the QoS, energy causality and the MEC server's transmit power, respectively, C15 ensures that each IoT node is allocated with at most one subchannel and one mode to offload tasks, and C16 ensures that each subchannel is allocated to no more than one IoT node in the BackCom or AR phase.

Due to the multiple integer variables and the coupled relationships among different optimization variables, $\mathbf{P}_4$ has a non-convex objective function and non-convex constraints hence is hard to solve directly.

B. Solution

By introducing a slack variable $\Delta' = \min\{\sum_{k=1}^{K} R_k^{\mathrm{D}}, R_{\mathrm{m}}\}$ to remove the min operation in the objective function (given in (20)) of $\mathbf{P}_4$, we have

$$\begin{aligned}\mathbf{P}_5: &\max_{\mathcal{V}_{\mathrm{D}},\Delta'} \quad \Delta' + \textstyle\sum_{k=1}^{K} R_k^{\mathrm{loc}} \\ &\text{s.t. C3} - \text{C5, C7, C8, C12} - \text{C16}, \\ &\quad \text{C17}: \textstyle\sum_{k=1}^{K} R_k^{\mathrm{D}} \geq \Delta', \text{C18}: R_{\mathrm{m}} \geq \Delta'.\end{aligned}$$

To solve $\mathbf{P}_5$, we present the following proposition to determine the optimal local computing time $\{\tau_k^*\}$ of the k-th IoT node and the MEC server's optimal computation frequency f_{c}^*.

Proposition 3: The amount of bits computed by the investigated network is maximized when each IoT node executes its task bits locally during the whole transmission block, i.e., $\tau_k^* = T$, $\forall k$, and the MEC server computes its received task bits with its maximum allowed computation frequency, namely $f_{\mathrm{c}}^* = f_{\max}$.

Proof. We can prove Proposition 3 by using proof of contradiction in a way similar to Appendix A, and omit the proof here for brevity. ■

According to Proposition 3, $\mathbf{P}_5$ is transformed as

$$\begin{aligned}\mathbf{P}_6: &\max_{\mathcal{V}'_{\mathrm{D}},\Delta'} \quad \Delta' + \textstyle\sum_{k=1}^{K} \frac{f_k T}{C_{\mathrm{cpu},k}} \\ &\text{s.t. C12}': R_k^{\mathrm{D}} \geq \lambda_k C_{\min,k}, \forall k, \textstyle\sum_{k=1}^{K} \lambda_k C_{\min,k} \leq \frac{f_{\max}\tau_{\mathrm{c}}}{C_{\mathrm{cpu}}}, \\ &\qquad \frac{f_k T}{C_{\mathrm{cpu},k}} \geq (1-\lambda_k) C_{\min,k}, \forall k, \\ &\quad \text{C13}': \sum_{c=1}^{C}\Big(\big(\alpha_{c,k}^{\mathrm{h}} + \alpha_{c,k}^{\mathrm{b}}\big) P_{\mathrm{b},k}\tau_{\mathrm{b}} + \big(\alpha_{c,k}^{\mathrm{h}} + \alpha_{c,k}^{\mathrm{a}}\big) p_{c,k}\tau_{\mathrm{a}}\Big) \\ &\qquad + \varepsilon_k f_k^3 T \leq E_{\mathrm{tot},k}^{\mathrm{D}}, \forall k \\ &\quad \text{C3}', \text{C4, C7, C8, C14} - \text{C17}, \\ &\quad \text{C18}': \frac{f_{\max}\tau_{\mathrm{c}}}{C_{\mathrm{cpu}}} \geq \Delta',\end{aligned}$$

where $\mathcal{V}'_{\mathrm{D}} = \{\tau_{\mathrm{e}}, \tau_{\mathrm{b}}, \tau_{\mathrm{a}}, \tau_{\mathrm{c}}, \{P_{c,k}^{\mathrm{e}}\}, \{P_{c,k}\}, \{\alpha_{c,k}^{\mathrm{h}}\}, \{\alpha_{c,k}^{\mathrm{b}}\}, \{\alpha_{c,k}^{\mathrm{a}}\}, \{\beta_{c,k}\}, \{p_{c,k}\}, \{f_k\}, \{\lambda_k\}\}$. It can be observed that $\mathbf{P}_6$ is a mixed integer programming problem and the coupled relationships between the integer variables (such as $\alpha_{c,k}^{\mathrm{a}}$, $\alpha_{c,k}^{\mathrm{b}}$ and $\alpha_{c,k}^{\mathrm{h}}$) and the continuous variables (such as $\tau_{\mathrm{e}}, \tau_{\mathrm{b}}, \tau_{\mathrm{a}}, P_{c,k}^{\mathrm{e}}$) make it difficult to solve.

