

Resource Allocation in Full-Duplex Mobile-Edge Computing Systems with NOMA and Energy Harvesting

Zhaohui Yang, Jiancao Hou and Mohammad Shikh-Bahaei

Centre for Telecommunications Research, Department of Informatics, King's college London, UK

E-mail: {yang.zhaohui, jiancao.hou, m.sbahaei}@kcl.ac.uk

Abstract—This paper considers a full-duplex (FD) mobile-edge computing (MEC) system with non-orthogonal multiple access (NOMA) and energy harvesting (EH), where one group of users simultaneously offload task data to the base station (BS) via NOMA and the BS simultaneously receive data and broadcast energy to other group of users with FD. We aim at minimizing the total energy consumption of the system via power control, time scheduling and computation capacity allocation. To solve this nonconvex problem, we first transform it into an equivalent problem with less variables. The equivalent problem is shown to be convex in each vector with the other two vectors fixed, which allows us to design an iterative algorithm with low complexity. Simulation results show that the proposed algorithm achieves better performance than the conventional methods.

Index Terms—Full-duplex, mobile-edge computing, non-orthogonal multiple access, energy harvesting.

I. INTRODUCTION

Mobile-edge computing (MEC) has been deemed as a promising technology for future communications due to that it can improve the computation capacity of users in applications, such as, augmented reality (AR) [1]. With MEC, users can offload the tasks to the MEC servers that locate at the edge of the system. Since the MEC servers can be deployed near to the users, system with MEC can provide users with low energy consumption and low latency [2].

The basic idea of MEC is to utilize the powerful computing facilities within the radio access system, such as the MEC server integrated into the base station (BS). Users can benefit from offloading the computationally intensive tasks to the MEC server. There are two operation modes for MEC, i.e., partial and binary computation offloading. In partial computation offloading, the computation tasks can be divided into two parts, where one part is locally executed and the other part is offloaded to the MEC servers [3]–[9]. In binary computation offloading, the computation tasks are either locally executed or offloaded to the MEC servers [10].

In wireless systems, the system performance is always constrained due to limited battery capacity of users. To prolong the system lifetime, many contributions [11]–[15] investigate energy harvesting (EH), where users can harvest energy in a wireless way from the dedicated energy transmitter. Combining EH with MEC is a promising technique to provide sustainable computation experience for users. Due to the fact that EH generally occupies non-negligible bandwidth, full-

duplex (FD) [16]–[19] can be applied to improve the spectral efficiency by means of simultaneous energy transmission and computation task offloading in the same bandwidth [20]. Integrating EH and FD technologies into MEC, the max-min energy efficiency optimization problem was investigated for a FD-MEC system with EH in [4].

Recently, non-orthogonal multiple access (NOMA) has been recognized as a potential technology for the next generation mobile communication systems to tackle the explosive growth of data traffic [21]–[27]. Due to superposition coding at the transmitter and successive interference cancelation (SIC) at the receiver, NOMA can achieve higher spectral efficiency than conventional orthogonal multiple access (OMA), such as time division multiple access (TDMA) and orthogonal frequency division multiple access (OFDMA). Many previous contributions [2]–[9] only considered OMA. Motivated by the benefits of NOMA over OMA, a NOMA-based MEC system was investigated in [28], where users simultaneously offload their computation tasks to the BS and the BS uses SIC for information decoding. Besides, both NOMA uplink and downlink transmissions were applied to MEC [29], where analytical results were developed to show that the latency and energy consumption can be reduced by applying NOMA-based MEC offloading. The benefits of NOMA and EH were investigated in [30]–[32]. However, the above NOMA-based MEC systems [28], [29] did not consider EH even though EH can further prolong the lifetime of the system. To our best knowledge, FD-MEC systems with NOMA and EH have not been investigated in the literature.

In this paper, we investigate the resource allocation in a FD-MEC system with NOMA and EH, where users simultaneously offload computation tasks to the BS through NOMA and the BS simultaneously broadcast energy and receive computation tasks via FD. The main contributions of this paper are summarized as follows:

- 1) The total energy consumption of the system is formulated for a FD-MEC system with NOMA and EH via power control, time scheduling and offloading data allocation.
- 2) By using the recursion method, the uplink transmission power of each user can be presented as a function with scheduled time, transmission power of the BS and offloading data. Based on this finding, the original problem

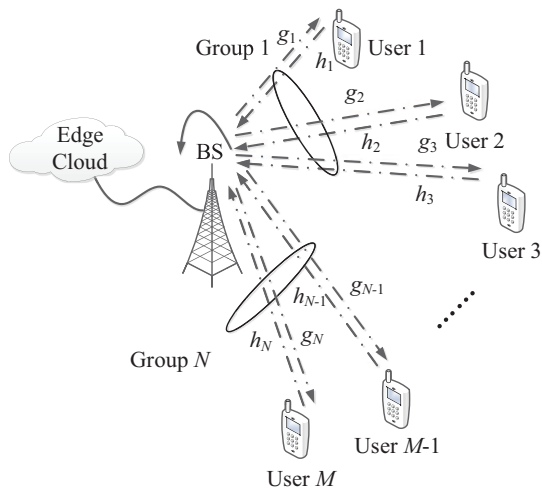


Fig. 1. Multi-user MEC system.

can be equivalent to a problem with less variables.

