Computation Offloading and Resource Allocation for Wireless Powered Mobile Edge Computing With Latency Constraint

Jie Feng, Qingqi Pei, F. Richard Yu, *Fellow, IEEE*, Xiaoli Chu, and Bodong Shang

***Abstract*—In this letter, we consider a multi-user wireless powered mobile edge computing (MEC) system, in which a base station (BS) integrated with an MEC server transfers energy to wireless devices (WDs) as an incentive to encourage them to offload computing tasks to the MEC server. We formulate an optimization problem to contemporaneously maximize the data utility and minimize the energy consumption of the operator under the offloaded delay constraint, by jointly controlling wireless-power allocation at the BS as well as offloaded data size and power allocation at the WDs. To solve this problem, the offloaded delay constraint is first transformed into an offloaded data rate constraint. Then an iterative algorithm is designed to obtain the optimal offloaded data size and power allocation at the WDs by using Lagrangian dual method. The results are applied to derive the optimal wireless-power allocation at the BS. Finally, simulation results show that our algorithm outperforms existing schemes in terms of operator's reward.**

***Index Terms*—Wireless powered MEC, offloaded delay, resource allocation.**

I. INTRODUCTION

MOBILE edge computing (MEC) offloads intensive computing tasks to MEC servers located in proximity to wireless devices (WDs). Although MEC can reduce the energy consumption effectively, computing tasks may be still interrupted because of insufficient energy. This problem can be tackled by using wireless power transfer (WPT) technique as a user incentive for charging WDs [1].

The application of WPT to MEC has received considerable attention recently [2]–[5]. In particular, the authors in [2] proposed a wireless powered MEC system using cooperative communication to minimize the access point's (AP) transmit energy. In [3], the problem of joint computation mode selection and time allocation was studied for wireless powered MEC network with the aim to maximize the weighted sum computation rate. In [4], a network framework was proposed to study the tradeoff between energy efficiency (EE) and delay. The authors in [5] studied the number of offloading users maximization problem. The existing works on wireless powered MEC systems have only studied the performance metrics of the system from the user's perspective [3]–[5]. Although the work in [2] considered the AP's energy consumption, the MEC server has not been taken into account the impact of energy consumption. From the operator's perspective, it is important to understand the potential operational benefits from wireless powered MEC. However, none of these works have studied the operator's reward in wireless powered MEC network.

Motivated by the above, this letter studies a multi-user wireless powered MEC system controlled by an operator, in which a multiple-antenna base station (BS) integrated with an MEC server transfers energy to WDs. Each WD utilizes the harvested energy to perform partial computation offloading. We formulate an optimization problem for simultaneously maximizing data utility and minimizing energy consumption at the operator side, by jointly optimizing the offloaded data size, the transmit power allocation, and the wireless-power allocation. To solve this problem efficiently, we first transform the offloaded delay constraint into an offloaded data rate constraint. Then, we obtain the optimal offloaded data size and power allocation at the WDs by using Lagrangian dual method. The results are applied to derive the optimal wireless-power allocation at the BS. Finally, simulation results show that our proposed algorithm has good performance in terms of operator's reward.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a wireless powered MEC system consisting of K single-antenna WDs and a multi-antenna BS, in which the WDs are running independent and fine-grained computing tasks, and the BS is equipped with an MEC server. The BS employs RF signal to recharge the low-power WDs as an incentive for performing partial computation offloading. In our model, we employ the harvest-then-transmit model [2]. Similar to [6], we assume that the MEC server has a certain amount of computational resource, and we focus on a particular fixed time period for system operation, which is divided into two phases: one for WPT and the other for computation offloading. In the computation offloading phase, computational tasks are offloaded to the MEC server to execute. Data offloading is enabled through transmissions over orthogonal channels as allocated by the BS to WDs based on orthogonal frequency-division multiple access (OFDMA). The time duration of data offloading is denoted by τ. The bandwidth is B Hz, and the noise power is N_0.

