SCIENCE CHINA
Information Sciences

• RESEARCH PAPER •

August 2021, Vol. 64 182303:1–182303:10
https://doi.org/10.1007/s11432-020-2925-1

Resource optimization in wireless powered cooperative mobile edge computing systems

Qibin YE[1], Weidang LU[2], Su HU[1*] & Xiaohan XU[2]

[1]*National Key Laboratory on Communications, University of Electronic Science and Technology of China, Chengdu 611731, China;*
[2]*College of Information Engineering, Zhejiang University of Technology, Hangzhou 310023, China*

Received 11 January 2020/Revised 19 March 2020/Accepted 25 May 2020/Published online 8 July 2021

Abstract Mobile edge computing (MEC) meets the high-bandwidth and ultra-low-latency requirements of mobile networks and improves communication reliability by reducing the networks' load. In this study, we study a wireless powered MEC system, which includes an access point (AP) and two mobile devices. The endurance of mobile devices can be effectively enhanced using the wireless power transfer technology and user cooperation. However, during user cooperation, a closer user assists a farther user with forwarding tasks by sharing the same bandwidth, which causes interference. To overcome the interference issue, the closer user can instead assist other users in forwarding tasks by using a different bandwidth. We aim to minimize the power of the AP by joint power and bandwidth optimization while satisfying the delay and users' computational tasks. Simulation results show that the proposed user collaboration method can overcome user interference, reduce energy consumption, and improve user performance compared with the baseline policies.

Keywords mobile edge computing, user cooperation, wireless power transfer, energy consumption, resource management

Citation Ye Q B, Lu W D, Hu S, et al. Resource optimization in wireless powered cooperative mobile edge computing systems. Sci China Inf Sci, 2021, 64(8): 182303, https://doi.org/10.1007/s11432-020-2925-1

1 Introduction

With the development of the Internet of Things and 5G communication technology, intelligent mobile devices influence all aspects of our modern lives through smart cities, virtual reality, and augmented reality [1–3]. Smart applications consume high volumes of storage and power resources to provide users with high quality of service (QoS). This situation pushes mobile communication device development toward the requirements of ultra-low latency, ultra-high reliability, low power consumption, and high-density connections [4, 5].

Mobile edge computing (MEC) has emerged to solve the challenges of existing mobile devices performing computationally intensive and latency-sensitive tasks [6]. This technology utilizes wireless access networks to provide cloud computing services for mobile devices. Therefore, the wireless networks must have an ultra-low-latency and high-bandwidth service environment and solve heavy computing tasks [7,8]. By offloading computing tasks to nearby access points (APs), communication security is improved, and the network load and latency of execution tasks are effectively reduced [9]. To meet the ultra-reliable, low-latency requirements of applications, a new system design is proposed in [10]. This design uses the extreme value theory to impose probabilistic and statistical constraints on a task queue length. To tackle resource allocation and content caching policy issues, the authors formulate a computation-shunting framework, which takes the total network revenue into consideration [11]. To study the offloading mechanism of MEC tasks in 5G heterogeneous networks, an optimization problem with the purpose of minimizing energy consumption under the constraint of minimizing delay is proposed in [12]. The authors design a low-complexity algorithm for joint offloading, load balancing, and power distribution to reduce system

* Corresponding author (email: husu@uestc.edu.cn)

energy consumption [13]. In [14], the authors establish a multiuser MEC model, which interprets the system for computation, storage, and communication and analyzes possible problems in uninstall processes. In a dynamic environment, the authors formulate a Markov decision process (MDP) to minimize delay with respect to communication, computing, handover, and migration [15]. In [16], the authors discuss the machine learning technique of stochastic online learning and its promising applications for MEC.

Despite the multiple advantages of MEC, it still presents numerous challenges. First, the battery capacity limitation of mobile devices is a major issue. Wireless power transfer (WPT) can provide a sustainable, low-cost energy supply for low-power mobile devices from radio frequency (RF) signals, which can greatly extend the standby time of such devices [17, 18]. It thus makes sense to use the WPT technology for the long-distance charging of mobile devices. In a multicarrier WPT-based cognitive radio (CR) network, a "harvest-then-transmit" protocol is used to coordinate users' WPT and wireless information transfer (WIT) [19]. Combined with WPT, wireless resources are utilized at an edge cloud, and a computational offload algorithm is designed and implemented to minimize delay or mobile terminal energy consumption [20–24]. The authors in [20] use the MDP approach to address the problem of delay minimization. In [21], a dynamic offloading scheme for energy harvesting is proposed to reduce the cost of time delays. In [22], wireless power supply cooperation is used to optimize the performance of an MEC system, and in [23], a binary computational offload strategy is employed to maximize the computational rate of wirelessly powered MEC. To solve the problem of optimal resource allocation for multiple users, a multiuser MEC offloading system is proposed in [24].

However, wireless power communication networks (WPCNs) are susceptible to the double near-far effect, which refers to the fact that devices which are far away from energy emissions harvest less energy but communicate across longer distances [25,26]. To improve the transmission rate of information on poor channels, extensive research has been conducted on user collaboration. In particular, the work in [27,28] is focused on the impact of user collaboration between near-far devices and manages to further promote the impact of WPCNs. A closer user assists a farther user with forwarding tasks by sharing the same bandwidth, which causes interference. This interference results in degraded system performance.