- 3) The equivalent problem is proved to be convex in power vector or time vector or offloading data vector with the other two vectors fixed. Owing to this characteristic, an iterative algorithm is accordingly proposed with low complexity.

The rest of the paper is organized as follows. In Section II, we introduce the system model and formulate the total energy minimization problem. Section III provides the optimal conditions and an iterative algorithm. Some numerical results are shown in Section IV and conclusions are finally drawn in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider a multi-user FD MEC system with M users and one BS that is the gateway of an edge cloud, as shown in Fig. 1. To perform NOMA, all users are classified into N small groups. Denote the sets of users and groups by $\mathcal{M} = \{1, \dots, M\}$ and $\mathcal{N} = \{1, \dots, N\}$, respectively. The set of users in group i is denoted by $\mathcal{J}_i = \{J_{i-1} + 1, \dots, J_i\}$, where $J_0 = 0$, $J_N = M$, $J_i = \sum_{l=1}^i |\mathcal{J}_l|$, and $|\cdot|$ is the cardinality of a set. Obviously, we have $\bigcup_{i \in \mathcal{N}} \mathcal{J}_i = \mathcal{M}$.

The time slot with duration T is divided into N phases, as shown in Fig. 2. Note that the computation latency at the BS and downloading time of computation results are low and negligible [9]. In the i -th phase with time t_i , the users in group i simultaneously communicate with the BS by using NOMA. For user j , it is required to transmit R_j -bits input data within the time slot. To save energy and meet the latency constraint, user j offload d_j bits out of R_j bits to the BS. Besides, the BS has fixed energy supply, while users do not have stable energy supply and need to harvest energy from the BS. During the whole transmission phase, the BS keeps transforming energy to users.

Let h_j denote the uplink channel gain between user j and the BS. Without loss of generality, the uplink channels between users in group i and the BS are sorted as $h_{J_{i-1}+1} \geq \dots \geq h_{J_i}$.

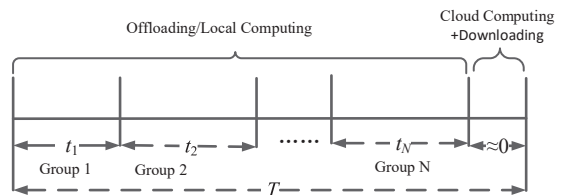


Fig. 2. Transmission period.

With NOMA and FD technologies, the uplink achievable rate for user $j \in \mathcal{J}_i$ is

$$r_{ij} = B \log_2 \left(1 + \frac{h_j p_j}{\sum_{l=j+1}^{J_i} h_l p_l + \sigma^2 + \gamma q_i} \right), \quad (1)$$

where B is the bandwidth of the system, p_j is the transmission power of user j , σ^2 represents the noise power, γ is the self-interference coefficient at the BS, and q_i is the broadcasting power of the BS in the i -th phase. In equation (1), γq_i represents the residual self-interference at the BS due to the finite receiver dynamic range and imperfect channel estimation. To successfully offload d_j bits to the BS for user j , we have

$$r_{ij} t_i \geq d_j, \quad \forall j \in \mathcal{J}_i. \quad (2)$$

Considering uplink transmission energy at the user side, the energy consumption for offloading at user $j \in \mathcal{J}_i$ is

$$E_{ij}^{\text{Off}} = p_j t_i. \quad (3)$$

Since only d_j bits are offloaded to the BS, the remaining $R_j - d_j$ bits are needed to be computed locally at user j . Based on the local computing model in [9], the total energy consumption for local computation at user $j \in \mathcal{J}_i$ is given by

$$E_{ij}^{\text{Loc}} = (R_j - d_j) C_j P_j, \quad (4)$$

where C_j is the number of CPU cycles required for computing 1-bit input data at user j , and P_j stands for the energy consumption per cycle for local computing at this user.

Due to the fact that the BS broadcasts energy to users all the time, the energy harvested by user j in group i is given by [11]–[13]

$$E_{ij}^{\text{H}} = \zeta_j g_j \sum_{k \in \mathcal{N} \setminus \{i\}} q_k t_i, \quad \forall j \in \mathcal{J}_i, \quad (5)$$

where ζ_j is the energy efficiency of the EH process for user j , and g_j is the channel gain between the BS and user j . According to the energy causality constraint in EH systems, the harvested energy should no less than the consumed energy for user j , i.e.,

$$E_{ij}^{\text{H}} \geq E_{ij}^{\text{Off}} + E_{ij}^{\text{Loc}}. \quad (6)$$

Denote F_j as the computation capacity of user j , which is measured by the number of CPU cycles per second. To meet the computation latency, we have

$$C_j (R_j - d_j) \leq F_j T. \quad (7)$$

For the BS, the total energy consumption includes both the broadcasting and the the energy consumption for computation. As a result, the total energy consumption of the BS is

$$E^{\text{BS}} = \sum_{i=1}^N q_i t_i + P_0 \sum_{j=1}^M C_j d_j, \quad (8)$$

where P_0 is the energy consumption per cycle at the BS. The first term in the left-hand side of (8) is the broadcasting energy, while the second term in the left-hand side of (8) represents the computation energy.