To transform $\mathbf{P}_6$ into a more tractable form, we introduce the following binary integer variables, $s1_{c,k} = \alpha_{c,k}^{\mathrm{a}} + \alpha_{c,k}^{\mathrm{h}}$, $s2_{c,k} = \alpha_{c,k}^{\mathrm{b}} + \alpha_{c,k}^{\mathrm{h}}$ and $s3_{c,k} = \alpha_{c,k}^{\mathrm{a}} + \alpha_{c,k}^{\mathrm{b}} + \alpha_{c,k}^{\mathrm{h}}$. By substituting $\alpha_{c,k}^{\mathrm{b}} = s3_{c,k} - s1_{c,k}$, $\alpha_{c,k}^{\mathrm{a}} = s3_{c,k} - s2_{c,k}$ and $\alpha_{c,k}^{\mathrm{h}} = s1_{c,k} + s2_{c,k} - s3_{c,k}$ into $\mathbf{P}_6$, we have

$$\begin{aligned}\mathbf{P}_7: &\max_{\mathcal{V''}_{\mathrm{D}},\Delta'} \quad \Delta' + \textstyle\sum_{k=1}^{K} \frac{f_k T}{C_{\mathrm{cpu},k}} \\ &\text{s.t. C12}'': \tau_{\mathrm{b}} W \log_2\left(1 + \frac{\xi \sum_{c=1}^{C} s2_{c,k}\beta_{c,k}P_{c,k}h_{c,k}^2}{W\sigma^2}\right) \\ &\qquad + \tau_{\mathrm{a}} W \log_2\left(1 + \frac{\sum_{c=1}^{C} s1_{c,k}p_{c,k}h_{c,k}}{W\sigma^2}\right) \geq \lambda_k C_{\min,k}, \forall k, \\ &\qquad \textstyle\sum_{k=1}^{K} \lambda_k C_{\min,k} \leq \frac{f_{\max}\tau_{\mathrm{c}}}{C_{\mathrm{cpu}}}, \frac{f_k T}{C_{\mathrm{cpu},k}} \geq (1-\lambda_k) C_{\min,k}, \forall k, \\ &\quad \text{C13}'': \sum_{c=1}^{C} \left(s2_{c,k}P_{\mathrm{b},k}\tau_{\mathrm{b}} + s1_{c,k}p_{c,k}\tau_{\mathrm{a}}\right) + \varepsilon_k f_k^3 T \\ &\qquad \leq \eta \sum_{c=1}^{C} h_{c,k}\bigg(s3_{c,k}\left(\tau_{\mathrm{e}}P_{c,k}^{\mathrm{e}} + \tau_{\mathrm{b}}P_{c,k}\right) \\ &\qquad - s2_{c,k}\tau_{\mathrm{b}}\beta_{c,k}P_{c,k}\bigg), \forall k, \\ &\quad \text{C3}', \text{C4, C7, C8, C18}', \\ &\quad \text{C14}': \textstyle\sum_{k=1}^{K}\sum_{c=1}^{C} s2_{c,k}P_{c,k}^{\mathrm{e}} \leq P_{\max}, \\ &\qquad \textstyle\sum_{k=1}^{K}\sum_{c=1}^{C} s2_{c,k}P_{c,k} \leq P_{\max}, \\ &\quad \text{C15}': \textstyle\sum_{c=1}^{C} s3_{c,k} \leq 1, \forall k, \\ &\quad \text{C16}': \textstyle\sum_{k=1}^{K} s2_{c,k} \leq 1, \sum_{k=1}^{K} s1_{c,k} \leq 1, \forall c, \\ &\qquad s1_{c,k}, s2_{c,k}, s3_{c,k} \in \{0,1\}, \forall k, \forall c, \\ &\quad \text{C17}': \textstyle\sum_{k=1}^{K} \tau_{\mathrm{b}} W \log_2\left(1 + \frac{\xi \sum_{c=1}^{C} s2_{c,k}\beta_{c,k}P_{c,k}h_{c,k}^2}{W\sigma^2}\right) \\ &\qquad + \tau_{\mathrm{a}} W \log_2\left(1 + \frac{\sum_{c=1}^{C} s1_{c,k}p_{c,k}h_{c,k}}{W\sigma^2}\right) \geq \Delta',\end{aligned}$$

where $\mathcal{V}''_{\mathrm{D}} = \{\tau_{\mathrm{e}}, \tau_{\mathrm{b}}, \tau_{\mathrm{a}}, \tau_{\mathrm{c}}, \{P_{c,k}^{\mathrm{e}}\}, \{P_{c,k}\}, \{s1_{c,k}\}, \{s2_{c,k}\}, \{s3_{c,k}\}, \{\beta_{c,k}\}, \{p_{c,k}\}, \{f_k\}, \{\lambda_k\}\}$.

It can be found that $\mathbf{P}_7$ is still a non-convex optimization problem mainly due to the binary integer variables $\{s1_{c,k}\}, \{s2_{c,k}\}$, and $\{s3_{c,k}\}$. In the following, we first obtain suboptimal solutions of $\{s1_{c,k}\}, \{s2_{c,k}\}$ and $\{s3_{c,k}\}$ by leveraging the relevant constraints of $\mathbf{P}_7$, thereby determine the subchannel assignment and mode selection for all the IoT nodes. Then, we obtain the optimal values of the other variables in $\mathcal{V}''_{\mathrm{D}}$ by solving $\mathbf{P}_7$ under given $s1_{c,k}$, $s2_{c,k}$ and $s3_{c,k}$, $\forall c$, $\forall k$.