1) Wireless Power Transfer Model: The BS transfers wireless energy concurrently to the K WDs by pointing K narrow

Manuscript received March 21, 2019; accepted May 1, 2019. Date of publication May 8, 2019; date of current version October 11, 2019. This work was supported in part by the National Key Research and Development Program of China under Grant 2016YFB0800601, in part by the Key Program of NSFC–Tongyong Union Foundation under Grant U1636209, and in part by the Doctoral Student's Short-Term Study Abroad Scholarship Fund of Xidian University. The associate editor coordinating the review of this paper and approving it for publication was B. Makki. *(Corresponding author: Qingqi Pei.)*

J. Feng and Q. Pei are with the State Key Laboratory of ISN, School of Telecommunications Engineering, Xidian University, Xi'an 710071, China (e-mail: jiefengcl@163.com; qqpei@mail.xidian.edu.cn).

F. R. Yu is with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON K1S 5B6, Canada (e-mail: richardyu@cunet.carleton.ca).

X. Chu is with the Department of Electronic and Electrical Engineering, University of Sheffield, Sheffield S1 3JD, U.K. (e-mail: x.chu@sheffield.ac.uk).

B. Shang is with the Wireless@VT, Department of ECE, Virginia Tech, Blacksburg, VA 24061 USA (e-mail: bdshang@vt.edu).

Digital Object Identifier 10.1109/LWC.2019.2915618

2162-2345 © 2019 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

radio beams to the K WDs, respectively, within a fixed duration of T_0. Let $\boldsymbol{P} = \{P_k\}$ and $\boldsymbol{H} = \{h_k\}$, where P_k and h_k are the transmit power of the corresponding beam and the downlink large-scale channel gain from the BS to WD k, respectively. Then, the energy harvested by WD k is expressed as $E_{hav,k} = \mu h_k P_k T_0$, where $\mu \in (0, 1)$ is the energy conversion efficiency.

2) Local Computation Model: Given time-slot duration τ, denote by C_k the number of CPU cycles required for processing one bit of input data at WD k, and let P'_k be the energy consumption per cycle for local execution at this user. Thus, the total energy consumption for local execution at WD k is given by $E_{local,k} = (1 - \alpha_k)L_k C_k P'_k$, where L_k (in bits) and α_k represent the input data size and the proportion of the offloaded data of WD k within the time slot, respectively. Let F_k be the computing capacity (in CPU cycles/s) of WD k. Then, the local execution time is given by $t_{local} = \frac{(1-\alpha_k)L_k C_k}{F_k} \le \tau$, which is the latency constraint.

As a result, the proportion of the offloaded data must meet $\alpha_k \ge 1 - \frac{\tau F_k}{C_k L_k}$.

3) Computation Offloading Model: Let $\boldsymbol{p} = \{p_k\}$ and $\boldsymbol{G} = \{g_k\}$, where p_k and g_k are the transmit power and the uplink channel gain from WD k to the BS, respectively. Then, the transmit rate of WD k is given by $R_k = B \log_2(1 + \frac{p_k g_k}{N_0})$.

Accordingly, the transmit time of WD k is given by $\delta_k = \frac{\alpha_k L_k}{R_k}$. The energy consumption of WD k is expressed as $E_{off,k} = p_k \delta_k = \frac{\alpha_k L_k N_0}{g_k R_k}(2^{\frac{R_k}{B}} - 1)$.

4) Offloaded Delay Model: The offloaded data is first stored in buffer of WD k for transmission. Assume that the offloaded data are served by first input first output (FIFO) scheme. The task arrival process is independent and identically distributed (i.i.d.) and follows Poisson distribution with arrival rate λ_k. The i-th task data size of WD k, $L_k(i)$, is i.i.d. and follows an exponent distribution with parameter σ_k. Then the offloaded delay of the i-th task in the k-th WD's buffer is given by $t_{off,k}(i) = W_k(i) + \delta_k(i)$, where $W_k(i)$ is the waiting time of the i-th task of WD k before it is transmitted. We apply the max-plus convolution principle to describe the offloaded delay, i.e., $\hat{t}_{off,k}(i) = \hat{W}_k(i) + \hat{\delta}_k(i)$. Then the waiting time of the i-th task of WD k is $\hat{W}_k(i) = \max_{0 \le i \le n} [\sum_{i=m}^{n-1} \hat{\delta}_k(i) - \sum_{i=m}^{n-1} \tau_k(i)]$, where $\tau_k(i)$ is the inter-arrival time between two computing tasks.