To overcome the interference problem, the closer user, which is closer to the AP, can utilize a different bandwidth to assist the farther user, which is farther to the AP, in forwarding tasks. We aim to minimize the power of the AP by considering the limitation of the users' computational tasks, delay, power, and bandwidth optimization. The tasks of mobile devices exploit cooperative communication, in which the entire process is powered entirely by wireless power transmission from the AP. In the first period, the two mobile devices harvest energy from the AP. In the second period, the farther user transmits its offloading task to the closer user using harvested energy from the AP. In the third period, to deal with the interference issue, the closer user allocates bandwidth. It utilizes some energy from the AP and a part of the bandwidth to assist the farther user in forwarding tasks and utilizes the remaining power and bandwidth to transmit its own task to the AP. The main contributions of this paper can be summarized as follows:

- We propose a wireless resource cooperative MEC scheme. To overcome the information interference caused when the closer user assists the farther user with forwarding tasks by sharing the same bandwidth, this scheme allows the relay to transmit information for different users, using different bandwidth.

- Joint resource optimization, including transit power at two mobile devices, power, and bandwidth allocation, is obtained to minimize the transmit power of the AP while satisfying delay and computing task size.

- Simulation results verify the theoretical feasibility of the proposed collaborative computing offloading scheme. By comparison with several baselines, it is shown that collaboration reduces energy consumption and demonstrates the effectiveness of processing computation-intensive, latency-critical tasks.

The rest of the paper is structured as follows. In Section 2, the WPT-MEC system model is described, and the corresponding mathematical problem is then formulated. In Section 3, an optimal solution for solving minimum transmission energy is proposed. In Section 4, the simulation results are explained and analyzed. In Section 5, we conclude this study and discuss some possible directions for future work.

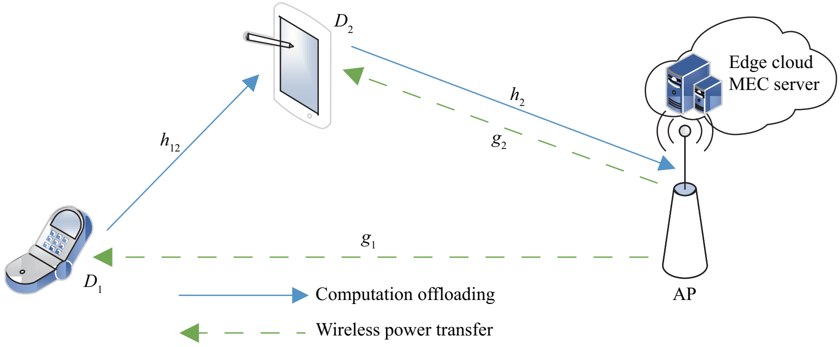

Figure 1 (Color online) The model for the two-user WPT-MEC system.

Table 1 Time division structure of the harvest-then-offload protocol

WPT	Computation offloading	
$T/3$	$T/3$	$T/3$
AP $\rightarrow D_1, D_2$	$D_1 \rightarrow D_2$	$D_2\,(D_1, D_2) \rightarrow$ AP

2 System model and problem formulation

2.1 System model

We consider a wireless powered MEC system, as shown in Figure 1, which consists of an AP and two mobile devices D_1 and D_2. D_1 and D_2 work in the same frequency band and need to complete some computationally intensive latency critical tasks. AP powers D_1 and D_2 in the downlink through the WPT method. Then D_1 and D_2 utilize harvested energy to complete their respective computing tasks by allocating power and bandwidth resource during the partial offloading manner. Due to shadowing or interference, AP cannot correctly receive the information from direct transmission with the D_1 to AP link, then D_1 needs D_2's help to forward its information to AP. The input bits of a task are bit-independent and can be arbitrarily divided. Thus the task can be traded off locally on the mobile device and offloaded on the MEC server. After computation at AP, the result of the offloading will be sent to the devices by feedback. We assume that D_1 and D_2 transmit in half-duplex mode. Then the local calculation and WPT can be completed simultaneously while the wireless communication for offloading and the WPT do not overlap. Thus we consider the time-division structure of the harvest-then-offload protocol for wireless powered computation offloading at the Table 1. A time division multiple access (TDMA) structure based on a block of T seconds is employed.

Each device D_i ($i \in \{1, 2\}$) has compute-intensive latency-critical tasks to complete. The size of the input calculated task is expressed as I_i, e.g., audio or video information, and it is difficult to satisfy latency constraints considering local calculations. Thus, the computation data task needs to be offloaded.

Let T_i denote the maximum tolerable delay time of D_i. We assume that D_1 and D_2 have the same maximum tolerable delay time, which equals to the block time, i.e., $T_i = T$ ($i \in \{1, 2\}$). AP with integrated MEC services can provide sufficient wireless computing resources. The calculation result is usually much smaller than the input data, i.e., $O_i \ll I_i$, and O_i ($i \in \{1, 2\}$) is the size of output data. Therefore, the decoding and calculation time spent on AP and the time of sending back the calculation result are negligible. For D_2, the decoding time for D_1 messages is negligible compared to the time for uplink offloading of D_1 messages. It is only necessary to take the time of WPT and offloading to be the total delay time.

