Joint Optimization Strategy for Partial Offloading and Resource Allocation in Mobile Edge Computing Based on Energy Harvesting

Jingqiu Ren, Shang Liu, and Guanghua Zhang(✉)

School of Electrical Engineering and Information, Northeast Petroleum University, Daqing 163318, China
dqzgh@nepu.edu.cn

Abstract. The article addresses a Mobile Edge Computing (MEC) network with a focus on wireless power transfer technology. It considers a MEC system with multiple end-users and a single edge server based on energy harvesting techniques. The study formulates the Weighted Time Minimization Problem within the MEC system, and it transforms this problem into two sub-problems: power optimization for offloading users and bit optimization for offloading users. In the first phase, given the task bits for a specific user, the convex approximation of the problem is obtained by introducing an upper bound, The Lagrangian method is employed to derive the closed-form solution for the user's transmission power, and the optimal solution for the transmission rate is obtained through sub-gradient iteration methods.In the second phase, the optimization of offloading users bits is addressed. The optimal offloading bits for users are obtained by using the Alternating Direction Method of Multipliers (ADMM). Simulation experiments (ADMM).Simulation experiments show that the proposed algorithm can effectively reduce system latency.

Keywords: Mobile Edge Computing · Energy Harvesting · convex approximation · Multiple End-Users · Single Edge Server

1 Introduction

With the exponential growth of mobile data services, relying solely on traditional cloud computing is no longer sufficient to meet the demands. To adapt to this continuous growth in demand and enhance user experience, Mobile-Edge Computing (MEC) technology has become a current research hot spot [1]. With the proliferation and application of networks, the demand from mobile users for resource intensive applications such as interactive games and augmented reality is also increasing. However, the development of these emerging applications and services is limited by the computing capabilities of terminals [2]. Therefore, the emergence of Mobile-Edge Computing effectively addresses this issue by not only meeting the computing capacity requirements of terminal devices but also efficiently resolving the problem of long latency in cloud computing. At the same time, the development of energy harvesting technology provides a new avenue for

H.-H. Chen and W. Meng (Eds.): WiSATS 2024, LNICST 606, pp. 128–139, 2025.
https://doi.org/10.1007/978-3-031-86203-8_11

the sustainable energy utilization of mobile terminals. Because the battery of the device is limited, the computation will be interrupted when the battery runs out. It is of great significance to utilize renewable energy to power mobile terminals, thereby improving computational efficiency and achieving green computing. Combining Energy Harvesting (EH) technology with Mobile-Edge Computing (ME-C) can yield satisfactory sustained computational performance. EH-enabled devices in MEC open up new possibilities for cloud computing while also bringing new design challenges. In addition, by designing resource allocation strategies, it is possible to efficiently utilize the harvested energy. Therefore, researching the resource allocation problem of energy harvesting communication systems combined with MEC is of great significance [3].

In reference [4], the Analytic Hierarchy Process (AHP) was utilized to determine the priority sequence of required vehicles at service nodes. Additionally, multiple sequence combination auction schemes were proposed to ensure the maximum economic benefits while meeting the demand requirements [4]. In reference [5], a joint optimization method for multiuser offloading and resource allocation is proposed. This method aims to reduce the overall system cost when resources at the Mobile-Edge Computing (MEC) server are limited [5]. However, the aforementioned studies did not take into account the impact of latency on system performance. In reference [6] addressing the issues of computation, storage, and energy efficiency in mobile terminals, a model for the Mobile-Edge Computing (MEC) system is first established. Based on this model, a joint optimization objective function is formulated to balance offloading latency and resource allocation. The objective is to minimize offloading latency by optimally distributing resources of mobile edge computing servers, thereby achieving optimal solutions and rational computation and offloading. Consequently, this approach effectively reduces the average load latency for multiple users [6]. In reference [7], under the consideration of both smartphone battery capacity and latency sensitivity, network resources are optimized. Additionally, the remaining battery level of mobile terminals is incorporated into the energy consumption and latency optimization. An iterative approach is employed to solve the optimal load balancing decision, thus achieving a balance between energy and latency [7]. In reference [8], a deep learning algorithm based on mobile edge computing is proposed, which optimizes the overall network power consumption [8]. However, the aforementioned studies did not comprehensively consider the impact of both energy consumption and latency on network performance. In reference [9], a two-layer tandem queueing method is employed to analyze M-EC networks. Based on the derived effective capacity, the paper proposes a method for joint bandwidth and computation resource allocation to maximize total revenue while ensuring the quality of service requirements for devices, including statistical delay guarantee and supported arrival rate, aiming to maximize network revenue [9]. In reference [10], the authors propose that MEC and WPT are two promising techniques widely present on the Internet of Things (IoT) for enhancing computational capabilities and prolonging the operation time of low power wireless devices. The study investigates a Mobile-Edge Computing system supported by unmanned aerial vehicles (UA-Vs). Experimental results demonstrate that this method outperforms non-intersecting algorithms in terms of performance [10]. However, the studies did not consider the impact of latency on system performance under energy scarcity conditions.