Due to the latency constraint, the task generated by WD should be offloaded in a limited time span. The latency outage probability requirement in task offloading is given by $P\{\hat{t}_{off,k}(i) > \tau\} \le \epsilon_k$, $\forall k$, where ϵ_k is the latency outage probability threshold.

5) Performance Metric: We consider the operator's reward as our performance metric. Specifically, it is the net data utility after subtracting the energy cost. Similar to [7], the utility of $\alpha_k L_k$ bits data performed by WD k locally is tackled by the logarithmic function $u_k \log(1 + \alpha_k L_k)$, where u_k is a weight factor relaying on the type of tasks. Then the operator's reward is modeled as

$$C(\boldsymbol{\alpha}, \boldsymbol{P}, \boldsymbol{p}) = \sum_{k=1}^{K} u_k \log(1 + \alpha_k L_k) - c \sum_{k=1}^{K} P_k T_0 - \sum_{k=1}^{K} \beta_k \alpha_k L_k C_k P_{k,ser}, \tag{1}$$

where c represents the price of unit energy in the WPT phase, and $\sum_{k=1}^{K} \beta_k \alpha_k L_k C_k P_{k,ser}$ is the sum energy consumption of the CPU at the MEC server, where β_k is the price of unit energy consumed by the CPU and $P_{k,ser}$ is the energy consumption per cycle at the MEC server.

B. Problem Formulation

In this letter, we investigate the operator's reward maximization problem in wireless powered MEC system by jointly optimizing the offloaded data size, and the power allocation at the WDs, as well as the wireless-power allocation at the BS. Then, the optimization problem is formulated as

$$\begin{aligned}
\mathcal{P}_1 :\ & \max_{\boldsymbol{p}, \boldsymbol{\alpha}, \boldsymbol{P}} C(\boldsymbol{\alpha}, \boldsymbol{P}, \boldsymbol{p}) \\
\text{s.t. } & (\text{C1}) : 1 - \frac{\tau F_k}{C_k L_k} \le \alpha_k \le 1, \quad \forall k, \\
& (\text{C2}) : \sum_{k=1}^{K} \alpha_k L_k C_k \le F, \\
& (\text{C3}) : P\{\hat{t}_{off,k}(i) > \tau\} \le \epsilon_k, \quad \forall k, \\
& (\text{C4}) : (1 - \alpha_k) L_k C_k P'_k + \frac{\alpha_k L_k p_k}{R_k} \le \mu h_k P_k T_0, \forall k, \\
& (\text{C5}) : \sum_{k=1}^{K} P_k \le P_{max}.
\end{aligned} \tag{2}$$

In $\mathcal{P}_1$, P_{max} and F are the maximum transmit power of the BS and the total computing capacity of the MEC server, respectively. (C1) indicates the offloaded data size constraint. (C2) is the computing capacity constraint of the MEC server. (C3) denotes the offloaded delay requirement constraint. (C4) is the energy consumption constraint. (C5) is the power constraint in the WPT phase.

III. Description of Proposed Algorithm

In this section, we first analyze the offloaded delay outage probability, and then we propose an iterative algorithm to solve $\mathcal{P}_1$.

A. Offloaded Delay Outage Probability

Since it is difficult to solve the offloaded delay $\hat{t}_{off,k}(i)$ directly, we need to transform (C3) into an offloaded data rate constraint. Then, we give the following theorem. The proof of Theorem 1 is similar to the proof of latency requirement in [8] and is omitted for brevity.