Without loss of generality, as shown in Figure 1, we assume that D_2 is closer to AP, and distances between AP and D_1, AP and D_2, D_1 and D_2 are denoted by d_1, d_2 and d_{12}, respectively, where $d_1 \geqslant d_2$. We also assume that $d_1 \geqslant d_{12}$, and D_2 is easier to decode D_1 transmitted information than AP.

In the first period $T/3$, D_i harvests wireless power from AP at the same time with the transmission power P_0. As D_i can only use the harvested energy to transmit the task, to guarantee D_i has enough energy to transmit the task, we assume D_1 and D_2 have enough battery storage. The harvested energy from AP can be shown as follows:

$$E_i = \frac{T}{3} v_i g_i P_0, \quad i \in \{1, 2\}, \tag{1}$$

where g_i $(0 < g_i \leqslant 1)$ denotes the channel power gain from AP to D_i and v_i $(0 < v_i \leqslant 1)$ is the energy conversion efficiency of D_i.

In the second period $T/3$, D_1 utilizes the harvested energy to transmit offloading task in average power p_1 to D_2. The offloading task $L_{1,12}(p_1)$ can be expressed as follows:

$$L_{1,12}(p_1) = \frac{T}{3} r_{1,12}(p_1) = \frac{T}{3} B \log_2\left(1 + \frac{p_1 h_{12}}{N_2}\right), \tag{2}$$

where B is the bandwidth, N_2 is receiver noise power at D_2, and $r_{1,12}(p_1)$ represents the achievable transmission rate according to channel for D_1's offloading, h_{12} is channel power gains from D_1 to D_2.

In the third period $T/3$, to achieve the interference cancellation, D_2 utilizes a part of bandwidth βB $(0 \leqslant \beta \leqslant 1$, β is the bandwidth allocation factor), and a part of the power αp_2 $(0 \leqslant \alpha \leqslant 1$, α is the power allocation factor), to forward the received data task information from D_1 to AP. Thus, offloading data size of D_1 from D_2 to AP can be shown as

$$L_{1,2}(p_2) = \frac{T}{3} r_{1,2}(p_2) = \frac{T}{3} \beta B \log_2\left(1 + \frac{\alpha p_2 h_2}{\beta N_0}\right), \tag{3}$$

where $r_{1,2}(p_2)$ represents achievable transmission rate according to the channel for D_1's offloading, h_2 is channel power gains from D_2 to AP. The receiver noise power is N_0. In order not to lose generality, we assume $N_0 = N_2$.

Power allocation vector is expressed as $\boldsymbol{p} = [p_1, p_2]$. In the case of given $\boldsymbol{p}$, the offloaded data size of D_1 with the relaying of D_2 can be written as

$$L_1(\boldsymbol{p}) = \min\left\{L_{1,12}(p_1), L_{1,2}(p_2)\right\}. \tag{4}$$

Similarly, D_2 utilizes the another part of bandwidth $(1-\beta)B$ to forward D_2's offloading task to the AP under the power $(1-\alpha)p_2$, and the offloaded data of D_2 is expressed as

$$L_2(\boldsymbol{p}) = \frac{T}{3} r_2(p_2) = \frac{T}{3} (1-\beta) B \log_2\left(1 + \frac{(1-\alpha) p_2 h_2}{(1-\beta) N_0}\right), \tag{5}$$

where $r_2(p_2)$ indicates transfer rate of offloading data of D_2. The energy consumed for offloading task transmission from D_1 to D_2 and D_2 to AP can be shown as

$$E_{\mathrm{off},i}(\boldsymbol{p}) = \frac{T}{3} p_i, \quad i \in \{1, 2\}. \tag{6}$$

As shown in the WPT-MEC model, the size of task offloaded by users should not be larger than its corresponding calculated task size, i.e., $L_i(\boldsymbol{p}) \leqslant I_i$ $(i \in \{1,2\})$. Considering the local calculations, the left $I_i - L_i(\boldsymbol{p})$ part of tasks need to be computed locally at D_i if the offloaded data sizes are $L_i(\boldsymbol{p})$. For local calculations, the CPU computing resources of D_i are limited. To meet the constraint of latency

$$\frac{\left(I_i - L_i(\boldsymbol{p})\right) C_i}{f_i} \leqslant T, \tag{7}$$

where C_i represents the amount of computing resources for computing 1-bit input data and f_i represents the CPU frequency. The minimum unload data of D_i can be expressed as

$$L_i(\boldsymbol{p}) \geqslant M_i^{+}, \tag{8}$$

where $M_i = (I_i - f_i T)/C_i$, $(x)^{+} = \max\{x, 0\}$. The energy consumption per CPU cycle of the local calculation of D_i is expressed as $Q_i = k_i f_i^2$, where k_i is the effective capacitance coefficient, which depends on the chip architecture. Thus, the energy consumption of D_i for local computation can be written as

$$E_{\mathrm{loc},i}(\boldsymbol{p}) = \left(I_i - L_i(\boldsymbol{p})\right) C_i Q_i. \tag{9}$$

Thus, D_i's saving energy can be expressed as

$$E_{s,i}\left(P_0, \boldsymbol{p}\right) = E_i - E_{\mathrm{off},i}(\boldsymbol{p}) - E_{\mathrm{loc},i}(\boldsymbol{p}). \tag{10}$$

The AP can calculate the optimal power and bandwidth allocation factors and optimally allocate wireless computing resources. The purpose of the paper is to minimize the transmit power of AP to complete the computation tasks of devices.