In response to the issues, this paper aims to investigate the problem of minimizing latency in partial offloading for Mobile-Edge Computing under an energy harvesting model. The main contributions of this study are as follows:

(1) Establishing a system model, the paper investigates the problem of minimizing latency in Mobile-Edge Computing (MEC) systems under constraints of energy harvesting, total computational tasks, and the maximum tolerated latency by users. By jointly optimizing the user's transmission power, local transmission bits, and MEC transmission bits, the proposed problem is addressed to minimize the system latency.
(2) In the first stage, an upper bound is introduced to obtain a convex approximation of the problem. Then, the Lagrangian method is employed to derive a closed-for-m solution for user power, and the subgradient iteration method is utilized to find the optimal solution for user power consumption. In the second stage, local variables are introduced, and the ADMM (Alternating Direction Method of Multipliers) method is employed to determine the optimal bits for offloading users.

2 System Model

2.1 Network Model

In this section, a brief introduction to the system model involved in this paper will be provided, along with discussions on the computational model and energy harvesting model. Specifically, a Mobile-Edge Computing (MEC) model with Energy Harvesting (EH) devices will be explored. As shown in Fig. 1, the system consists of M mobile devices and one MEC server. Computational tasks are offloaded from users to the MEC server through wireless links. There are M users, $m \in M$, M users complete computational tasks through partial offloading, utilizing both local and MEC server resources.The mobile devices are equipped with EH components, and all electrical energy is harvested from recovered renewable energy sources.

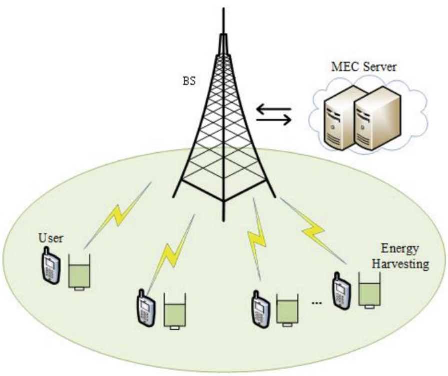

Fig. 1. System Model

The paper considers a block-based model for MEC, where T represents the length of each block. Each of the M users rely on the wireless energy harvested within each block to perform their respective computational tasks.

2.2 Energy Harvesting Model

In the partial computation offloading mode, each user's computational task can be divided into two parts: one part can be computed locally, and the other part is offloaded to the MEC for computation [11]. Both local computation and task offloading consume energy harvested from energy harvesting. This paper adopts a linear energy harvesting model. Therefore, the energy harvested by user m in this time block is:

$$E_m = T\eta_0 h_m p_0, m \in M. \tag{1}$$

where η_0 represents the energy conservation efficiency, $0 \leq \eta_0 \leq 1$. h_m denote the channel gain between the MEC and user m. p_0 stands for the transmission power of the energy harvesting system. In this paper, the energy harvesting system adopts constant power transmission.

2.3 Communication Model

Let $A_m \geq 0$ denote the number of task input bits arriving at user m. The uplink transmission rate for transmitting tasks from user m to the MEC is provided as follows:

$$R_m = B\log_2(1 + \frac{h_m p_m}{\sigma_0^2}), m \in M. \tag{2}$$

where σ_0^2 represents the noise power at user m, B denotes the communication band width, and p_m stands for the transmission power of user m.