Based on (3), (4), (5) and (8), the total energy consumption of the system can be given by

$$E^{\text{Total}} = E^{\text{BS}} + \sum_{i=1}^N \sum_{j=J_{i-1}+1}^{J_i} (E_{ij}^{\text{Off}} + E_{ij}^{\text{Loc}} - E_{ij}^{\text{H}}). \quad (9)$$

For edge cloud, it is assumed that the edge cloud has finite computation capacity, denoted as F , measured as the maximum CPU cycles allowed for computing the sum offloaded data in each slot, i.e.,

$$\sum_{j=1}^M C_j d_j \leq F, \quad (10)$$

which ensures low computing time at the edge cloud.

B. Problem Formulation

Now it is ready to investigate the total energy minimization problem. Mathematically, it is formulated as

$$\min_{\mathbf{p}, \mathbf{q}, \mathbf{t}, \mathbf{d}} E^{\text{Total}} \quad (11a)$$

$$\text{s.t.} \quad r_{ij} t_i \geq d_j, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i \quad (11b)$$

$$E_{ij}^{\text{H}} \geq E_{ij}^{\text{Off}} + E_{ij}^{\text{Loc}}, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i \quad (11c)$$

$$C_j (R_j - d_j) \leq F_j T, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i \quad (11d)$$

$$\sum_{j=1}^M C_j d_j \leq F \quad (11e)$$

$$\sum_{i=1}^N t_i \leq T \quad (11f)$$

$$0 \leq p_j \leq P_j, q_i \leq Q, t_i \geq 0, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i, \quad (11g)$$

where $\mathbf{p} = [p_1, \dots, p_M]^T$, $\mathbf{q} = [q_1, \dots, q_N]^T$, $\mathbf{t} = [t_1, \dots, t_N]^T$, $\mathbf{d} = [d_1, \dots, d_M]^T$, P is the maximal transmission power of each user and Q is the maximal transmission power of the BS. The objective function (11a) is the total energy consumption of the system including transmission and computation energy. Constraints (11b) represent the the minimal transmitted data constraints for uplink. The consumed energy of each user should not exceed its harvested energy, as stated in constraints (11c). The computation delay constraints for users to compute tasks locally are given in (11d), while (11e) ensures the low computing time at the BS. Constraint (11f) is the time division constraint. The maximal transmission power limits for the BS and users are given in (11g).

III. ALGORITHM DESIGN

Due to nonconvex objective function ((11a) and nonconvex constraints (11b)-(11c), total energy minimization problem (11) is nonconvex. To solve this nonconvex problem, we first obtain the optimal conditions and then accordingly propose an iterative algorithm with low complexity.

A. Optimal Conditions

By analyzing problem (11), we have the following lemma.

Lemma 1: The optimal $(\mathbf{p}^*, \mathbf{q}^*, \mathbf{t}^*, \mathbf{d}^*)$ of problem (11) satisfies the following conditions

$$r_{ij} t_i = d_j, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i. \quad (12)$$

Lemma 1 can be proved by using the contradictory method. Obviously, we can show that $r_{ij} t_i = d_j$ for the optimal solution, as otherwise (11a) can be further improved by decreasing p_j with all constraints satisfied, contradicting that the solution is optimal. Lemma 1 states that transmitting with minimal number of data bits is optimal. This is intuitive since transmitting with less resource is always energy saving.

B. Joint Power Control, Time Scheduling and Computation Capacity Allocation

To solve nonconvex problem (11), we first have the following theorem.

Theorem 1: Problem (11) is equivalent to the following problem:

$$\begin{aligned} \min_{\mathbf{q}, \mathbf{t}, \mathbf{d}} \quad & \sum_{i=1}^N q_i t_i + P_0 \sum_{j=1}^M C_j d_j + \sum_{i=1}^N \sum_{j=J_{i-1}+1}^{J_i} t_i f_{ij}(t_i, q_i, \mathbf{d}) \\ & + \sum_{i=1}^N \sum_{j=J_{i-1}+1}^{J_i} \left((R_j - d_j) C_j P_j - \zeta_j g_j \sum_{k \in \mathcal{N} \setminus \{i\}} q_k t_k \right) \end{aligned} \quad (13a)$$

$$\text{s.t.} \quad \zeta_j g_j \sum_{k \in \mathcal{N} \setminus \{i\}} q_k t_k \geq t_i f_{ij}(t_i, q_i, \mathbf{d}) + (R_j - d_j) C_j P_j, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i \quad (13b)$$

$$C_j (R_j - d_j) \leq F_j T, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i \quad (13c)$$

$$\sum_{j=1}^M C_j d_j \leq F \quad (13d)$$

$$\sum_{i=1}^N t_i \leq T \quad (13e)$$

$$f_{ij}(t_i, q_i, \mathbf{d}) \leq P_j, \quad \forall i \in \mathcal{N}, j \in \mathcal{J}_i, \quad (13f)$$

$$q_i \leq Q, t_i \geq 0, \quad \forall i \in \mathcal{N}, \quad (13g)$$

where

$$\begin{aligned} f_{ij}(t_i, q_i, \mathbf{d}) \triangleq & \frac{(\sigma^2 + \gamma q_i)}{h_j} \left(2^{\frac{d_j}{B t_i}} - 1 \right) \\ & + \sum_{l=j+1}^{J_i} \frac{(\sigma^2 + \gamma q_i)}{h_j} \left(2^{\frac{d_l}{B t_i}} - 1 \right) \left(2^{\frac{d_j}{B t_i}} - 1 \right) 2^{\frac{\sum_{s=j+1}^{l-1} d_s}{B t_i}}. \end{aligned} \quad (14)$$