1) The subchannel assignment and mode selection for each IoT node with $C < K \leq 2C$: Based on C15′ and C16′, each subchannel is either allocated to one IoT node for HAPR or shared by two IoT nodes performing pure BackCom or pure AR, respectively. In the case of $C < K \leq 2C$, at least $K - C$ IoT nodes need to share a subchannel with another IoT node, and hence at most $2C - K$ subchannels can each be allocated to a distinct IoT node for performing HAPR. Previous results in [8], [10], [12], [13], [21], [25], [26] have shown that via a given subchannel, HAPR always offloads more computation bits than pure BackCom/AR. Therefore, to maximize the SCB, as many subchannels as possible, i.e., $2C - K$ subchannels, should be allocated to different IoT nodes to perform HAPR, while each of the remaining $K - C$ subchannels will be shared by a pair of IoT nodes that perform pure BackCom or AR, respectively. Considering that pure BackCom/AR relies more on a high-gain subchannel to offload a large amount of computation bits than HAPR, the subchannel that offers the largest channel gains to two of the IoT nodes will be selected to be shared by those two IoT nodes for pure BackCom or AR. Such selection will be repeated among the remaining subchannels and remaining IoT nodes until $K - C$

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subchannels have been selected. Then, each of the remaining $2C-K$ IoT nodes will perform HAPR and will be assigned with a distinct subchannel that offers the largest possible channel gain among the remaining $2C-K$ subchannels. The above subchannel assignment and mode selection scheme is presented in Algorithm 1.

Similar to sort algorithms, the complexity of Algorithm 1 mostly depends on the number of instructions that find the subchannel with the largest channel gain for each IoT node. Thus, the complexity of Algorithm 1 is determined by $O(K(K-C))$.

Algorithm 1 Subchannel Assignment and Mode Selection Scheme for $C<K\leq 2C$

```
Subchannel set: 𝒞 = {1,2,...,C}, IoT nodes set: 𝒦 = {1,2,...,K}, s1_{c,k} = s2_{c,k} = s3_{c,k} = 0, ∀c ∈ 𝒞, ∀k ∈ 𝒦, and subchannel gains set: ℋ = {h_{c,k}}_{c∈𝒞,k∈𝒦};
Set i = 1 and ii = 1;
Find (c*, k*) = arg max_{c∈𝒞,k∈𝒦}(ℋ);
Set {h_{c,k*}}_{c∈𝒞} = 0 and update ℋ;
Set kk(i) = k*, cc(i) = c*, α^h_{c*,k*} = 1 and α^b_{c*,k*} = α^a_{c*,k*} = 0;
repeat
    Find (c*, k*) = arg max_{c∈𝒞,k∈𝒦}(ℋ);
    if c* ∈ {cc(j)}_{j=1,...,i} then
        Set {h_{c*,k}}_{k∈𝒦} = 0 and update ℋ;
        if ii ≤ K − C then
            Set {h_{c,k*}}_{c∈𝒞} = 0 and update ℋ;
            Set α^a_{c*,k*} = 1 and α^h_{c*,k*} = α^b_{c*,k*} = 0;
            Find jj = arg_j({cc(j)}_{j=1,...,i} == c*) and set α^b_{cc(jj),kk(jj)} = 1, α^h_{cc(jj),kk(jj)} = α^a_{cc(jj),kk(jj)} = 0;
            Set i = i + 1, ii = ii + 1, kk(i) = k* and cc(i) = c*;
        end if
    else
        Set {h_{c,k*}}_{c∈𝒞} = 0 and update ℋ;
        Set i = i + 1, kk(i) = k* and cc(i) = c*;
        Set α^h_{c*,k*} = 1 and α^b_{c*,k*} = α^a_{c*,k*} = 0;
    end if
until i = K.
for i = 1 to K do
    Compute s1_{cc(i),kk(i)} = α^a_{cc(i),kk(i)} + α^h_{cc(i),kk(i)}, s2_{cc(i),kk(i)} = α^b_{cc(i),kk(i)} + α^h_{cc(i),kk(i)} and s3_{cc(i),kk(i)} = α^a_{cc(i),kk(i)} + α^b_{cc(i),kk(i)} + α^h_{cc(i),kk(i)};
end for
```

2) Optimal resource allocation given $s1_{c,k}$, $s2_{c,k}$ and $s3_{c,k}$: With $s1_{c,k}$, $s2_{c,k}$ and $s3_{c,k}$ determined by Algorithm 1, $\mathbf{P}_7$ can be transformed as follows

$$\mathbf{P}_{\mathrm{sub}}:\ \max_{\mathcal{V}_{\mathrm{s}}}\quad \Delta'+\textstyle\sum_{k=1}^{K}\frac{f_kT}{C_{\mathrm{cpu},k}}$$
$$\text{s.t. } \mathrm{C3}',\mathrm{C4},\mathrm{C7},\mathrm{C8},\mathrm{C12}'',\mathrm{C13}'',\mathrm{C14}',\mathrm{C17}',\mathrm{C18}',$$

where $\mathcal{V}_{\mathrm{s}}=\{\tau_{\mathrm{e}},\tau_{\mathrm{b}},\tau_{\mathrm{a}},\tau_{\mathrm{c}},\{P^{\mathrm{e}}_{c,k}\},\{P_{c,k}\},\{\beta_{c,k}\},\{p_{c,k}\},\{f_k\},\{\lambda_k\},\Delta'\}$.