All communication users must meet the minimum transfer rate of the channel $R_m^{\min}$, which is given by:

$$R_m \geq R_m^{\min}, m \in M. \tag{3}$$

2.4 Computation Model

Consider completing computing tasks through local computation and task offloading at the user and MEC respectively. At each user m, let $\ell_m \geq 0$ and $d_m \geq 0$ denote the number of task input bits for local calculation and task offloading to the MEC respectively.The execution of computing tasks at the user is subject to causality constraints, meaning that at the user end, the cumulative number of task input bits completed through local computation and task offloading should not exceed the cumulative total number of arrived tasks.

$$\sum_{m=1}^{M}(\ell_m + d_m) \leq \sum_{m=1}^{M} A_m, m \in M. \tag{4}$$

(1) Local Computation: The energy harvesting circuit, communication circuit, and computational unit are all independent. Therefore, each user can perform energy harvesting, local computation, and task offloading simultaneously. Let C represent the number of CPU cycles required for each user to compute one bit. To fully utilize the harvested energy, the CPU power consumption is adaptively adjusted through frequency scaling. The computational capability of the device at the m th user is denoted by f_m^l. Therefore, the time required for the m th user to compute ℓ_m bits is given by:

$$T_m^l = \frac{C\ell_m}{f_m^l}, m \in M. \tag{5}$$

The energy consumed for computing ℓ_m bits at the m th user is given by:

$$E_m^l = C\gamma_c \ell_m (f_m^l)^2, m \in M. \tag{6}$$

where γ_c is the effective capacitance coefficient associated with the processor chip architecture at the m th user.

(2) Task Offloading: Each time slot T consists of three stages: offloading stage, computation stage, and downloading stage. Due to the characteristics of large capacity, high power consumption, low computational workload, and low energy consumption of edge computing nodes, this paper only considers the energy consumption of offloading to the MEC, while ignoring the computational consumption of the MEC. The computational capability of the MEC at the m th user is denoted by f^c. Therefore, the time required for computing d_m bits in the MEC is:

$$T_m^o = \frac{Cd_m}{f^c}, m \in M. \tag{7}$$

The time required to transmit d_m bits at the m th user is:

$$T_m^{up} = \frac{d_m}{R_m}, m \in M. \tag{8}$$

The energy consumed for offloading d_m bits to the MEC at the m th user is:

$$E_m^o = \frac{d_m}{R_m} p_m, m \in M. \tag{9}$$

All users have a tolerable maximum delay $T_m^{\max}$, which is given by:

$$\sum_{m=1}^{M} \left(\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m}\right) \le T_m^{\max}, m \in M. \tag{10}$$

Since the energy required for local computation and task offloading is obtained from harvested energy, the following energy harvesting causality constraint should be satisfied:

$$\sum_{m=1}^{M} \{C\gamma_c \ell_m (f_m^l)^2 + \frac{d_m}{R_m} p_m\} \le \sum_{m=1}^{M} T\eta_0 h_m p_0, m \in M. \tag{11}$$

3 Problem Formation

3.1 Model Problem Description

In this section, we study the resource allocation problem under partial computation offloading mode. In the partial computation offloading mode, the time minimization problem in wireless powered MEC systems is formulated as follows:

$$P1 : \min_{P,\ell,d} F(P, \ell, d) = \sum_{m=1}^{M} (\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m})$$

$$s.t.$$

$$C1 : \sum_{m=1}^{M} (\ell_m + d_m) \leq \sum_{m=1}^{M} A_m, m \in M$$

$$C2 : \sum_{m=1}^{M} (\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m}) \leq T_m^{\max}, m \in M$$

$$C3 : \sum_{m=1}^{M} \{C\gamma_c \ell_m (f_m^l)^2 + \frac{d_m}{R_m} p_m\} \leq \sum_{m=1}^{M} T\eta_0 h_m p_0, m \in M$$