Theorem 1: For any WD k, its transmit rate R_k satisfies the following inequation to ensure the delay requirement.

$$\frac{R_k}{\alpha_k} \ge R'_k, \tag{3}$$

where $R'_k = -\frac{\sigma_k}{\tau}[W_{-1}(\frac{\epsilon_k \lambda_k \tau}{1 - e^{\lambda_k \tau}} e^{\frac{\lambda_k \tau}{1 - e^{\lambda_k \tau}}}) + \frac{\lambda_k \tau}{e^{\lambda_k \tau} - 1}]$ and $W_{-1}(x)$ denotes the lower branch of the Lambert-W function with $x \in [-e^{-1}, 0]$, i.e., $ye^y = x$ then $y = W_{-1}(x)$.

Based on Theorem 1, $\mathcal{P}_1$ is rewritten as

$$\begin{aligned}
\mathcal{P}_2 :\ & \max_{\boldsymbol{p}, \boldsymbol{\alpha}, \boldsymbol{P}} \ C(\boldsymbol{\alpha}, \boldsymbol{P}, \boldsymbol{p}) \\
& \text{s.t. } (\text{C1}), (\text{C2}), (\text{C4}), (\text{C5}), \\
& \qquad (\text{C3}) : \frac{R_k}{\alpha_k} \ge R'_k, k = 1, 2, \ldots, K.
\end{aligned} \tag{4}$$

B. Iterative Algorithm Design

Since $\mathcal{P}_2$ is non-convex, we introduce a new variable $\omega_k = \frac{\alpha_k}{R_k}$, and let $\boldsymbol{\omega} = \{\omega_k\}$. $\mathcal{P}_2$ can be rearranged as

$$\begin{aligned}
\mathcal{P}_3: \max_{\boldsymbol{\omega},\boldsymbol{\alpha},\boldsymbol{P}} \quad & C(\boldsymbol{\alpha},\boldsymbol{P},\boldsymbol{\omega}) \\
\text{s.t. } (\text{C1}): & \ 1-\frac{\tau F_k}{C_k L_k} \le \alpha_k \le 1, \quad \forall k, \\
(\text{C2}): & \ \sum_{k=1}^{K} \alpha_k L_k C_k \le F, \quad \forall k, \\
(\text{C3})': & \ 0 \le \omega_k \le 1/R_k', k = 1,2,\ldots,K, \\
(\text{C4}): & \ (1-\alpha_k) L_k C_k P_k' + \frac{N_0 L_k \omega_k}{g_k}(2^{\frac{\alpha_k}{\omega_k B}}-1) \\
& \le \mu h_k P_k T_0, \forall k, \\
(\text{C5}): & \ \sum_{k=1}^{K} P_k \le P_{max}.
\end{aligned} \tag{5}$$

It is easy to prove that $\mathcal{P}_3$ is a convex optimization problem. Meanwhile, we prove that $\mathcal{P}_3$ can be reduced to the problem of $\boldsymbol{\alpha}$ and $\boldsymbol{\omega}$.

1) Optimal Offloaded Data and Power Allocation: $\mathcal{P}_3$ is solved as follows. Firstly, we observe that $\mathcal{P}_3$ is always feasible. Next, we give a necessary condition for the optimal solution, as specified in Theorem 2. It is easy to prove the theorem by contradiction. The proof is omitted due to the limited space.

Theorem 2: As result of solving $\mathcal{P}_3$, the optimal offloaded data size $\boldsymbol{\alpha}^*$, the optimal $\boldsymbol{\omega}^*$, and the optimal wireless-power allocation $\boldsymbol{P}^*$ satisfy the following:

$$(1-\alpha_k^*) L_k C_k P_k' + \frac{N_0 L_k \omega_k^*}{g_k}(2^{\frac{\alpha_k^*}{\omega_k^* B}}-1) = \mu h_k P_k^* T_0 \tag{6}$$

Based on the equality (6), $\boldsymbol{P}^*$ can be rewritten as function of $\boldsymbol{\alpha}^*$ and $\boldsymbol{\omega}^*$. Then, $\mathcal{P}_3$ is equivalently transformed into the following problem.