2.2 Problem formulation

By optimizing jointly offloaded data powers of D_i, power allocation factor α and bandwidth allocation factor β, transmission energy of AP is minimized considering energy harvesting and latency constraints. The specific optimization problem is expressed as follows:

$$\text{(P1)}: \quad \min_{P_0>0,\boldsymbol{p},\alpha,\beta} P_0 \tag{11}$$

$$\text{s.t.}\ E_{s,i}\left(P_0,\boldsymbol{p}\right) \geqslant 0, \quad i\in\{1,2\}, \tag{12}$$

$$M_i^+ \leqslant L_i(\boldsymbol{p}) \leqslant I_i, \quad i\in\{1,2\}, \tag{13}$$

$$0\leqslant\alpha\leqslant 1, \quad 0\leqslant\beta\leqslant 1, \tag{14}$$

$$T\geqslant 0, \quad p_i\geqslant 0, \quad i\in\{1,2\}. \tag{15}$$

By making the optimal offload decision for users, we can get the optimal power and bandwidth allocation factors while satisfying the delay and the users' computational tasks. Then we can minimize the total transmission power of the AP through maximizing the saving energy of users.

3 Optimal solution to problem

To solve the above problem, we firstly consider formulations (1), (6), (9), and (12), and get the range of P_0,

$$P_0 \geqslant \frac{1}{v_1 g_1 T}\left(Tp_1 + 3C_1Q_1\left(I_1 - L_1(\boldsymbol{p})\right)\right), \tag{16}$$

$$P_0 \geqslant \frac{1}{v_2 g_2 T}\left(Tp_2 + 3C_2Q_2\left(I_2 - L_2(\boldsymbol{p})\right)\right). \tag{17}$$

From (12), we can find that minimum value of P_0 is gained when $L_1(\boldsymbol{p})$ achieves the maximum value. Obviously, maximum value of $L_1(\boldsymbol{p})$ is taken at $L_{1,12}(p_1) = L_{1,2}(p_2)$, thus

$$\alpha^* = \frac{\beta(m+1)^{\frac{1}{\beta}} - \beta}{n}, \tag{18}$$

$$L_1(m) = \frac{TB}{3}\log_2(1+m) \leqslant I_1, \tag{19}$$

$$L_2(m,n) = \frac{T}{3}(1-\beta)B\log_2\left(\frac{n-\beta(m+1)^{\frac{1}{\beta}}+1}{1-\beta}\right) \leqslant I_2, \tag{20}$$

where $m = \frac{p_1 h_{12}}{N_2}$, $n = \frac{p_2 h_2}{N_0}$. The problem (P1) can be rewritten as follows:

$$\text{(P1)}: \quad \min_{P_0>0,m,n} P_0 \tag{21}$$

$$\text{s.t.}\ P_0 \geqslant \frac{1}{v_1 g_1}\left(\frac{N_2}{h_{12}}m + \frac{3}{T}I_1C_1Q_1 - BC_1Q_1\log_2(m+1)\right), \tag{22}$$

$$P_0 \geqslant \frac{1}{v_2 g_2}\left(\frac{N_0}{h_2}n + \frac{3}{T}I_2C_2Q_2 - (1-\beta)BC_2Q_2\log_2\left(\frac{n-\beta(m+1)^{\frac{1}{\beta}}+1}{1-\beta}\right)\right), \tag{23}$$

$$\left(A_1 - 1\right) \leqslant m \leqslant \left(A_2 - 1\right), \tag{24}$$

$$K_1(1-\beta) \leqslant \left(n - \beta(m+1)^{\frac{1}{\beta}} + 1\right) \leqslant K_2(1-\beta), \tag{25}$$

$$T\geqslant 0,\ m\geqslant 0,\ n\geqslant 0, \tag{26}$$

where $A_1 = 2^{\frac{3}{B}(\frac{I_1}{T}-\frac{f_1}{C_1})^+}$, $A_2 = 2^{\frac{3I_1}{BT}}$, $K_1 = 2^{\frac{3}{(1-\beta)B}(\frac{I_2}{T}-\frac{f_2}{C_2})^+}$, and $K_2 = 2^{\frac{3I_2}{(1-\beta)BT}}$.

In order to analyze Eq. (21), we define a function:

$$f(m) = \frac{N_2}{h_{12}}m - BC_1Q_1\log_2(1+m). \tag{27}$$

From (22) we can find that when $f(m)$ gets the maximum value, P_0 arrives the minimum value. Getting the first derivation of m for $f(m)$, we can get

$$f'(m) = \frac{N_2}{h_{12}} - \frac{BC_1Q_1}{\ln 2(1+m)}. \tag{28}$$

Let $f'(m) = 0$, we can obtain that $m^* = \frac{BC_1Q_1h_{12}}{N_2 \ln 2} - 1$, and $f(m)$ is a monotonic increasing function when $m > m^*$, and $f(m)$ is a monotonic decreasing function for $m \in (0, m^*)$. Thus the $f_{\max}(m)$ depends on the upper limit m and lower limit m^*.