$$C4 : R_m \geq R_m^{\min}, m \in M$$

$$C5 : \sum_{m=1}^{M} \ell_m \leq \ell_m^{\max}, m \in M$$

$$C6 : \sum_{m=1}^{M} d_m \leq d_m^{\max}, m \in M$$

In $P1$, constraint $C1$ represents the total input computing task constraint. $C2$ represents the maximum tolerable delay requirement at the user end, where $T_m^{\max}$ denotes the maximum tolerable delay for the user. $C3$ represents the energy harvesting constraint. $C4$ represents the uplink transmission rate constraint for transmitting tasks from the m th user to the MEC. $C5$ represents the maximum bit constraint accepted for local computation at the m th user. $C6$ represents the maximum bit constraint accepted for offloading computation at the edge server.

3.2 Power Allocation and Task Offloading Bit Joint Optimization Strategy in Mobile Edge Computing Systems

Due to the necessity for users to complete task execution by the end of the entire time slot T, the task completion constraint is:

$$\sum_{m=1}^{M}(\ell_m + d_m) = \sum_{m=1}^{M} A_m, m \in M. \tag{12}$$

Therefore, the optimization problem $P1$ can be reformulated as $P2$:

$$P2:$$
$$\min_{P,\ell,d} F(P,\ell,d) = \sum_{m=1}^{M}\left(\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m}\right)$$
$$s.t. C2 \sim C6, (12)$$

To solve problem $P2$, it is transformed into two subproblems: power optimization and offloading bit optimization.

Offloading User's Power Optimization
For a given sum of ℓ_m and d_m in $P2$, the original optimization problem is a convex problem with respect to p_m,namely:

$$P3:$$
$$\min_{P,\ell,d} F(P,\ell,d) = \sum_{m=1}^{M}\left(\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m}\right)$$
$$s.t. C2 \sim C4$$

Let $\frac{d_m}{R_m} \le \xi_m$, the Lagrangian expression for $P3$ can be provided as follows:

$$L = \sum_{m=1}^{M}\left\{\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \xi_m\right\} + \sum_{m=1}^{M}\lambda_m\left\{\eta_0 h_m P_0 - C\gamma_c \ell_m (f_m^l)^2 - \xi_m P_m\right\}$$
$$+ \sum_{m=1}^{M}\alpha_m\{A_m - \ell_m - d_m\} + \sum_{m=1}^{M}\beta_m\left(R_m - R_m^{\min}\right) \tag{13}$$

Solving Eq. (13) yields the optimal transmission power for the user.

$$p_m^* = \left[\frac{\beta_m B}{\lambda_m \xi_m \ln 2} - \frac{\sigma_0^2}{h_m}\right]^+ \tag{14}$$

Building upon this, the optimal transmission power p_m^* is obtained using the subgradient iteration method. The concrete steps are as follows (Table 1):

In summary, in each iteration, based on the current values of the Lagrange multipliers, the optimal transmission power allocation scheme and the system's optimal total load are obtained by solving based on Eq. (14) and problem $P3'$. The Lagrange multipliers are then adjusted according to Eq. (15) until the termination condition is met. The obtained p_m^* represents the optimal solution to problem $P3'$, and F^* represents the optimal overall offloading load for the system.