Proof: Please refer to Appendix A. \square

In (14), $f_{ij}(t_i, q_i, \mathbf{d})$ is the transmission power of user j in group i , which is shown to be a function of scheduled time, transmission power of the BS and offloading data. According to Theorem 1, problem (11) can be simplified by solving an equivalent problem (13) with less variables. By analysing problem (13), we can obtain the following theorem.

Theorem 2: Problem (13) is convex in each variable with the other two variables fixed, i.e., problem (13) is convex in \mathbf{q} with fixed (\mathbf{t}, \mathbf{d}) , \mathbf{t} with fixed (\mathbf{q}, \mathbf{d}) , and \mathbf{d} with fixed (\mathbf{q}, \mathbf{t}) .

Proof: Please refer to Appendix B. \square

Based on theorem 1, we can easily optimize each variable with the other two variables fixed through solving a correspondingly convex problem, which can be solved by using the popular interior method [33, Page 561]. Owing to this characteristic, we can propose an iterative algorithm to effectively solve problem (13) in Algorithm 1, i.e., iterative power control, time scheduling and offloading data allocation algorithm.

Algorithm 1: Iterative Power Control, Time Scheduling and Offloading Data Allocation Algorithm

- 1: Set the initial solution $(\mathbf{q}^{(0)}, \mathbf{t}^{(0)}, \mathbf{d}^{(0)})$, and iteration number $n = 1$.
 - 2: **repeat**
 - 3: With fixed $(\mathbf{t}^{(n-1)}, \mathbf{d}^{(n-1)})$, obtain the optimal $\mathbf{q}^{(n)}$ of convex problem (13).
 - 4: With fixed $(\mathbf{q}^{(n)}, \mathbf{d}^{(n-1)})$, obtain the optimal $\mathbf{t}^{(n)}$ of convex problem (13).
 - 5: With fixed $(\mathbf{q}^{(n)}, \mathbf{t}^{(n)})$, obtain the optimal $\mathbf{d}^{(n)}$ of convex problem (13).
 - 6: Set $n = n + 1$.
 - 7: **until** the objective function (13a) converges.
-

According to Algorithm 1, the complexity of the proposed algorithm lies in solving three convex problems. Since the dimension of variable \mathbf{q} is N , the complexity of solving problem (13) with fixed (\mathbf{t}, \mathbf{d}) by using the standard interior point method [33, Pages 487, 569] is $\mathcal{O}(N^3)$. With the same analysis, the complexities of solving \mathbf{t} and \mathbf{d} are $\mathcal{O}(N^3)$ and $\mathcal{O}(M^3)$, respectively. Since the number of groups is less than the number of users, i.e., $N < M$, the total complexity for solving problem (13) is $\mathcal{O}(LM^3)$, where L denotes the total number of iterations of Algorithm 1.

IV. NUMERICAL RESULTS

In this section, numerical results are presented to evaluate the performance of the proposed algorithm. The MEC system consists of $M = 20$ users. The path loss model is $128.1 + 37.6 \log_{10} d$ (d is in km) and the standard deviation of shadow fading is 4 dB [34]–[39]. In addition, the bandwidth of the system is $B = 10$ MHz, and the noise power is $\sigma^2 = -104$ dBm. For MEC parameters, the data size and the required number of CPU cycles per bit are set to follow equal distributions with $R_j \in [100, 500]$ Kbits and $C_j \in [500, 1500]$ cycles/bit. The CPU computation of each user is set as the same $F_j = 1$ GHz and the local computation energy per cycle

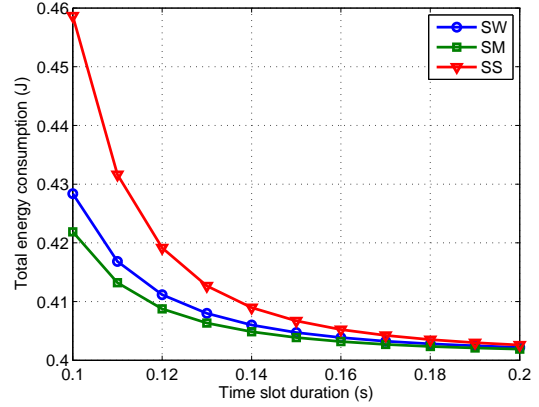


Fig. 3. Impact of user pairing on the total energy consumption of the proposed algorithm.

for each user or the BS is also set as equal $P_j = 10^{-10}$ J/cycles for all $j \in \mathcal{M}$ and $j = 0$. The self-interference coefficient at the BS is $\gamma = 10^{-5}$ and the energy efficiency of the EH process for each user is $\zeta_j = 0.8$. Besides, the maximal transmission power of each user and the BS are respectively set as $P = 30$ dBm and $Q = 47$ dBm. Unless specified otherwise, the system parameters are set as time slot duration $T = 0.1$ s, and the edge computation capacity $F = 6 \times 10^9$ cycles per slot.