We define the minimum value of P_0 obtained from Eq. (22) as P_{01}. Thus the minimum value of P_{01} can be written as

$$P_{01} = \max\left\{\frac{1}{v_1g_1}\left(\frac{N_2}{h_{12}}(A_1-1) + \frac{3I_1f_1Q_1}{T} - 3C_1Q_1\left(\frac{I_1}{T} - \frac{f_1}{C_1}\right)^+\right), \frac{N_2}{v_1g_1h_{12}}(A_1-1)\right\}. \tag{29}$$

For analysing the inequality (23), we define another function:

$$F(m,n) = \frac{N_0}{h_2}n - (1-\beta)BC_2Q_2\log_2\left(\frac{n - \beta(m+1)^{\frac{1}{\beta}} + 1}{1-\beta}\right). \tag{30}$$

For $F(m,n)$, we can find that when $F(m,n)$ gets the maximum value, P_0 gets the minimum value. Getting the first derivation of m and n for $F(m,n)$ separately, we can obtain F'_m and F'_n, as follows:

$$F'_m = \frac{(1-\beta)(m+1)^{\frac{1}{\beta}-1}BC_2Q_2}{\ln 2(n - \beta(m+1)^{\frac{1}{\beta}} + 1)}, \tag{31}$$

$$F'_n = \frac{N_0}{h_2} - \frac{(1-\beta)BC_2Q_2}{\ln 2(n - \beta(m+1)^{\frac{1}{\beta}} + 1)}. \tag{32}$$

On the one hand, we find that $F'_m > 0$, the constant is established, when m reaches the maximum value in a feasible domain, the original function $F(m,n)$ takes maximum value. On the other hand, let $F'_n = 0$, we can obtain

$$n^* = \frac{BC_2Q_2h_2(1-\beta)}{N_0\ln 2} + \beta(m+1)^{\frac{1}{\beta}} - 1. \tag{33}$$

We can conclude that $F(m,n)$ is a monotonic increasing function when $n > n^*$, and $F(m,n)$ is a monotonic decreasing function for $n \in (0, n^*)$. Thus the $F_{\max}(m,n)$ depends on the upper limit n and lower limit n^*.

We define the minimum value of P_0 obtained from Eq. (23) as P_{02}. Thus the minimum value of P_{02} can be written as

$$P_{02} = \max\left\{\begin{array}{l}\frac{1}{v_1g_1}\left(\frac{N_0}{h_2}\left(K_1(1-\beta) + \beta A_2^{\frac{1}{\beta}} - 1\right) + \frac{3I_1f_1Q_1}{T} - 3C_1Q_1\left(\frac{I_1}{T} - \frac{f_1}{C_1}\right)^+\right), \\ \frac{N_2}{v_1g_1h_2}\left(K_2(1-\beta) + \beta A_2^{\frac{1}{\beta}} - 1\right).\end{array}\right. \tag{34}$$

The minimum value of P_{02} depends on variable β. Let

$$H_i(\beta) = K_i(1-\beta) + \beta A_2^{\frac{1}{\beta}} - 1, \tag{35}$$

we can get the first derivation of β from $H_i(\beta)$ separately, as follows:

$$H'_1(\beta) = \left(\frac{3\ln 2}{(1-\beta)B}\left(\frac{I_1}{T} - \frac{f_1}{C_1}\right)^+ - 1\right)K_1 + \left(1 - \frac{3I_1\ln 2}{BT\beta}\right)A_2^{\frac{1}{\beta}}, \tag{36}$$

$$H'_2(\beta) = \left(\frac{3I_1\ln 2}{(1-\beta)BT} - 1\right)K_2 + \left(1 - \frac{3I_1\ln 2}{BT\beta}\right)A_2^{\frac{1}{\beta}}. \tag{37}$$

Obviously, from (35) and (37), we can obtain a β_i^* by using the one-dimensional search. $H_i(\beta)$ is a monotonic increasing function when $\beta > \beta_i^*$, and $H_i(\beta)$ is a monotonic decreasing function for $\beta \in (0, \beta_i^*)$. Finally, the minimum value of AP transmit power is $P_0 = \max\{P_{01}, P_{02}\}$.

Table 2 Simulation parameters

Parameter	Value
Carrier frequency	60 GHz
Channel bandwidth, W	500 MHz
Block time, T	10–30 s
Distance between D_1 and D_2, d_{12}	8 m
Distance between D_1 and AP, d_1	15 m
Distance between D_2 and AP, d_2	12 m
Coefficient of chips, k_i	10^{-28}
Energy conversion efficiency of D_i, v_i	1.0
Data size for D_1, I_1	[50,500] MB
Data size for D_2, I_2	$I_1/2$
CPU frequency of D_1	0.1 GHz
CPU frequency of D_2	0.12 GHz
Power of white Gaussian noise at AP, N_0	10^{-7} W
Power of white Gaussian noise at D_2, N_2	10^{-7} W
Number of CPU cycles, C_i	2000 cycle/bit

4 Simulation results

Here, using computer simulations to study the performance of our proposed WPT-MEC scheme with joint optimizing power and bandwidth allocation and user collaboration.

We set the simulation parameters as follows. We assume that the uplink and downlink channel gains are the same, and thus $g_1 = h_1$, $g_2 = h_2$. The gain of channel is modelled as $h_j = d_j^{-\theta}$, $j \in \{1, 2, 12\}$. For the path-loss index θ, we set to be 2. At AP and D_2, the noise power is assumed as $N_0 = N_2 = 10^{-7}$ W. At a carrier frequency of 60 GHz, the bandwidth $B = 500$ MHz, the block time $T = 10$–30 s, and the distance $d_1 = 15$ m, $d_2 = 12$ m and $d_{12} = 8$ m. For D_i, the CPU frequency $f_1 = 0.1$ GHz and $f_2 = 0.12$ GHz, the number of CPU cycles required for each bit of data is $C_i = 2000$ cycle/bit. We set $v_i = 1.0$ and $k_i = 10^{-28}$ [21]. For computation task, the size of input data is $I_1 \in [50, 500]$ MB and $I_2 = I_1/2$. Table 2 shows simulation parameters. The following simulation figures are modeled from real computing scenarios.