Due to the coupled relationships among multiple optimization variables, e.g., $\beta_{c,k}$, $P_{c,k}$ and τ_{b}, $\mathbf{P}_{\mathrm{sub}}$ is a non-convex problem. To tackle this problem, we replace $\beta_{c,k},P_{c,k},p_{c,k}$, and $P^{\mathrm{e}}_{c,k}$ with $x^{\mathrm{D}}_{c,k}=\beta_{c,k}P_{c,k}\tau_{\mathrm{b}}$, $y^{\mathrm{D}}_{c,k}=P_{c,k}\tau_{\mathrm{b}}$, $z^{\mathrm{D}}_{c,k}=p_{c,k}\tau_{\mathrm{a}}$, and $b^{\mathrm{D}}_{c,k}=\tau_{\mathrm{e}}P^{\mathrm{e}}_{c,k}$, in $\mathbf{P}_{\mathrm{sub}}$ and obtain

$$
\begin{aligned}
&\mathbf{P}'_{\mathrm{sub}}:\ \max_{\mathcal{V}'_{\mathrm{s}}}\quad \Delta'+\textstyle\sum_{k=1}^{K}\frac{f_kT}{C_{\mathrm{cpu},k}}\\
&\text{s.t. } \mathrm{C3}',\mathrm{C4},\mathrm{C8},\mathrm{C18}',\\
&\quad \mathrm{C7}':0\leq x^{\mathrm{D}}_{c,k}\leq y^{\mathrm{D}}_{c,k},\forall c,\forall k,\\
&\quad \mathrm{C12}''':\tau_{\mathrm{b}}W\log_2\left(1+\frac{\xi\sum_{c=1}^{C}s2_{c,k}x^{\mathrm{D}}_{c,k}h^2_{c,k}}{\tau_{\mathrm{b}}W\sigma^2}\right)\\
&\qquad +\tau_{\mathrm{a}}W\log_2\left(1+\frac{\sum_{c=1}^{C}s1_{c,k}z^{\mathrm{D}}_{c,k}h_{c,k}}{\tau_{\mathrm{a}}W\sigma^2}\right)\geq\lambda_kC_{\min,k},\forall k,\\
&\qquad \textstyle\sum_{k=1}^{K}\lambda_kC_{\min,k}\leq\frac{f_{\max}\tau_{\mathrm{c}}}{C_{\mathrm{cpu}}},\ \frac{f_kT}{C_{\mathrm{cpu},k}}\geq(1-\lambda_k)C_{\min,k},\forall k,\\
&\quad \mathrm{C13}''':\textstyle\sum_{c=1}^{C}\left(s2_{c,k}P_{\mathrm{b},k}\tau_{\mathrm{b}}+s1_{c,k}z^{\mathrm{D}}_{c,k}\right)+\varepsilon_kf_k^3T\\
&\qquad \leq\eta\textstyle\sum_{c=1}^{C}h_{c,k}\left(s3_{c,k}\left(b^{\mathrm{D}}_{c,k}+y^{\mathrm{D}}_{c,k}\right)-s2_{c,k}x^{\mathrm{D}}_{c,k}\right),\forall k,\\
&\quad \mathrm{C14}'':\textstyle\sum_{k=1}^{K}\sum_{c=1}^{C}s2_{c,k}b^{\mathrm{D}}_{c,k}\leq P_{\max}\tau_{\mathrm{e}},\\
&\qquad \textstyle\sum_{k=1}^{K}\sum_{c=1}^{C}s2_{c,k}y^{\mathrm{D}}_{c,k}\leq P_{\max}\tau_{\mathrm{b}},\forall k,\ b^{\mathrm{D}}_{c,k}\geq 0,\forall c,\\
&\quad \mathrm{C17}'':\textstyle\sum_{k=1}^{K}\tau_{\mathrm{b}}W\log_2\left(1+\frac{\xi\sum_{c=1}^{C}s2_{c,k}x^{\mathrm{D}}_{c,k}h^2_{c,k}}{\tau_{\mathrm{b}}W\sigma^2}\right)\\
&\qquad +\tau_{\mathrm{a}}W\log_2\left(1+\frac{\sum_{c=1}^{C}s1_{c,k}z^{\mathrm{D}}_{c,k}h_{c,k}}{\tau_{\mathrm{a}}W\sigma^2}\right)\geq\Delta',
\end{aligned}
$$

where $\mathcal{V}'_{\mathrm{s}}=\{\tau_{\mathrm{e}},\tau_{\mathrm{b}},\tau_{\mathrm{a}},\tau_{\mathrm{c}},\{b^{\mathrm{D}}_{c,k}\},\{y^{\mathrm{D}}_{c,k}\},\{x^{\mathrm{D}}_{c,k}\},\{z^{\mathrm{D}}_{c,k}\},\{f_k\},\{\lambda_k\},\Delta'\}$, $\beta_{c,k}=\frac{x^{\mathrm{D}}_{c,k}}{y^{\mathrm{D}}_{c,k}}$, $P_{c,k}=\frac{y^{\mathrm{D}}_{c,k}}{\tau_{\mathrm{b}}}$, $p_{c,k}=\frac{z^{\mathrm{D}}_{c,k}}{\tau_{\mathrm{a}}}$, and $P^{\mathrm{e}}_{c,k}=\frac{b^{\mathrm{D}}_{c,k}}{\tau_{\mathrm{e}}}$.

Proposition 4: $\mathbf{P}'_{\mathrm{sub}}$ is convex, and can be efficiently solved by applying the convex optimization tools.