Due to decoding complexity and error propagation, it is recommended that each resource is multiplexed by small number of users (for example, two users) [40]. In simulations, we consider that each group has two users. We study the influence of user pairing by considering three different user-pairing methods [41]. For strong-weak (SW) pair selection, the user with the strongest channel condition is paired with the user with the weakest, and the user with the second strongest is paired with one with the second weakest, and so on. For strong-middle (SM) pair selection, the user with the strongest channel condition is paired with the user with the middle strongest user, and so on. For strong-strong (SS) pair selection, the user with the strongest channel condition is paired with the one with the second strongest, and so on. In Fig. 3, we show the total energy consumption of the proposed algorithm. It is observed that SM outperforms the other two methods in terms of total energy consumption. This is due to the fact that two users in any group of the SM scheme have relative large channel gain difference. Due to the superiority of SM, the following simulations are based on SM pair selection.

Fig. 4 illustrates the convergence behaviours for the proposed algorithm under different cloud computation capacities. It can be seen that the proposed algorithm converges rapidly, and only three times are sufficient to converge, which shows the effectiveness of the proposed algorithm.

We compare the total energy consumption performance of the proposed algorithm (labelled as ‘Proposed NOMA FD’) with the algorithm for a half-duplex (HD) MEC system with NOMA [28] (labelled as ‘NOMA HD’), and the algorithm for a FD-MEC system with OMA [4] (labelled as ‘OMA FD’).

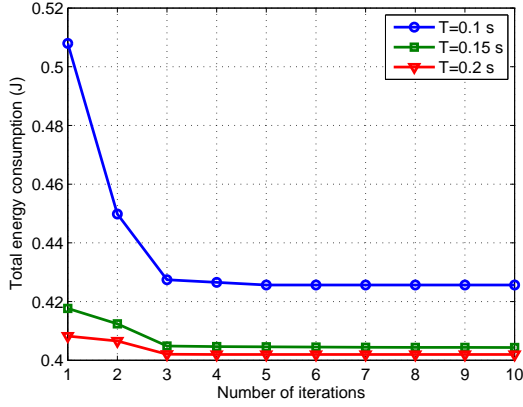


Fig. 4. Convergence behaviour of the proposed algorithm under different cloud computation capacities.

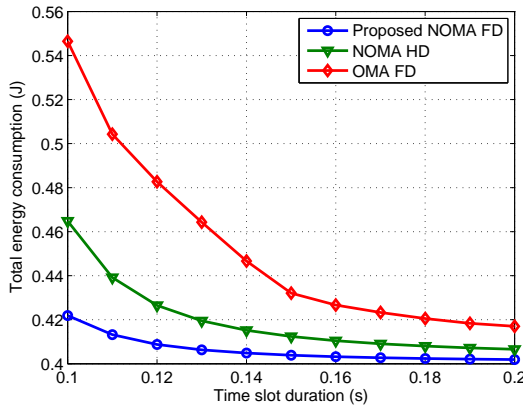


Fig. 5. Total energy consumption versus time slot duration.

The total energy consumption versus time slot duration is depicted in Fig. 5. From this figure, we find that the total energy consumption decreases with time slot duration. It can be shown that the proposed algorithm yields best performance among all algorithms. Since FD enables simultaneously energy transfer and data reception, the proposed algorithm yields lower energy consumption than NOMA HD. Compared with OMA FD, NOMA reduces the total energy consumption of all users at the cost of adding computing complexity at the BS due to SIC.

In Fig. 6, we show the total energy consumption versus cloud computation capacity. It is observed that the total energy consumption decreases with cloud computation capacity since higher cloud computation capacity allows users to offload more data to the BS, resulting lower energy consumption at users. The proposed algorithm achieves the best performance according to this figure, which shows the effectiveness of the proposed algorithm. Besides, the total energy consumption keeps stable when the cloud computation capacity exceeds a threshold which coincides with previous findings in [9].

V. CONCLUSION

In this paper, we have investigated the total energy minimization problem for a FD-MEC system with NOMA and

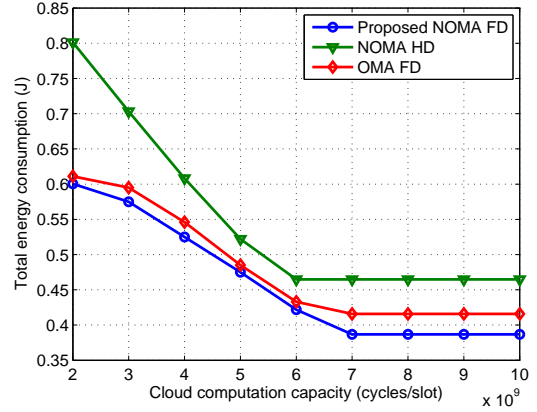


Fig. 6. Total energy consumption versus cloud computation capacity.