Figure 2 shows the AP's minimum transmit power versus the computational task of I_1 during each block time. We can find that when the computational task of I_1 increases, AP's minimum transmit power continues to increase. If the mobile devices have a large task to complete, AP needs to transmit more power to mobile devices. Comparing situations of fixed $\beta = 0.5$ and without bandwidth allocation, we can find that AP needs to transmit less power to mobile devices at the same block time with fixed $\beta = 0.5$. It is because that closer-user overcomes the information interference during transmitting different tasks of users. This indicates that the WPT-MEC system will have a better performance by introducing the bandwidth allocation factor. Comparing the situations of fixed $\beta = 0.5$, variable β^* and without bandwidth allocation, we can find that AP needs to transmit the least power to mobile devices at the same block time with variable β^*. This indicates that the WPT-MEC system will have the best performance with optimized β^*. Comparing with the scheme proposed in [22], we can find that AP needs to transmit more power to mobile devices at the same block time than our proposed scheme with optimized β^*. It is because our scheme overcomes the information interference during transmitting different tasks of users, and makes the WPT-MEC system have better performance.

Figure 3 shows the AP's minimum transmit power versus block time T. With achieving the same user tasks, we can find that when block time T increases, AP's minimum transmit power continues to decrease. Obviously, if mobile devices have a longer time to complete, AP needs to transmit less power to mobile devices. We can also observe in Figure 3 that AP's minimum transmit power becomes smaller when I_1 becomes smaller in the same situation. If mobile devices have smaller tasks to complete, AP needs to transmit less power to mobile devices. Comparing the situations of fixed $\beta = 0.5$, variable β^* and without bandwidth allocation, we can find that AP needs to transmit the least power to mobile devices at the same computational task with variable β^*. This indicates that the WPT-MEC system will have the best performance with variable β^*.

Figure 4 shows the optimal bandwidth allocation β^* versus I_1 with different values of block time. In Figure 4, we can find that when the computational task of I_1 increases, the optimal bandwidth allocation

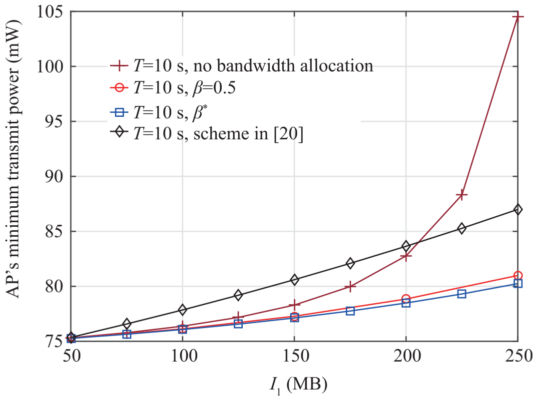

Figure 2 (Color online) AP's minimum transmit power versus I_1.

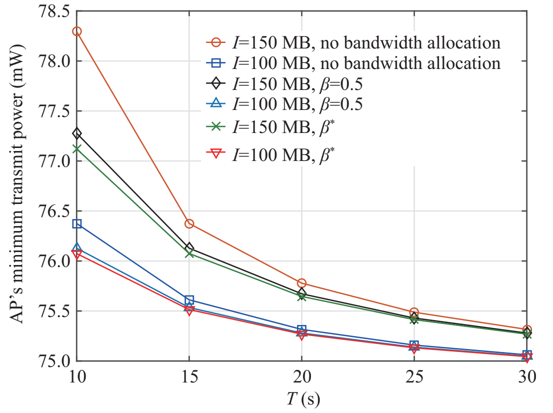

Figure 3 (Color online) AP's minimum transmit power versus T.

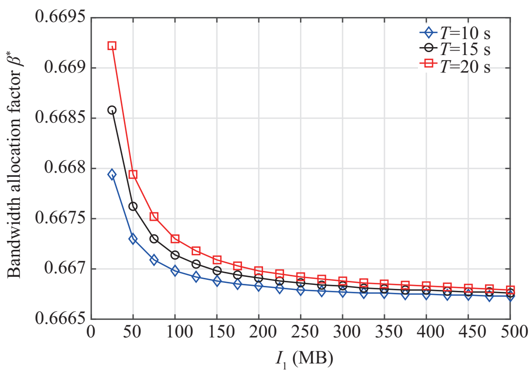

Figure 4 (Color online) Optimal bandwidth allocation β^* versus I_1.

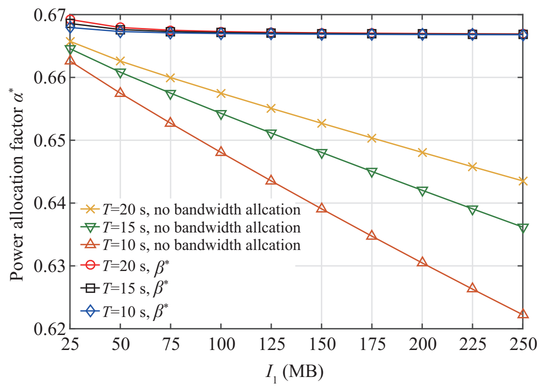

Figure 5 (Color online) Optimal power allocation α^* versus I_1.