Proof. The detailed process is similar to Appendix B and is omitted here for brevity. ■

Based on Algorithm 1 and Proposition 4, $\mathbf{P}_7$ can be solved by first using Algorithm 1 to obtain the subchannel assignment and mode selection for each IoT node and then using the existing convex optimization tools, i.e., the Lagrange duality method, to optimally solve $\mathbf{P}'_{\mathrm{sub}}$.

V. Numerical Results

The basic simulation parameters are set as $T=1$ s, $B=40$ MHz, $C=40$, $C_{\mathrm{cpu},k}=1000$ cycles/bit, $C_{\mathrm{cpu}}=1000$ cycles/bit, $P_{\mathrm{b},k}=10$ μW, $P_{\max}=1$ W, $\eta=0.7$, $\xi=-15$ dB, $\sigma^2=-120$ dBm/Hz, $K=4$, $\varepsilon_k=10^{-26}$, $f_k^{\max}=500$ MHz, $f_{\max}=10$ GHz, and $C_{\min,k}=500$ kbits [2], [10], [12], [19]. Here a standard channel fading model with the small-scale fading $h'_{c,k}$, the path loss exponent ς and the distance d_k is applied to model the channel gain from the k-th IoT node to the MEC server on the c-th subchannel. Accordingly, we set $\varsigma=3$, $d_1=10$ m, $d_2=9$ m, $d_3=12$ m and $d_4=11$ m.

In the following part, we first introduce four benchmark schemes which are wireless powered AR for MEC, backscatter assisted MEC, the complete offloading scheme and the fully local computing scheme, respectively, and illustrate the superiority of the proposed schemes by comparing the computation performance under the proposed schemes with that under the above four benchmark schemes.

- **Wireless powered AR for MEC**: In the wireless powered AR for MEC, the partial offloading scheme is considered, where a part of tasks at each IoT node will be offloaded to the MEC server for computation via AR and the others will be computed locally. In order to avoid co-channel interference among different IoT nodes, each subchannel is assigned to no more than one IoT node for task offloading. Note that when $K > C$, at least one IoT node can not access a subchannel, leading to unsatisfied QoS constraints. Thus, the wireless powered AR for MEC is only applicable for the case of $K \leq C$.

- **Backscatter assisted MEC**: In the backscatter assisted MEC, each IoT node offloads its part of tasks via BackCom and computes the other tasks locally. Likewise, each IoT node only chooses a distinct subchannel to backscatter tasks to avoid co-channel interference. Similar to the wireless powered AR for MEC, the backscatter assisted MEC is only applicable for the case of $K \leq C$.
- **Complete offloading scheme**: In this scheme, all the task bits at each IoT node will be offloaded to the MEC server for computation and all IoT nodes choose the HAPR to transmit their tasks. Note that this scheme is applicable for both cases of $K \leq C$ and $C < K \leq 2C$. Specifically, for the case with $K \leq C$, each IoT node can access a distinct subchannel for task offloading while for the case with $C < K \leq 2C$, $2C - K$ subchannels are allocated to $2C - K$ IoT nodes to perform HAPR and the rest $K - C$ subchannels are assigned to $2(K - C)$ IoT nodes to perform BackCom or AR. The subchannel assignment and mode selection of each IoT node can be determined by Algorithm 1.
- **Fully local computing scheme**: In this scheme, each IoT node only computes its tasks locally. This scheme is applicable for both cases of $K \leq C$ and $C < K \leq 2C$. For convenience, Algorithm 1 is used to decide the subchannel assignment of each IoT node.

It is worth noting that the above four benchmark schemes can be obtained by using the similar methods for solving $\mathbf{P}_1$ and $\mathbf{P}_4$ after making a few changes. Specifically, for the wireless powered AR for MEC with $K \leq C$, the convex optimization tool is used to solve $\mathbf{P}_3$ by letting $\tau_{\mathrm{b}} = 0$ and $x_{c,k} = y_{c,k} = 0, \forall c, \forall k$. For the backscatter assisted MEC with $K \leq C$, this scheme is optimized by solving $\mathbf{P}_3$ with $\tau_{\mathrm{a}} = 0$ and $z_{c,k} = 0, \forall c, \forall k$. For the complete offloading scheme with $K \leq C$, this scheme is obtained by solving $\mathbf{P}_3$ with $f_k = 0$ and $\lambda_k = 1, \forall k$. For the complete offloading scheme with $C < K \leq 2C$, Algorithm 1 is adopted to determine the subchannel assignment and mode selection of each IoT node first and then the existing convex optimization tool is used to solve $\mathbf{P}'_{\mathrm{sub}}$ with $f_k = 0$ and $\lambda_k = 1, \forall k$. Likewise, the fully local computing scheme with $K \leq C$ is achieved by solving $\mathbf{P}_3$ with $\tau_{\mathrm{b}} = \tau_{\mathrm{a}} = \tau_{\mathrm{c}} = 0$, $x_{c,k} = y_{c,k} = z_{c,k} = 0, \forall c, \forall k$ and $\lambda_k = 0, \forall k$. As for the fully local computing scheme with $C < K \leq 2C$, Algorithm 1 is used to decide the subchannel assignment of each IoT node first and then the existing convex optimization tool is used to solve $\mathbf{P}'_{\mathrm{sub}}$ with $\tau_{\mathrm{b}} = \tau_{\mathrm{a}} = \tau_{\mathrm{c}} = 0$, $x^{\mathrm{D}}_{c,k} = y^{\mathrm{D}}_{c,k} = z^{\mathrm{D}}_{c,k} = 0, \forall c, \forall k$ and $\lambda_k = 0, \forall k$.