EH. The original nonconvex problem is first equivalent to a problem with less variables. Then, an iterative algorithm is accordingly proposed with low complexity. Numerical results show that it is energy efficient to pair the user with the strongest channel condition is paired with the user with the middle strongest user and the proposed algorithm achieves better performance than conventional schemes in terms of energy consumption.

APPENDIX A PROOF OF THEOREM 1

According to Lemma 1, setting offloading constraints (11b) with equality yields

$$2^{\frac{d_j}{Bt_i}} \sum_{l=j+1}^{J_i} h_l p_l + (\sigma^2 + \gamma q_i) \left(2^{\frac{d_j}{Bt_i}} - 1 \right) = \sum_{l=j}^{J_i} h_l p_l, \quad (\text{A.1})$$

for $j = J_{i-1} + 1, \dots, J_i$. To solve equations (A.1), we define

$$u_j = \sum_{l=j}^{J_i} h_l p_l, \quad \forall j \in \mathcal{J}_i, \quad (\text{A.2})$$

which is expressed as the summation of transmission power multiplied by from user j in group i to the last user J_i in group i . Based on (A.1) and (A.2), we can obtain

$$u_j = 2^{\frac{d_j}{Bt_i}} u_{j+1} + (\sigma^2 + \gamma q_i) \left(2^{\frac{d_j}{Bt_i}} - 1 \right), \quad \forall j \in \mathcal{J}_i. \quad (\text{A.3})$$

Due to the fact that $\sum_{l=J_i+1}^{J_i} p_j = 0$, we have

$$u_{J_i+1} = 0. \quad (\text{A.4})$$

Based on (A.4), we solve (A.3) by using the recursion method and obtain

$$u_j = (\sigma^2 + \gamma q_i) \sum_{l=j}^{J_i} \left(2^{\frac{d_l}{Bt_i}} - 1 \right) 2^{\frac{\sum_{s=j}^{l-1} d_s}{Bt_i}}, \quad \forall j \in \mathcal{J}_i, \quad (\text{A.5})$$

where we define $2^{\sum_{s=j}^{j-1} \frac{d_s}{Bt_i}} = 2^0$.

From (A.2) and (A.4), we can obtain the transmission power of user j as

$$\begin{aligned}
p_j &= \frac{u_j - u_{j+1}}{h_j} \\
&= \sum_{l=j}^{J_i} \frac{(\sigma^2 + \gamma q_i)}{h_j} \left(2^{\frac{d_l}{B t_i}} - 1 \right) 2^{\frac{\sum_{s=j}^{l-1} d_s}{B t_i}} \\
&\quad - \sum_{l=j+1}^{J_i} \frac{(\sigma^2 + \gamma q_i)}{h_j} \left(2^{\frac{d_l}{B t_i}} - 1 \right) 2^{\frac{\sum_{s=j+1}^{l-1} d_s}{B t_i}} \\
&= f_{ij}(t_i, q_i, \mathbf{d}). \tag{A.6}
\end{aligned}$$

Substituting (A.6) into problem (11) yields the equivalent problem (13).

APPENDIX B PROOF OF THEOREM 2

We first prove that problem (13) is convex in \mathbf{q} with fixed (\mathbf{t}, \mathbf{d}) . Based on (13), $f_{ij}(t_i, q_i, \mathbf{d})$ is a linear function of q_i with fixed (\mathbf{t}, \mathbf{d}) . Because the objective function and all constraints of problem (13) are linear with fixed (\mathbf{t}, \mathbf{d}) , problem (13) is a linear problem (also convex problem) with fixed (\mathbf{t}, \mathbf{d}) .

We then prove that problem (13) is convex in \mathbf{t} with fixed (\mathbf{q}, \mathbf{d}) . To show this, we define a function

$$u(x) = (e^{ax} - 1)(e^{bx} - 1)e^{cx}, \quad \forall x \geq 0. \tag{B.1}$$

Then, the second-order derivative follows

$$\begin{aligned}
u''(x) &= (a^2 + 2ac)(e^{bx} - 1)e^{(a+c)x} \\
&\quad + 2abe^{(a+b+c)x} \\
&\quad + (b^2 + 2bc)(a^{ax} - 1)e^{(b+c)x} \\
&\quad + c^2(e^{ax} - 1)(e^{bx} - 1)e^{cx} \geq 0, \tag{B.2}
\end{aligned}$$

which shows that $u(x)$ is a convex function in x . According to [33, Page 89], the perspective of $u(x)$ is the function $v(x, t)$ defined by $v(x, t) = tu(x/t)$, $\mathbf{dom} v = \{(x, t) | x/t \in \mathbf{dom} u, t > 0\}$. If $u(x)$ is a convex function, then so is its perspective function $v(x, t)$ [33, Page 89]. Then, $v(x, t) = tu(x/t)$ is convex in (x, t) , and $v(1, t)$ is also convex in x . As a result, $t_i f_{ij}(t_i, q_i, \mathbf{d})$ is convex in t_i . Due to the fact that $f_{ij}(t_i, q_i, \mathbf{d})$ is a decreasing function of t_i , $f_{ij}(t_i, q_i, \mathbf{d}) \leq P_i$ can be equivalent to a linear equation $t_i \geq t_i^{\min}$, where $f_{ij}(t_i^{\min}, q_i, \mathbf{d}) = P_i$. Because the objection function and all the constraints of problem (13) are convex, problem (13) is convex in \mathbf{t} with fixed (\mathbf{q}, \mathbf{d}) .

