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Optimization of Energy Consumption in the MEC-Assisted Multi-User FD-SWIPT System

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ABSTRACT That alleviating the heavy computing task, improving spectral efficiency and prolonging battery lifetime have been the key design challenges in Internet of Things (IoT) and intelligent connected vehicles (ICV). This paper studies the optimization of communication, computation and energy resource to minimize the energy consumption in the mobile terminal, where some superior technologies are included, such as Full-Duplex (FD), Simultaneous Wireless Information and Power Transfer (SWIPT), Mobile-Edge Computing (MEC) and Multi-input Multi-output (MIMO). In this model, the MEC-assisted Base station (BS) works in FD mode, then it can transmit and receive signals in the same frequency and time. Moreover, the mobile devices offload some computation tasks to the BS and complete local computations at the same time. Besides, the mobile device harvests the energy from the BS to support its energy consumption. And, our target is to minimize the energy consumption of mobile devices. Since the problem is non-convex, we propose an iterative solving algorithm including a multi-step optimization. First, we obtain the closed-form solution of the CPU frequency. And then, we transform the remain problem into a convex one to solve it by the interior point algorithm. Finally, we obtain the approximate solution by multiple iterations. Simulation results show that the proposed algorithm is superior to the compared schemes.

INDEX TERMS Mobile-edge computing, simultaneous wireless information and power transfer, multi-input multi-output, full-duplex, multi-step iteration, vehicular communications.

I. INTRODUCTION

With the explosion of data traffic [1], mobile devices, such as ICVs in the vehicular communication network, need to handle more computation tasks, although their computation capability are insufficient [2], [3]. Moreover, higher requirements of ultra-low latency, ultra-high efficiency, ultra-high reliability and ultra-high density connection have become essential issues in future vehicular communications [4]–[6]. So far, many novel application scenarios have put forward, including cognitive radio network [7], [8], augmented reality (AR), artificial intelligence (AI) applications [9], [10], smart city [11] and intelligent connected vehicles [12]. To achieve these requirements, the key technologies, such as Non-Orthogonal Multiple Access (NOMA), massive MIMO [13], MEC [14], FD [15] and energy harvest (EH) [16], have attracted significant attentions.

The limitation of computing capability makes mobile devices (such as ICVs) unable to complete heavy computation tasks. Accordingly, researchers focus on MEC technology [17]. Through the MEC processing at the network edge, the data transmission consumes less energy and produces lower latency [18]–[20]. So far, researchers have employed some key technologies of MEC, including Software Defined Network (SDN) [21], Virtualization [22], and Cloud technology [23], in typical applications, such as Intelligent video acceleration, Computing intensive applications, Internet of vehicles and Internet of things (IoT) [24]–[27]. Besides the limited computating ability, some mobile device also suffer from insufficient energy, such as Unmanned Aerial Vehicle (UAV) and IoT [28], [29]. In 2008, Varshney proposed SWIPT technology to harvest energy from surrounding

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environment [30], [31]. R. Zhang, et al. proposed some fundamental issue for maximizing the efficiency of SWIPT [32]. Gao *et al.* [33] investigated the outage probability and the reliable throughput of SWIPT system in Nakagami-m fading channels. On the other hand, the issue of spectrum efficiency can be relaxed by the FD technology [34], in which the maturity of self interference cancelation (SIC) [35], [36] guarantees quality of service (QoS).