$$\begin{aligned}
\mathcal{P}_4: \max_{\boldsymbol{\omega},\boldsymbol{\alpha}} \ & \sum_{k=1}^{K} u_k \log(1+\alpha_k L_k) - \sum_{k=1}^{K} \beta_k \alpha_k L_k C_k P_{k,ser} \\
& - c\sum_{k=1}^{K} \frac{1}{\mu h_k}[(1-\alpha_k) L_k C_k P_k' + \frac{N_0 L_k \omega_k}{g_k}(2^{\frac{\alpha_k}{\omega_k B}}-1)] \\
\text{s.t. } & (\text{C1}), (\text{C2}), (\text{C3})', \\
& (\text{C5})': \sum_{k=1}^{K} \frac{1}{\mu h_k}[(1-\alpha_k) L_k C_k P_k' \\
& \quad + \frac{N_0 L_k \omega_k}{g_k}(2^{\frac{\alpha_k}{\omega_k B}}-1)] \le P_{max} T_0.
\end{aligned} \tag{7}$$

Since (7) is a convex optimization problem, we can obtain its optimal solutions by Lagrangian dual method. Then the partial Lagrangian is expressed as

$$\begin{aligned}
L(\boldsymbol{\alpha},\boldsymbol{\omega},\boldsymbol{\gamma},\nu,\varpi) = & \sum_{k=1}^{K} -(\nu+c)\frac{1}{\mu h_k}[(1-\alpha_k) L_k C_k P_k' \\
& + \frac{N_0 L_k \omega_k}{g_k}(2^{\frac{\alpha_k}{\omega_k B}}-1)] + \sum_{k=1}^{K} u_k \log(1+\alpha_k L_k) \\
& + \nu P_{max} T_0 - \sum_{k=1}^{K} \gamma_k (\omega_k - 1/R_k') - \sum_{k=1}^{K} \beta_k \alpha_k L_k C_k P_{k,ser} \\
& + \varpi(F - \sum_{k=1}^{K} \alpha_k L_k C_k),
\end{aligned} \tag{8}$$

where $\boldsymbol{\gamma} \succeq 0$, ϖ and $\nu \ge 0$ are the Lagrangian multipliers corresponding to (C2), (C3)′ and (C5)′ in (7), respectively. To facilitate the subsequent analysis, we define a function $h(x)$ as $h(x) = f(x) - xf'(x)$, $x > 0$.

Because (7) is convex and satisfies Salterąŕs condition, the duality gap is zero. Therefore, we can obtain the optimal solutions of (7) by solving the following dual problem.

$$\begin{aligned}
& \min_{\boldsymbol{\gamma},\nu} \max_{\boldsymbol{\alpha},\boldsymbol{\omega}} \ L(\boldsymbol{\alpha},\boldsymbol{\omega},\boldsymbol{\gamma},\nu) \\
& \qquad = \min_{\boldsymbol{\gamma},\nu} \max_{\boldsymbol{\alpha}} \max_{\boldsymbol{\omega}} L(\boldsymbol{\alpha},\boldsymbol{\omega},\boldsymbol{\gamma},\nu)
\end{aligned} \tag{9}$$

Observing (9), we can first obtain $\{\omega_k^*\}$, with the assumption that $\boldsymbol{\gamma}$, ν and $\{\alpha_k\}$ are given previously. Then, using the standard optimization and the Karush-Kuhn-Tucker (KKT) conditions, $\{\omega_k^*\}$ is equal to

$$\omega_k^* = \frac{\alpha_k \ln 2}{B[W(\frac{\gamma_k \mu h_k g_k}{(\nu+c)eN_0 L_k} - \frac{1}{e}) + 1]}. \tag{10}$$

After obtaining the optimal solution ω_k^*, we define α_k^* as the optimal offloaded data size. Similarly, based on the KKT conditions, we define $x_k^m = X_k(\nu^m)$ as the solution to

$$\begin{aligned}
& -2^{-\frac{1}{\omega_k^* B L_k}} 2^{\frac{x_k^m}{\omega_k^* B L_k}} + \frac{g_k h_k \mu u_k B}{(\nu^m + c) N_0 (\ln 2)^2} \frac{1}{x_k^m} \\
& \quad = \frac{C_k g_k B(\mu h_k(\varpi + \beta_k P_{k,ser}) - P_k'(\nu^m + c))}{(\nu^m + c) N_0 \ln 2}.
\end{aligned} \tag{11}$$