Finally, we show that problem (13) is convex in \mathbf{d} with fixed (\mathbf{q}, \mathbf{t}) . From (14), $f_{ij}(t_i, q_i, \mathbf{d})$ is convex in d_i . Based on this finding, we can prove that problem (13) is convex in \mathbf{d} with fixed (\mathbf{q}, \mathbf{t}) .

REFERENCES

[1] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2322–2358, Fourth Quarter 2017.

[2] A. Al-Shuwaili and O. Simeone, "Energy-efficient resource allocation for mobile edge computing-based augmented reality applications," *IEEE Wireless Commun. Lett.*, vol. 6, no. 3, pp. 398–401, June 2017.

[3] H. Q. Le, H. Al-Shatri, and A. Klein, "Efficient resource allocation in mobile-edge computation offloading: Completion time minimization," in *Proc. IEEE Int. Symp. Information Theory*, Aachen, Germany, June 2017, pp. 2513–2517.

[4] S. Mao, S. Leng, K. Yang, X. Huang, and Q. Zhao, "Fair energy-efficient scheduling in wireless powered full-duplex mobile-edge computing systems," in *Proc. IEEE Global Commun. Conf.*, Singapore, Dec 2017, pp. 1–6.

[5] C. You, K. Huang, H. Chae, and B. H. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.

[6] C. Wang, C. Liang, F. R. Yu, Q. Chen, and L. Tang, "Computation offloading and resource allocation in wireless cellular networks with mobile edge computing," *IEEE Trans. Wireless Commun.*, vol. 16, no. 8, pp. 4924–4938, Aug. 2017.

[7] J. Du, L. Zhao, J. Feng, and X. Chu, "Computation offloading and resource allocation in mixed fog/cloud computing systems with min-max fairness guarantee," *IEEE Trans. Commun.*, vol. 66, no. 4, pp. 1594–1608, Apr. 2018.

[8] L. Liu, Z. Chang, X. Guo, S. Mao, and T. Ristaniemi, "Multiobjective optimization for computation offloading in fog computing," *IEEE Internet Things J.*, vol. 5, no. 1, pp. 283–294, Feb. 2018.

[9] C. You and K. Huang, "Multiuser resource allocation for mobile-edge computation offloading," in *Proc. IEEE Global Commun. Conf.*, Washington, DC, USA, Dec. 2016, pp. 1–6.

[10] W. Zhang, Y. Wen, K. Guan, D. Kilper, H. Luo, and D. O. Wu, "Energy-optimal mobile cloud computing under stochastic wireless channel," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4569–4581, Sep. 2013.

[11] X. Zhou, R. Zhang, and C. K. Ho, "Wireless information and power transfer in multiuser OFDM systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 4, pp. 2282–2294, 2014 Dec.

[12] F. Yuan, S. Jin, K. K. Wong, J. Zhao, and H. Zhu, "Wireless information and power transfer design for energy cooperation distributed antenna systems," *IEEE Access*, vol. 5, pp. 8094–8105, 2017.

[13] H. Ju and R. Zhang, "Throughput maximization in wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 418–428, Jan. 2014.

[14] Y. Li, N. Huang, J. Wang, Z. Yang, and W. Xu, "Sum rate maximization for VLC systems with simultaneous wireless information and power transfer," *IEEE Photonics Technol. Lett.*, vol. 29, no. 6, pp. 531–534, Mar. 2017.

[15] Z. Yang, W. Xu, Y. Pan, C. Pan, and M. Chen, "Optimal fairness-aware time and power allocation in wireless powered communication networks," *IEEE Trans. Commun.*, vol. 66, no. 7, pp. 3122–3135, July 2018.

[16] V. Towhidlou and M. Shikh-Bahaei, "Improved cognitive networking through full duplex cooperative ARQ and HARQ," *IEEE Wireless Commun. Lett.*, vol. 7, no. 2, pp. 218–221, 2018.

[17] M. Naslcheraghi, S. A. Ghorashi, and M. Shikh-Bahaei, "FD device-to-device communication for wireless video distribution," *IET Commun.*, vol. 11, no. 7, pp. 1074–1081, 2017.

[18] K. Nehra, A. Shadmand, and M. Shikh-Bahaei, "Cross-layer design for interference-limited spectrum sharing systems," in *Proc. IEEE Global Commun. Conf.*, 2010, pp. 1–5.

[19] V. Towhidlou and M. Shikh-Bahaei, "Cooperative ARQ in full duplex cognitive radio networks," in *Proc. IEEE Annu. Symp. Personal, Indoor and Mobile Radio Commun.*, 2016, pp. 1–5.