β^* decreases. Obviously, if farther-user D_1 has a large task to complete, D_2 needs wider bandwidth to offload the computational task to AP. We can also observe in Figure 4 that AP's minimum transmit power becomes larger when T becomes larger with the same user tasks. It is because that with larger block time, mobile devices just need to transmit the data with a smaller transmission rate to finish the transmission which will cause closer-user to need smaller bandwidth to assist farther-user with transmitting task.

Figure 5 shows the optimal power allocation α^* versus I_1 with different values of the block time. In Figure 5, we can find that when the computational task of I_1 increases, the optimal power allocation α^* decreases. Analyzing in conjunction with Figure 4, with the variable β^*, closer-user D_2 allocates smaller bandwidth for offloading the computational task from D_1 to the AP at the same computational task. Comparing the situations of variable β^* and without bandwidth allocation, the optimal power allocation α^* is larger at the same block time with variable β^*. It is because that the closer-user allocates bandwidth for different tasks and more power needs to be allocated for farther-user.

Figure 6 shows the transmission rate of D_1 and D_2 versus I_1/I_2. In Figure 6, we can find that when the ratio between I_1 and I_2 increases, the D_2' transmission rate continues to decrease at the same block time. It is because that if D_2 has fewer tasks to complete, it will offload tasks with a smaller transmission rate. Comparing the situations of different tasks of D_1, we can also observe in Figure 6 that the D_2' transmission rate is larger when the tasks of D_1 are larger. It is because D_2 needs a larger transmission rate to offload more tasks. As the ratio of I_1 and I_2 increases, the transmission rate of D_1 remains unchanged, which is because that all of the tasks of D_1 are offloaded to AP.

Figure 7 shows the transmit powers of D_1 and D_2 versus I_1. In Figure 7, we can find that when the computational task of I_1 increases, mobile devices' transmit power continues to increase at the same block time. If mobile devices have more tasks to complete, they need to offload tasks with larger transmit power. Comparing the situations of variable β^* and without bandwidth allocation, we can also observe

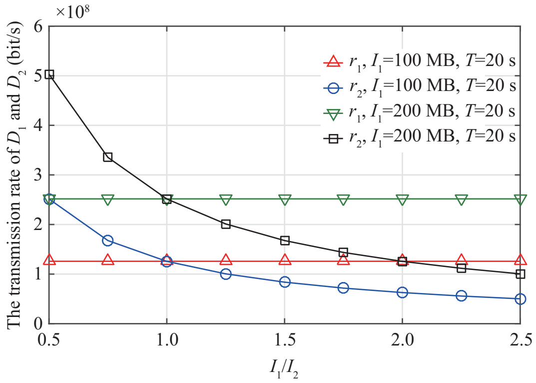

Figure 6 (Color online) The transmission rate of D_i versus I_1/I_2.

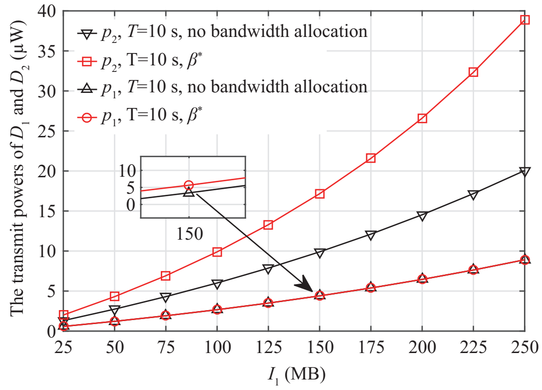

Figure 7 (Color online) The transmit powers of D_i versus I_1.

in Figure 7 that the users' transmit power are larger under the variable β^*. It is because that closer-user overcomes information interference with variable β^*, closer-user will transmit more tasks and its transmission power is larger.

5 Conclusion and future work

In this paper, we study the user collaboration MEC system, combined with the wireless power transmission technology and the decoding and forwarding technology, in the multi-tasking network scenario, the power and bandwidth allocation factors are introduced, and two devices' tasks are completed in a coordinated manner through partial offloading. It overcomes the interference of users, computation-intensive and delay-sensitive tasks and minimizes the transmission power of AP. Simulation results show that the proposed user cooperation method can make full use of the harvested energy, allocate computing resources reasonably and solve the interference problem of user collaboration. Thus, the transmission power of the AP is minimized, the performance of the WPT-MEC system is improved, and ultra-low latency and ultra-reliability in the mobile network are achieved.

In the future, we can further increase the number of mobile devices, and further reduce the power consumption of the whole system. Besides that, computing resource sharing is also a possible extension to improve the performance of mobile networks and achieve ultra-low latency and ultra-reliability.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant No. 61971092). We thank the reviewers for their detailed review and constructive comments, which have improved the quality of this paper.