Table 1. Sub gradient Iteration Algorithm

Algorithm 1：Sub-gradient Iteration Algorithm for Solving Optimal Transmission Power
Input：$B, M, C, \ell_m, d_m, A_m, f_m^l, f^c$
Initialization: Take $\varepsilon > 0$ as a very small positive number, which determines the accuracy of the subgradient iteration method. Set the iteration count $s = 0$. Use $\lambda_m(0)$ and $\beta_m(0)$ to record the current values of the Lagrange multipliers (LM).
Step1：Calculate $p_m^*(0)$ according to equation (14), and substitute it into problem $P3'$ to obtain the initial overall offloading load $F^*(s)$.
Step2：$s = s + 1$.
Step3:At the s -th iteration, calculate $p_m^*(s)$ based on the current values of the Lagrange multipliers (LM) using equation (19), and substitute it into problem $P3'$ to obtain the overall offloading load $F^*(s)$ for the system.
Step4：If the current overall offloading load $\left\| F^*(s+1) - F^*(s) \right\| \le \varepsilon$ satisfies the system requirements or the Lagrange multiplier gradient (LM Gradient, LG) is zero, then terminate the iteration. Otherwise, move on.
Step5：Update the Lagrange multipliers (LM) according to the following formula and proceed to Step 2: $$\begin{aligned} \lambda_m(s+1) &= \left\lceil \lambda_m(s) + \kappa(s)\partial L / \partial \lambda_m \right\rceil^+ \\ \beta_m(s+1) &= \left\lceil \beta_m(s) + \kappa(s)\partial L / \partial \beta_m \right\rceil^+ \end{aligned} \quad (15)$$
In equation (15), $\kappa(s)$ represents the step size for the sub-gradient, while $\partial L / \partial \lambda_m$ and $\partial L / \partial \beta_m$ represent the Lagrange Gradient (LG).

Offloading User's Bit Optimization

In the previous section, we obtained the power allocation mechanism p_m^* for offloading users. Now, we need to solve the task allocation for offloading users given p_m^*.

Specifically, the optimization variables ℓ_m and d_m are considered global variables, as they are inseparable for all devices in $P2$ (more precisely, constraints $C5$ and $C6$ make $P2$ inseparable). Therefore, local variables $\hat{\ell}_m$ and d_m are introduced, representing the local values of ℓ_m and d_m, respectively. Thus, we have:

$$\begin{cases} \hat{\ell}_m = \ell_m \\ \hat{d}_m = d_m \end{cases} \tag{16}$$

Based on (16), constraints $C5$ and $C6$ can be rewritten as:

$$\sum_{m=1}^{M} \hat{\ell}_m \le \ell_m, m \in M. \tag{17}$$

$$\sum_{m=1}^{M} \hat{d}_m \leq d_m, m \in M. \tag{18}$$

Therefore, the equivalent version of $P2$ can be obtained as follows:

$$P4: \min_{\ell,d} F(\ell, d) = \sum_{m=1}^{M} \frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m}$$

s.t.C2~C4, (16), (17), (18)

According to (17), (18), We can obtain the augmented Lagrangian function for $P4$ as follows:

$$\begin{aligned}\mathcal{L}_\rho\left(\ell, d, \hat{\ell}, \hat{d}, a, b\right) = &\sum_{m=1}^{M}\left\{\frac{C\ell_m}{f_m^l} + \frac{Cd_m}{f^c} + \frac{d_m}{R_m}\right\} + \sum_{m=1}^{M} a_m(\ell_m - \hat{\ell}_m) + \sum_{m=1}^{M} b_m(d_m - \hat{d}_m) \\ &+ \sum_{m=1}^{M} \frac{\rho}{2}(\ell_m - \hat{\ell}_m)^2 + \sum_{m=1}^{M} \frac{\rho}{2}(d_m - \hat{d}_m)^2\end{aligned} \tag{19}$$

In which, a_m and b_m are Lagrange multipliers with respect to the constraints, and ρ is the augmented Lagrangian parameter.

Based on the Lagrange multiplier (LM) constraint, the KKT conditions for the function are as follows:

$$\frac{\partial \mathcal{L}}{\partial \ell_m} = \frac{C}{f_m^l} + a_m + \rho\left(\ell_m - \hat{\ell}_m\right) = 0 \tag{20}$$

can be solved

$$\ell_m^* = \hat{\ell}_m - \frac{C}{f_m^l \rho} - \frac{a_m}{\rho} \tag{21}$$

$$d_m^* = \hat{d}_m - \frac{C}{f^c \rho} - \frac{a_m}{\rho} \tag{22}$$

3.3 Complexity Analysis

The complexity of Algorithm 1 comes from two aspects. The first aspect is from the computation of the optimal transmission power for the user. The second aspect is from the sub-gradient method for computing the La-Grange multipliers. Let s denote the number of iterations required for the Algorithm 1. Let χ denote the tolerance error for the sub-gradient method. Thus, the total complexity of Algorithm 1 is $\mathrm{O}\left[s\left(2M + M\log_2\left(\chi / T\right)\right)\right]$ and $\mathrm{O}(\cdot)$ is the big O notation.