Fig. 2. SCB versus $P_{\max}$ for the case of $K \leq C$.

A. Computation performance for the proposed resource allocation scheme with $K \leq C$

Fig. 2 shows the SCB versus the maximum allowed transmit power of the MEC server $P_{\max}$ under different schemes. It can be observed that the SCB under the proposed scheme, the wireless powered AR for MEC and the backscatter assisted MEC increase with the increasing of $P_{\max}$, while the SCB under the complete offloading scheme and the fully local computing scheme are always 0. The reasons are given below. For the proposed scheme, the wireless powered AR for MEC and the backscatter assisted MEC, a larger $P_{\max}$ allows each IoT node to harvest more energy and transmit/backscatter stronger signals, thus offloading more computation bits; while for the complete offloading scheme and the fully local computing scheme, the QoS constraint for each IoT node cannot be satisfied for all the considered values of $P_{\max}$, leading to the poor performance. By comparison, we observe that the proposed scheme outperforms the wireless powered AR for MEC and the backscatter assisted MEC in terms of the SCB since the proposed scheme combines the advantages of the BackCom and AR, bringing a more flexibility to utilize resources for maximizing the SCB.

Fig. 3 demonstrates the effect of the MEC server's computation capacity on the SCB, where the ratio of $f_{\max}$ to $f_k^{\max}$ varies from 10 to 50. From this figure, we can see that the SCB under the proposed scheme, the wireless powered AR for MEC, the backscatter assisted MEC and the complete offloading scheme increase as the MEC server's computation capacity improves. This is due to the fact that a larger computation capacity at the MEC server means shorter computing time at the MEC server and more time for each IoT node's task offloading, bringing higher offloading task bits and an improvement to the SCB. Since the improvement of the MEC server's computation capacity does not influence the SCB under the fully local computing scheme, the SCB under the fully local computing scheme keeps unchanged. Note that the fully local computing scheme achieves 0 computation bit due to the unsatisfied QoS constraint. By observations, we can also see that the SCB under the proposed scheme are higher than

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Fig. 3. SCB versus the ratio of $f_{\max}$ to $f_k^{\max}$ for the case of $K \leq C$.

Fig. 4. SCB versus $C_{\min}$ for the case of $K \leq C$.

those under the other schemes, which illustrates the superiority of the proposed scheme.

Fig. 4 plots the SCB versus the minimum required computation bits at each IoT node $C_{\min}$ with $C_{\min,1} = C_{\min,2} = C_{\min,3} = C_{\min,4} = C_{\min}$. $C_{\min}$ varies from 500 kbits to 1300 kbits and K is set as 4 and 10, respectively. From this figure, we can observe that the SCB under all the schemes decrease when $C_{\min}$ increases since a higher $C_{\min}$ brings a more strict QoS constraint for each IoT node and the IoT nodes with worse channels can be allocated more resources in order to satisfy the QoS constraint, resulting in a reduction to the SCB. Besides, we can also observe that when $C_{\min}$ is small, a larger K brings higher SCB, while with a large $C_{\min}$, not all the IoT nodes can satisfy the QoS constraint when K is larger, leading to the poor computation performance. Moreover, by comparing with the wireless powered AR for MEC and the backscatter assisted MEC, we find that the proposed scheme always achieves the highest SCB, which indicates the superiority of the proposed scheme.

Fig. 5 shows the SCB versus the number of IoT nodes K, where K varies from 5 to 25 and $C_{\min}$ is set as 5 kbits. Suppose that the distance from each IoT node to the MEC server randomly varies from 5 m to 10 m. It can be observed that when K is small, the SCB under the proposed scheme, the wireless powered AR for MEC and the backscatter assisted MEC increase with the increasing of K, while when K is large, there is a slight upward trend. The reasons are as follows. When K is small, the subchannels with good channel conditions will be allocated to the IoT nodes to satisfy the QoS constraints and achieve higher SCB, bringing an improvement to the SCB. When K is large, some subchannels with bad channel conditions may be assigned to some IoT nodes. In this case, more resources should be assigned to these IoT nodes to satisfy the QoS constraints, leading to a slight improvement to the SCB. Besides, by comparison, we also observe that the proposed scheme can achieve the best computation performance.

Fig. 5. SCB versus K for the case of $K \leq C$.

B. Computation performance for the proposed resource allocation scheme with $C < K \leq 2C$

In the following part, we illustrate the computation performance under the proposed resource allocation scheme for the case of $C < K \leq 2C$ in both Fig. 6 and Fig. 7. Here we set $K = 50$ and $C_{\min} = 5$ kbits. We consider that the distance from each IoT node to the MEC server randomly varies from 5 m to 10 m for convenience. In order to illustrate the superiority of the proposed scheme, the computation performance under the complete offloading scheme and the fully local computing scheme is plotted in above figures for comparisons. Note that the wireless powered AR for MEC and the backscatter assisted MEC are not included since they are not applicable for $C < K \leq 2C$.