References

1 Hu S, Yu B, Qian C, et al. Nonorthogonal interleave-grid multiple access scheme for industrial Internet of things in 5G network. IEEE Trans Ind Inf, 2018, 14: 5436–5446
2 Lu W D, Gong Y, Liu X, et al. Collaborative energy and information transfer in green wireless sensor networks for smart cities. IEEE Trans Ind Inf, 2018, 14: 1585–1593
3 Lu W D, Hu S, Liu X, et al. Incentive mechanism based cooperative spectrum sharing for OFDM cognitive IoT network. IEEE Trans Netw Sci Eng, 2020, 7: 662–672
4 Na Z Y, Wang Y Y, Li X T, et al. Subcarrier allocation based simultaneous wireless information and power transfer algorithm in 5G cooperative OFDM communication systems. Phys Commun, 2018, 29: 164–170
5 Lu W D, Zhang Y A, Wang M Y, et al. Cooperative spectrum sharing in OFDM two-way relay systems with bidirectional transmissions. IEEE Commun Lett, 2017, 21: 1349–1352
6 Mao Y Y, You C S, Zhang J, et al. A survey on mobile edge computing: the communication perspective. IEEE Commun Surv Tutor, 2017, 19: 2322–2358
7 Zheng J C, Cai Y M, Wu Y, et al. Dynamic computation offloading for mobile cloud computing: a stochastic game-theoretic approach. IEEE Trans Mobile Comput, 2019, 18: 771–786
8 Wu Y, Chen J C, Qian L P, et al. Energy-aware cooperative traffic offloading via device-to-device cooperations: an analytical approach. IEEE Trans Mobile Comput, 2017, 16: 97–114
9 Panaousis E, Karapistoli E, Elsemary H, et al. Game theoretic path selection to support security in device-to-device communications. Ad Hoc Netw, 2017, 56: 28–42
10 Liu C F, Bennis M, Debbah M, et al. Dynamic task offloading and resource allocation for ultra-reliable low-latency edge computing. IEEE Trans Commun, 2019, 67: 4132–4150
11 Wang C M, Liang C C, Yu F R, et al. Computation offloading and resource allocation in wireless cellular networks with mobile edge computing. IEEE Trans Wirel Commun, 2017, 16: 4924–4938

12 Zhang K, Mao Y M, Leng S P, et al. Energy-efficient offloading for mobile edge computing in 5G heterogeneous networks. IEEE Access, 2016, 4: 5896–5907

13 Li S L, Zhai D S, Du P F, et al. Energy-efficient task offloading, load balancing, and resource allocation in mobile edge computing enabled IoT networks. Sci China Inf Sci, 2019, 62: 029307

14 Taleb T, Samdanis K, Mada B, et al. On multi-access edge computing: a survey of the emerging 5G network edge cloud architecture and orchestration. IEEE Commun Surv Tutor, 2017, 19: 1657–1681

15 Zhang X F, Zhang J, Liu Z T, et al. MDP-based task offloading for vehicular edge computing under certain and uncertain transition probabilities. IEEE Trans Veh Technol, 2020, 69: 3296–3309

16 Cui Q M, Gong Z Z, Ni W, et al. Stochastic online learning for mobile edge computing: learning from changes. IEEE Commun Mag, 2019, 57: 63–69

17 Zhou F H, Li Z, Cheng J L, et al. Robust AN-aided beamforming and power splitting design for secure MISO cognitive radio with SWIPT. IEEE Trans Wirel Commun, 2017, 16: 2450–2464

18 Lu W D, Nan T, Gong Y, et al. Joint resource allocation for wireless energy harvesting enabled cognitive sensor networks. IEEE Access, 2018, 6: 22480–22488

19 Xu D, Li Q. Resource allocation in cognitive wireless powered communication networks with wirelessly powered secondary users and primary users. Sci China Inf Sci, 2019, 62: 029303

20 Liu J, Mao Y Y, Zhang J, et al. Delay-optimal computation task scheduling for mobile-edge computing systems. In: Proceedings of IEEE International Symposium on Information Theory (ISIT), 2016. 1451–1455

21 Mao Y Y, Zhang J, Letaief K B. Dynamic computation offloading for mobile-edge computing with energy harvesting devices. IEEE J Sel Areas Commun, 2016, 34: 3590–3605

22 Hu X Y, Wong K K, Yang K. Wireless powered cooperation-assisted mobile edge computing. IEEE Trans Wirel Commun, 2018, 17: 2375–2388

23 Bi S Z, Zhang Y J. Computation rate maximization for wireless powered mobile-edge computing with binary computation offloading. IEEE Trans Wirel Commun, 2018, 17: 4177–4190

24 You C S, Huang K B, Chae H, et al. Energy-efficient resource allocation for mobile-edge computation offloading. IEEE Trans Wirel Commun, 2017, 16: 1397–1411

25 Lu W D, Wang J. Opportunistic spectrum sharing based on full-duplex cooperative OFDM relaying. IEEE Commun Lett, 2014, 18: 241–244

26 Lu W D, Zhao W L, Hu S, et al. OFDM based SWIPT for two-way AF relaying network. IEEE Access, 2018, 6: 73223–73231

27 Chen H, Li Y H, Rebelatto J L, et al. Harvest-then-cooperate: wireless-powered cooperative communications. IEEE Trans Signal Process, 2015, 63: 1700–1711

28 Liang H, Zhong C J, Suraweera H A, et al. Optimization and analysis of wireless powered multi-antenna cooperative systems. IEEE Trans Wirel Commun, 2017, 16: 3267–3281