4 Simulation Result Analysis

4.1 Parameter Settings

Considering an MEC base station with a coverage range of 60 m, there are a total of 10 mobile devices randomly distributed within the coverage area. Assuming the uplink and downlink channels have a bandwidth of $B = 2$ MHz, and the channel's noise power is denoted as $\sigma_0^2 = 10^{-9}$ W [13].

Set the length of each time slot as $T = 0.2$ s. For each user, user m computing capacity is denoted by $f_m^l = [1, 2][1, 2]$ GHz, and the effective capacitance coefficient is $\gamma_c = 10^{-28}$[14]. A single user can tolerate a maximum delay of $T_{\max} = 2$ s. For energy harvesting devices, set the energy conservation efficiency as $\eta_0 = 0.8$ [15], and the transmission power of the energy harvesting system as $p_0 = 0.1$ W. For each computing task, set the total task input bit number arriving at user m as $A_m = [0.8, 2]$ Mbits, and the CPU cycles required for computing one bit as $C = 10^3$ cycles/s. Additionally, the computing capacity of the edge server is set to $f^c = 6$ GHz.

4.2 Simulation Analysis

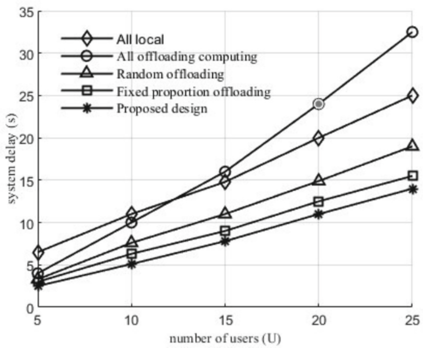

Fig. 2. The relationship between system delay and the number of users

Figure 2 shows the relationship between the system delay and the number of users. This paper selects all local schemes, all offloading schemes, random offloading schemes and fixed proportion offloading schemes for comparison. As shown in Fig. 2, as the number of users increases, the total delay of the five calculation methods is on the rise, and the performance of the proposed algorithm is the best. When the number of users is 15, the total delay of all offloading schemes exceeds that of all local schemes. This is due to the limitation of the computing capacity of the edge server. When the number of users increases, the computing resources that can be allocated to each user are reduced, thereby increasing the total delay of the system. In addition, when the number of users is 20, compared with all local schemes, all offloading schemes, random offloading schemes and fixed proportion offloading schemes, the proposed algorithm reduces the system delay by 43%, 30%, 13% and 5% respectively.

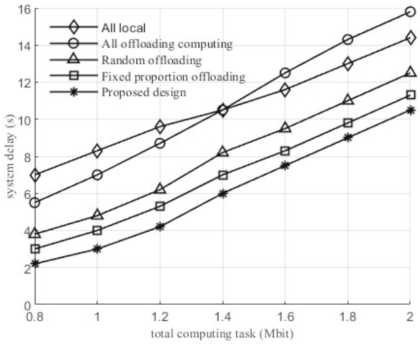

Fig. 3. The relationship between system delay and total computing task

Figure 3 shows the relationship between the total computing task and the total system delay. With the increase of the total computing task, the system delay of all local schemes, all offloading schemes, random offloading schemes, fixed proportional offloading schemes and the algorithm proposed in this paper will increase. This is because when the computing power of the mobile device and the computing power of the UAV assisted MEC are a constant, the larger the total computing task, the more time it takes to perform the task. Although the delay of each scheme increases with the increase of the total computing task, the system delay of all offloading schemes increases faster with the increase of the total computing task. When the total computing task exceeds 1.4 Mbit, the system delay exceeds the system delay of all local schemes. However, no matter how the total computing task increases, the system delay consumed by the proposed scheme is always less than that consumed by other schemes.