So far, the advanced technologies, including the above mentioned MEC technology, FD technology and SWIPT technology, have attracted much attention in the future wireless communication. Generally, how to select key technologies comprehensively and optimize the system performance is an important issue [37]–[40]. E.g., [37] addressed an optimization framework underlaying a NOMA-based cellular network with MEC to reduce the energy consumption. Analogously, D2D-based MEC system were presented in [38] to achieve energy-efficiency. In [39], N. Janatian, et al proposed a MEC design framework in the SWIPT-based multi-user system, aiming to minimize the total energy consumption. Wen *et al.* [40] formulated an optimization problem to investigate the minimal system energy consumption in MEC-assisted single-user SWIPT network with relays. Inspired by [40], we formulate the user energy minimization problem in the MEC-assisted multi-user FD-SWIPT system, in which the terminal equipment has insufficient computing power and energy. In our new optimization model, no relays are included to avoid the loss of time efficiency. Since the single-user model of [40] is difficult to be extended to multi-user scenarios, i.e., the IoT case addressed in this paper, since relays cause additional efficiency loss in the multi-user scenarios. Moreover, taking into consideration the urban area, we find that the public cellular network provides enough coverage without relay, therefore the proposed system design is more suitable for urban areas. By contrast, the relay-assisted single-user model in [40] is more suitable for the wild area with a large area and a small population. Besides, some researchers [5] deployed the small cell BSs as relays, which brings the possibility of relay communication to address urgent service demands in data traffic bursting areas, but this increase the burden of small cell BSs and may be not necessary for most urban areas. Meanwhile, yet the small cell relay leads to time efficiency loss.

To tackle all of above issues, we make use of MEC server located in the BS to bear partial computation tasks from mobile terminals. Meanwhile, BS deployed with the MIMO technology works in FD mode so as to transmit radio frequency (RF) signal to the mobile terminals as well as receive computation tasks from mobile terminals simultaneously, which can further improve spectral efficiency. Besides, mobile terminals with the SWIPT technology will ensure the self-sustainability of the battery, and then they can harvest energy for their missions. Finally, our target is to minimize the energy consumption of users. Accordingly, we formulate a new mathematical model to jointly optimize CPU frequency, the uplink transmitting power, the uplink rate and the offloading computation task. In order to solve this non-convex problem, we proposed a multi-step iterative algorithm. We first decouple this original problem into two subproblems. For the first one, we obtain the optimal closed-form solution of the CPU frequency. Then, substituting this closed-form solution into the original problem to formulate the second subproblem. For the second one, we decouple it into three linear problems, which substantially reduces the solving difficulty compared with the nonlinear decomposition of [40]. Next, we use interior point algorithm with multiple iterations to obtain the final approximate solutions. The simulation result demonstrates a superior energy efficiency among tested schemes. Meanwhile, the analysis on the influence of BS transmitting power indicates that the proposed scheme produces a good energy efficiency with variable BS transmitting powers, while the scheme from [40] is only effective with a high BS transmitting power.

To sum up, our paper has the following contributions compared with previous studies.

- We design a novel multi-user FD system assisted with MEC and SWIPT technologies, in which the mobile terminal is connected with public cellular networks. In the urban areas, such a system can avoid the efficiency loss caused by relays, and produce a reduced terminal energy consumption in comparison with its opponents. Moreover, the depth analysis demonstrates that the proposed scheme produces the best adaptability to the BS transmitting power, which must be beneficial in the real-world applications.
- We can decompose the nonlinear non-convex optimization problem into linear optimization sub-problems, which greatly simplifies the solving process and is beneficial for real-time applications.

II. SYSTEM MODEL

As shown in Fig.1, we consider a wireless communication model including N users as well as a BS integrated with a MEC server. Each single antenna user equipped with a PS (Power splitting) receiver works in HD (Half-Duplex) mode, while the M-antenna BS works in FD mode. According to conversion factor β $(0 \leq \beta \leq 1)$, the PS receiver can operate in both information decoding (ID) state and energy harvesting (EH) state.