Then, the offloaded data size is given by

$$\alpha_k^m = \frac{X_k(\nu^m) - 1}{L_k}, \quad (1 < X_k(\nu^m) < L_k + 1) \tag{12}$$

In order to solve the outer minimization problem in (9), a subgradient method is applied to update the dual variables. Then, the update can be expressed as

$$\gamma_k(l+1) = [\gamma_k(l) - \lambda_1(l)(1/R_k' - \omega_k^*)]^+ \tag{13}$$

$$\varpi(l+1) = [\varpi(l) - \lambda_2(l)(F - \sum_{k=1}^{K} \alpha_k^* L_k C_k)]^+ \tag{14}$$

$$\begin{aligned}
\nu(l+1) = & [\nu(l) - \lambda_3(l)(P_{max} T_0 - \sum_{k=1}^{K} \frac{1}{\mu h_k}[(1-\alpha_k^*) \\
& L_k C_k P_k' + \frac{N_0 L_k \omega_k^*}{g_k}(2^{\frac{\alpha_k^*}{\omega_k^* B}}-1)])]^+
\end{aligned} \tag{15}$$

where $\lambda_1(l)$, $\lambda_2(l)$ and $\lambda_3(l)$ are small positive step size, which are set $\lambda_1(l) = \lambda_2(l) = \lambda_3(l) = 0.1/l$.

2) Optimal Wireless-Power Allocation: Combining $\{\alpha_k^*\}$ and $\{\omega_k^*\}$ with the optimal condition in Theorem 2 yields the wireless-power allocation, which is given by

$$P_k^* = \frac{1}{\mu h_k T_0}[(1-\alpha_k^*) L_k C_k P_k' + \frac{N_0 L_k \omega_k^*}{g_k}(2^{\frac{\alpha_k^*}{\omega_k^* B}}-1)]. \tag{16}$$

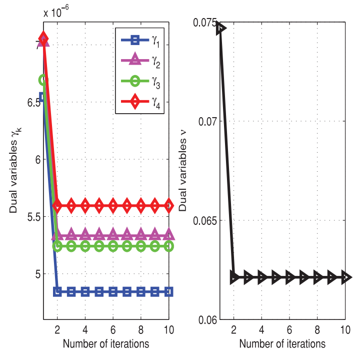

Fig. 1. Convergence of Algorithm.

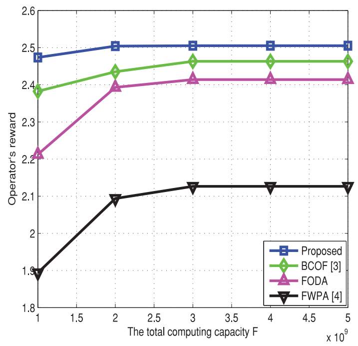

Fig. 2. Operator's reward vs. F.

IV. Simulation Results

In this section, three baseline strategies are considered for the performance comparison of the proposed scheme. The first one is the fixed wireless-power allocation (FWPA) strategy [4], which jointly optimizes offloaded data size and transmit power of WD. The second one is the fixed offloaded data allocation (FODA) strategy, which jointly optimizes transmit power of WD and wireless-power allocation at the BS. The third one is a binary computation offloading policy (BCOF) [3], which jointly optimizes time allocation and mode selection (i.e., local computing or offloading). Some preference settings are shown below: $K = 4$, $B = 180$ KHz, $P_{k,ser} = 10^{-10}$ J/cycle, $d_{max} = 0.1$ s, $N_0 = 10^{-9}$ W, $\lambda_k = 0.1$ bit/s [9], $\sigma_k = 10^3$ bit, $T_0 = 1$ s, $F = 2$ GHz, $\mu = 0.5$, $\epsilon_k = 10^{-3}$, F_k, C_k, and P'_k follow the uniform distribution with [0.1, 1] GHz, [500, 1500] cycle/bit, and [0, 20×10^{-11}] J/cycle, respectively. Note that each point in the following figures (except for Fig. 1) are based on the average values of 5000 runs.