5 Conclusion

This paper investigated a communication system with multiple terminal users and a single edge server. Under constraints such as the total input task bits and energy harvesting, the problem of minimizing the total system delay was formulated. By constructing the Lagrangian function and utilizing the KKT conditions, optimal transmission power was obtained. Simulation results demonstrate that compared to all local schemes, all offloading schemes, random offloading schemes and fixed proportion offloading schemes, the proposed approach effectively reduces latency and significantly improves system efficiency, thus confirming the effectiveness of the proposed method.

References

1. Ren, J., Yu, G., Cai, Y., et al.: Latency optimization for resource allocation in mobile-edge computation offloading. IEEE Trans. Wireless Commun. **17**(8), 5506–5519 (2018). https://doi.org/10.1109/TWC.2018.2845360
2. Chen, M., Hao, Y.: Task offloading for mobile edge computing in software defined ultra-dense network. IEEE J. Sel. Areas Commun. **36**(3), 587–597 (2018). https://doi.org/10.1109/JSAC.2018.2815360

3. Jiafa, C., Yisheng, Z., Jincheng, G., et al.: Resource allocation strategy for mobile -edge computing systems based on hybrid energy harvesting. J. Chongqing Univ. Posts Telecommun. (Nat. Sci. Edn.) **33**(02), 193–201 (2021)
4. Haibo, Z., Qiuji, L., Jiang, Z., et al.: V2X task offloading scheme based on mobile edge computing. J. Electron. Inf. Technol. **40**(11), 2736–2743 (2018)
5. Tian, Y., Jun, Y.: Offloading decision and resource allocation strategy in mobile edge computing. Comput. Eng. **47**(02), 19–25 (2021). https://doi.org/10.19678/j.issn.1000-3428.0058085
6. Wenzhu, Z., Peipei, C., Jinghua, Y.: A method for multi-user computation offloading in mobile edge computing. J. Xidian Univ. **47**(06), 131–138 (2020).https://doi.org/10.19665/j.issn1001-2400.2020.06.019
7. Longxian, C.: Energy-efficient task offloading decision in mobile edge computing. Inf. Technol. **44**(10), 127–132 (2020). https://doi.org/10.13274/j.cnki.hdzj.2020.10.024
8. Gao, Y., Yuanming, S.: Deep learning task offloading scheme in mobile edge networks. J. Chongqing Univ. Posts Telecommun. **32**(01), 38–46
9. Wang, Y., Tao, X., Hou, Y.T., et al.: Effective capacity-based resource allocation in mobile edge computing with two-stage tandem queues. IEEE Trans. Commun. **67**(9), 6221–6233 (2019). https://doi.org/10.1109/TCOMM.2019.2920835
10. Zhou, F., Wu, Y., Hu, R.Q., et al.: Computation rate maximization in UAV-enabled wireless-powered mobile-edge computing systems. IEEE J. Sel. Areas Commun. **36**(9), 1927–1941 (2018). https://doi.org/10.1109/JSAC.2018.2864426
11. Liu, L., Chang, Z., Guo, X., et al.: Multiobjective optimization for computation offloading in fog computing. IEEE Internet Things J. **5**(1), 283–294 (2018). https://doi.org/10.1109/JIOT.2017.2780236.7
12. Teng, Y., Cheng, K., Zhang, Y., et al.: Mixed timescale joint computational offloading and wireless resource allocation strategy in energy harvesting Multi-MEC server systems. IEEE Access **7**, 74640–74652 (2019). https://doi.org/10.1109/ACCESS.2019.2921317
13. Wang, F., Xing, H., Xu, J.: Optimal resource allocation for wireless powered mobile edge computing with dynamic task arrivals. In: IEEE International Conference on Communications (ICC), Shanghai, China, pp. 1–7 (2019). https://doi.org/10.1109/ICC.2019.8761143
14. Teng, J.: Research on energy harvesting-based computation offloading techniques in mobile edge computing , Master dissertation, Nanjing University of Posts and Telecommunications (2022)
15. Wang, F., Xu, J., Wang, X., et al.: Joint offloading and computing optimization in wireless powered mobile-edge computing systems. IEEE Trans. Wireless Commun. **17**(3), 1784–1797 (2018). https://doi.org/10.1109/TWC.2017.2785305