Fig. 6 demonstrates the effect of the SCB achieved by the different schemes on $P_{\max}$, where $P_{\max}$ ranges from 0.5 W to 2.5 W. It can be seen that the SCB under all the schemes increase when $P_{\max}$ increases. By comparison, we can see that the proposed scheme yields largest SCB among all the schemes due to the superiority of the partial offloading scheme. Besides, it can also be found that when $P_{\max}$ is small, the fully local computing scheme is superior to the one achieved by the complete offloading scheme, while with a large $P_{\max}$, the complete offloading scheme can achieve

Fig. 6. SCB versus $P_{\max}$ for the case of $C < K \leq 2C$.

Fig. 7. SCB versus K for the case of $C < K \leq 2C$.

a better computation performance. This is because with a small $P_{\max}$, each IoT node may not harvest enough energy to support task offloading, leading to the poor computation performance, while with a large $P_{\max}$, offloading tasks is more energy efficient than computing tasks locally.

Fig. 7 depicts the SCB versus K, and K is from 45 to 65. One observation is that when K increases, the SCB under the proposed scheme and the fully local computing scheme also increase, while the SCB under the complete offloading scheme decrease. This is because for the complete offloading scheme, when K is large, some subchannels with bad channel conditions may be assigned to some IoT nodes, leading to unsatisfied QoS constraints and bringing a reduction to the SCB. Another observation is that among these schemes, our proposed scheme achieves the best computation performance, which verifies its superiority again.

VI. Conclusion

In this work, we have investigated the SCB maximization problem in a wireless powered OFDMA-MEC network with HAPR, where each IoT node will offload part of tasks to the MEC server while computing the remaining tasks locally. For both cases of $K \leq C$ and $C < K \leq 2C$, we have formulated and solved the SCB maximization problem by jointly managing the EH time, transmit power, subchannel allocation, computation frequency and time of the MEC server, and the IoT nodes' BackCom time and reflection coefficients, transmit power and time for AR-based offloading, and local computing time and frequencies, as well as the IoT nodes' offloading mode selection (among HAPR, BackCom only, and AR only) in the latter case. Simulation results have shown that as compared with the benchmark schemes, including the wireless powered AR for MEC, the backscatter assisted MEC, the complete offloading scheme and the fully local computing scheme, the proposed schemes achieve a higher amount of the SCB because they effectively exploit the complementary tradeoffs between energy consumption and offloading data rate offered by BackCom and AR. For the case of $C < K \leq 2C$, the proposed scheme enables more IoT nodes than conventionally allowed by the limited number of subchannels to offload tasks in a wireless powered OFDMA-MEC network.

Based on this work, there are some research directions that can be further explored. First, this work can be extended to the scenario where the binary offloading mode is adopted at each IoT node. Second, when considering the battery level of each IoT node, the resource allocation scheme for the considered network will need to be carefully redesigned. Third, it will be interesting to consider multiple MEC servers and redesign the resource allocation scheme.

Appendix A

A. *Proof for* $f_{\mathrm{m}}^* = f_{\max}$

We assume that $\{\tau_{\mathrm{e}}^*, \tau_{\mathrm{b}}^*, \tau_{\mathrm{a}}^*, \tau_{\mathrm{c}}^*, \{P_{c,k}^{\mathrm{e}*}\}, \{P_{c,k}^*\}, \{\alpha_{c,k}^*\}, \{\beta_{c,k}^*\}, \{p_{c,k}^*\}, \{f_k^*\}, \{\lambda_k^*\}, \{\tau_k^*\}, f_{\mathrm{c}}^*, \Delta^*\}$ is the optimal solution to $\mathbf{P_1}$, where $f_{\mathrm{c}}^* < f_{\max}$ and $\Delta^* = \min\left\{\sum_{k=1}^{K}\sum_{c=1}^{C}\alpha_{c,k}^* W\left(\tau_{\mathrm{b}}^*\log_2\left(1+\frac{\xi\beta_{c,k}^* P_{c,k}^* h_{c,k}}{W\sigma^2}\right)+\tau_{\mathrm{a}}^*\log_2\left(1+\frac{p_{c,k}^* h_{c,k}}{W\sigma^2}\right)\right), \frac{f_{\mathrm{c}}^*\tau_{\mathrm{c}}^*}{C_{\mathrm{cpu}}}\right\}$ hold. Then the maximum SCB for the considered network C_{tot}^* can be computed as $\Delta^* + \sum_{k=1}^{K}\frac{f_k^*\tau_k^*}{C_{\mathrm{cpu},k}}$. Besides, we can also construct a feasible solution, denoted by $\{\tau_{\mathrm{e}}^+, \tau_{\mathrm{b}}^+, \tau_{\mathrm{a}}^+, \tau_{\mathrm{c}}^+, \{P_{c,k}^{\mathrm{e}+}\}, \{P_{c,k}^+\}, \{\alpha_{c,k}^+\}, \{\beta_{c,k}^+\}, \{p_{c,k}^+\}, \{f_k^+\}, \{\lambda_k^+\}, \{\tau_k^+\}, f_{\mathrm{c}}^+, \Delta^+\}$, where $\tau_{\mathrm{e}}^+ = \tau_{\mathrm{e}}^*, \tau_{\mathrm{b}}^+ = \tau_{\mathrm{b}}^*, \tau_{\mathrm{a}}^+ = \tau_{\mathrm{a}}^*, \tau_{\mathrm{c}}^+ = \tau_{\mathrm{c}}^*, P_{c,k}^{\mathrm{e}+} = P_{c,k}^{\mathrm{e}*}, P_{c,k}^+ = P_{c,k}^*, \alpha_{c,k}^+ = \alpha_{c,k}^*, \beta_{c,k}^+ = \beta_{c,k}^*, p_{c,k}^+ = p_{c,k}^*, f_k^+ = f_k^*, \lambda_k^+ = \lambda_k^*, \tau_k^+ = \tau_k^*, f_{\mathrm{c}}^+ = f_{\max}$ and the constructed solution satisfies all the constraints of $\mathbf{P_1}$. Thus, the SCB under the constructed solution, denoted by C_{tot}^+, can be given by $\Delta^+ + \sum_{k=1}^{K}\frac{f_k^+\tau_k^+}{C_{\mathrm{cpu},k}}$, where $\Delta^+ = \min\left\{\sum_{k=1}^{K}\sum_{c=1}^{C}\alpha_{c,k}^+ W\left(\tau_{\mathrm{b}}^+\log_2\left(1+\frac{\xi\beta_{c,k}^+ P_{c,k}^+ h_{c,k}}{W\sigma^2}\right)+\tau_{\mathrm{a}}^+\log_2\left(1+\frac{p_{c,k}^+ h_{c,k}}{W\sigma^2}\right)\right), \frac{f_{\mathrm{c}}^+\tau_{\mathrm{c}}^+}{C_{\mathrm{cpu}}}\right\}$. Since $f_{\mathrm{c}}^+ = f_{\max} > f_{\mathrm{c}}^*$ is satisfied, we have $\Delta^+ \geq \Delta^*$ and $C_{\mathrm{tot}}^+ \geq C_{\mathrm{tot}}^*$, which contradicts the above assumption of $f_{\mathrm{c}}^* < f_{\max}$. Thus, the assumption of $f_{\mathrm{c}}^* < f_{\max}$ does not hold for maximizing the SCB and $f_{\mathrm{c}}^* = f_{\max}$ should be satisfied for maximizing SCB in the considered network.