[20] R. Aslani and M. Rasti, "Distributed power control schemes for in-band full-duplex energy harvesting wireless networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 8, pp. 5233–5243, Aug. 2017.

[21] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (NOMA) for cellular future radio access," in *Proc. IEEE Veh. Technol. Conf.* Dresden, German, Jun. 2013, pp. 1–5.

[22] Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan, and V. K. Bhargava, "A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2181–2195, Oct. 2017.

[23] L. Dai, B. Wang, Y. Yuan, S. Han, C. I. I, and Z. Wang, "Non-orthogonal multiple access for 5G: Solutions, challenges, opportunities, and future

- research trends,” *IEEE Commun. Mag.*, vol. 53, no. 9, pp. 74–81, Sep. 2015.
- [24] Z. Yang, W. Xu, and Y. Li, “Fair non-orthogonal multiple access for visible light communication downlinks,” *IEEE Wireless Commun. Lett.*, vol. 6, no. 1, pp. 66–69, Feb. 2017.
- [25] Z. Yang, W. Xu, C. Pan, Y. Pan, and M. Chen, “On the optimality of power allocation for NOMA downlinks with individual QoS constraints,” *IEEE Commun. Lett.*, vol. 21, no. 7, pp. 1649–1652, July 2017.
- [26] Z. Yang, W. Xu, H. Xu, J. Shi, and M. Chen, “Energy efficient non-orthogonal multiple access for machine-to-machine communications,” *IEEE Commun. Lett.*, vol. 21, no. 4, pp. 817–820, Apr. 2017.
- [27] Z. Yang, C. Pan, W. Xu, and M. Chen, “Compressive sensing-based user clustering for downlink NOMA systems with decoding power,” *IEEE Signal Process. Lett.*, vol. 25, no. 5, pp. 660–664, May 2018.
- [28] F. Wang, J. Xu, and Z. Ding, “Optimized multiuser computation offloading with multi-antenna noma,” in *Proc. IEEE Globecom Workshops*, Singapore, Singapore, Dec. 2017, pp. 1–7.
- [29] Z. Ding, P. Fan, and H. V. Poor, “Impact of non-orthogonal multiple access on the offloading of mobile edge computing,” *CoRR*, vol. abs/1804.06712, 2018. [Online]. Available: <http://arxiv.org/abs/1804.06712>
- [30] Y. Xu, C. Shen, Z. Ding, X. Sun, S. Yan, G. Zhu, and Z. Zhong, “Joint beamforming and power-splitting control in downlink cooperative SWIPT NOMA systems,” *IEEE Trans. Signal Process.*, vol. 65, no. 18, pp. 4874–4886, Sept. 2017.
- [31] Z. Yang, W. Xu, Y. Pan, C. Pan, and M. Chen, “Energy efficient resource allocation in machine-to-machine communications with multiple access and energy harvesting for IoT,” *IEEE Internet Things J.*, vol. 5, no. 1, pp. 229–245, Feb. 2018.
- [32] Z. Yang, Y. Pan, W. Xu, R. Guan, Y. Wang, and M. Chen, “Energy efficient resource allocation for machine-to-machine communications with NOMA and energy harvesting,” in *Proc. IEEE Conf. Computer Commun. Workshops*, May 2017, pp. 145–150.
- [33] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.
- [34] Access. Evolved Universal Terrestrial Radio, “Further advancements for E-UTRA physical layer aspects, 3GPP TS 36.814,” *V9. 0.0*, Mar. 2010.
- [35] A. Olfat and M. Shikh-Bahaei, “Optimum power and rate adaptation for MQAM in rayleigh flat fading with imperfect channel estimation,” *IEEE Trans. Veh. Technol.*, vol. 57, no. 4, pp. 2622–2627, 2008.
- [36] A. Shadmand, K. Nehra, and M. Shikh-Bahaei, “Cross-layer design in dynamic spectrum sharing systems,” *EURASIP J. Wireless Commun. Network.*, vol. 2010, p. 1, 2010.
- [37] A. Shojaeifard, F. Zarringhalam, and M. Shikh-Bahaei, “Joint physical layer and data link layer optimization of CDMA-based networks,” *IEEE Trans. Wireless Commun.*, vol. 10, no. 10, pp. 3278–3287, 2011.
- [38] W. Xu, J. Liu, S. Jin, and X. Dong, “Spectral and energy efficiency of multi-pair massive MIMO relay network with hybrid processing,” *IEEE Trans. Commun.*, vol. 65, no. 9, pp. 3794–3809, Sep. 2017.
- [39] W. Xu, Y. Cui, H. Zhang, G. Y. Li, and X. You, “Robust beamforming with partial channel state information for energy efficient networks,” *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2920–2935, Dec. 2015.
- [40] A. Zafar, M. Shaqfeh, M. S. Alouini, and H. Alnuweiri, “On multiple users scheduling using superposition coding over rayleigh fading channels,” *IEEE Commun. Lett.*, vol. 17, no. 4, pp. 733–736, Apr. 2013.
- [41] Z. Ding, P. Fan, and H. V. Poor, “Impact of user pairing on 5G nonorthogonal multiple-access downlink transmissions,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 6010–6023, Aug. 2016.