In Fig. 1, we plot the dual variables $\boldsymbol{\gamma} = \{\gamma_k\}$ and ν versus the number of iterations to show the convergence of the proposed Algorithm. It is observed that it has a fast convergence rate. Fig. 2 shows the operator's reward vs. the total computing capacity of the MEC server. Observe that, the proposed strategy has better performance than the other three. We can observe that the operator's reward of FWPA is the lowest. This is because the operator's reward depends mainly on the energy consumption of the WPT phase, and the wireless-power allocation at the BS has a significant impact on the system performance.

Fig. 3 plots the curve for the operator's reward vs. the input data size. We can observe that operator's reward is monotone-increasing with the enhancement of input data size. This is because the computing capacity of the devices is limited so

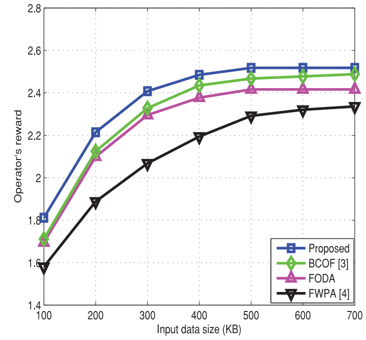

Fig. 3. Operator's reward vs. input data size.

that the amount of data processed by the MEC server increases. However, the growth rate of the operator's reward slows down with the input data size. It indicates that increasing a certain amount of input data size can substantially increase the operator's reward.

V. Conclusion

In this letter, we presented a multi-user wireless powered MEC system and investigated a joint optimization problem of offloaded data size, and power allocation at the WDs, as well as wireless-power allocation at the BS in the wireless powered MEC system, with the objective to maximize the operatorąŕs reward. More specifically, the operator encourages WDs to offload computing tasks to the MEC server by transferring energy to WDs as an incentive. Finally, simulation results exhibit that the proposed algorithm has good performance in terms of operator's reward.

References

[1] D. Zhai, R. Zhang, J. Du, Z. Ding, and F. R. Yu, "Simultaneous wireless information and power transfer at 5G new frequencies: Channel measurement and network design," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 1, pp. 171–186, Jan. 2019. doi: 10.1109/JSAC.2018.2872366.

[2] X. Hu, K.-K. Wong, and K. Yang, "Wireless powered cooperation-assisted mobile edge computing," *IEEE Trans. Wireless Commun.*, vol. 17, no. 4, pp. 2375–2388, Apr. 2018.

[3] S. Bi and Y. Zhang, "Computation rate maximization for wireless powered mobile-edge computing with binary computation offloading," *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 4177–4190, Jun. 2018.

[4] S. Mao, S. Leng, K. Yang, Q. Zhao, and M. Liu, "Energy efficiency and delay tradeoff in multi-user wireless powered mobile-edge computing systems," in *Proc. IEEE Glob. Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–6.

[5] F. Guo, L. Ma, H. Zhang, H. Ji, and X. Li, "Joint load management and resource allocation in the energy harvesting powered small cell networks with mobile edge computing," in *Proc. IEEE INFOCOM*, Honolulu, HI, USA, Apr. 2018, pp. 299–304.

[6] C. You, K. Huang, and H. Chae, "Energy efficient mobile cloud computing powered by wireless energy transfer," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1757–1770, May 2016.

[7] X. Li, C. You, S. Andreev, Y. Gong, and K. Huang, "Wirelessly powered crowd sensing: Joint power transfer, sensing, compression, and transmission," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 2, pp. 391–406, Feb. 2019. doi: 10.1109/JSAC.2018.2872379.

[8] L. Zhao and X. Wang, "Round-trip energy efficiency of wireless energy powered massive MIMO system with latency constraint," *IEEE Wireless Commun. Lett.*, vol. 21, no. 1, pp. 12–15, Jan. 2017.

[9] C. Chen, J. Hu, T. Qiu, M. Atiquzzaman, and Z. Ren, "CVCG: Cooperative V2V-aided transmission scheme based on coalitional game for popular content distribution in vehicular ad-hoc networks," *IEEE Trans. Mobile Comput.*, to be published.