B. Proof for $\tau_k^* = T$

When all the optimization variables expect f_k and τ_k are fixed, f_k and τ_k should be jointly optimized to maximize the SCB of the considered network. Suppose that f_k^* and $\tau_k^* < T$ are the optimal solutions which can satisfy all the constraints of $\mathbf{P_1}$ when other optimization variables are fixed. Then the maximum SCB $C_{\rm tot}^*$ should be calculated as $\Delta + \sum_{i=1,i\neq k}^{K} \frac{\tau_i f_i}{C_{{\rm cpu},k}} + \frac{\tau_k^* f_k^*}{C_{{\rm cpu},k}}$. Besides, we can also construct another solution $\{f_k^+, \tau_k^+\}$ with $\tau_k^+ = T$ and $\tau_k^+ f_k^+ (f_k^+)^2 = \tau_k^* f_k^* (f_k^*)^2$. Obviously, all the constraints of $\mathbf{P_1}$ hold for our constructed solution. Let $C_{\rm tot}^+$ denote the SCB under the constructed solution, where $C_{\rm tot}^+ = \Delta + \sum_{i=1,i\neq k}^{K} \frac{\tau_i f_i}{C_{{\rm cpu},k}} + \frac{\tau_k^+ f_k^+}{C_{{\rm cpu},k}}$. Since $\tau_k^+ = T > \tau_T^*$ and $\tau_k^+ f_k^+ (f_k^+)^2 = \tau_k^* f_k^* (f_k^*)^2$, we have $f_k^+ < f_k^*$ and $\tau_k^+ f_k^+ > \tau_k^* f_k^*$. Therefore, $C_{\rm tot}^+ > C_{\rm tot}^*$ can be obtained, which disagrees with $\tau_k^* < T$. Thereby, $\tau_k^* = T$ should be satisfied for achieving the maximum SCB of the considered network.

Appendix B

By observing $\mathbf{P}_3$, we know the objective function and the constraints, i.e., C3$'$, C4, C6$'$, C7$'$, C8, C9$'$ and C11$'$, are convex, which means that $\mathbf{P}_3$ is convex if C1$''$, C2$''$ and C11$'$ are convex.

1) The convexities of constraints C1$''$ *and* C11$'$*:* It can be observed that the convexity of C1$''$ and C11$'$ depends on the convexity of $f(x,y) = x\log_2\left(1+\frac{y}{x}\right)$ with respect to x and y. Since the convexity can be preserved by the perspective function, both $f(x,y)$ and $\log_2(1+y)$ have the same convexity. Recall that $\log_2(1+y)$ is concave, then, we can say that $f(x,y)$ is concave on x and y. This indicates that C1$''$ and C11$'$ are convex.

2) The convexity of constraint C2$''$*:* The convexity-concavity of C2$''$ is determined by the left side of C2$''$ whose convexity-concavity depends on the function $f_1(x) = x^3$ with $x \geq 0$. It is not hard to prove that $f_1(x) = x^3$ with $x \geq 0$ is convex, thereby, C2$''$ is also convex. Using the above results, $\mathbf{P}_3$ is proved to be convex.

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