In this communication scenario, the total time duration T is divided into N parts. Each user U_i $(i \in \{1, \ldots, N\})$ offloads partial/total computation task D_i^{off}/D_i to the BS within the time slot t_i^u in the uplink. At the same frequency, the BS transmits the computation task $D_j^r (D_j^r = \alpha D_j^{off}, j \neq i, j \in \{1, \ldots, N\}, \alpha \in \{0, 1\})$ completed by MEC server to the user U_j in the downlink simultaneously. The duration of this downlink process is denoted as t_j^d. Moreover, the local computation task D_i^{lo} which equals $D_i - D_i^{off}$ is executed in t_i^{lo}. Apparently, the offloading computation task should no more than the total computation task, i.e., $0 \leq D_i^{off} \leq D_i$. What's more, the time slot of each user should be less than

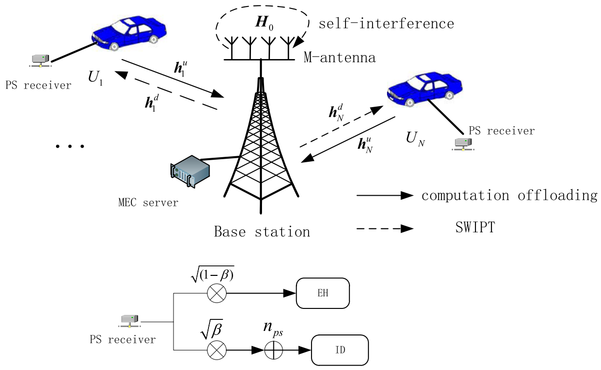


FIGURE 1. System model of MEC-assisted multi-user FD-SWIPT system.

TABLE 1. Symbol meaning.

Symbol	Meaning
N	Number of users
M	Number of antenna
AWGN	Additive White Gaussian Noise
$\boldsymbol{h}_i^u \in \mathbb{C}^{M\times 1}, i \in \{1, ..., N\}$	uplink channel matrix
$\boldsymbol{h}_j^d \in \mathbb{C}^{M\times 1}, j \in \{1, ..., N\}$	downlink channel matrix
$\boldsymbol{H}_0 \in \mathbb{C}^{M\times M}$	self-interference channel matrix of BS
s_i^u, satisfies $\lvert s_i^u\rvert^2 = 1$	signal from U_i to the BS
s_j^d, satisfies $\lvert s_j^d\rvert^2 = 1$	signal from the BS to U_j
$\boldsymbol{n}_{bs}, \delta_{bs}^2$	AWGN, AWGN power of the BS
n_j^d, δ_j^2	AWGN, AWGN power of U_j
n_{ps}, δ_{ps}^2	AWGN, AWGN power of PS receiver
p_i^u, p_j^d	transmit power of U_i, BS
B	bandwidth
$(.)^T$	transposition operation
$(.)^H$	conjugate transpose of matrix
$tr\{.\}$	trace of matrix

the total time duration T at the uplink and downlink process, i.e., $0 \le t_i^u \le T$, $0 \le t_j^d \le T$. In addition, we assume that the local computing time slot is within the uplink time duration, i.e., $0 \le t_i^{lo} \le t_i^u$. The details will be described in the following subsections.

In this paper, the channel fading model is Rayleigh distribution. Some symbol meanings are listed in Table.1.

A. COMMUNICATION OF MOBILE TERMINALS

In this subsection, we discuss uplink communication process. Users $(U_1, \ldots, U_N)$ offload their computation tasks in turn. In each time slot t_i^u, U_i offloads computation task to the BS, while the BS returns the completed computation task D_{i-1}^r to U_{i-1} at the same frequency simultaneously. Without loss of generality, we denote D_{i-1}^r and U_{i-1} as D_j^r and $U_j, j \neq i$, respectively. In addition, there is AWGN at the BS. Hence,the received signal at the BS with three components can be expressed as

$$\boldsymbol{y}_i^u = \sqrt{p_i^u}\boldsymbol{h}_i^u s_i^u + \boldsymbol{H}_0(\sqrt{p_j^d}\boldsymbol{s}_j^d) + \boldsymbol{n}_{bs} \tag{1}$$

In (1), the first component is the signal transmitted by U_i, the second component is the self-interference at the BS, and the last component is the AWGN at the BS.

In (1), the transmitting power p_i^u of U_i should satisfies $p_{min}^u \le p_i^u \le p_{max}^u$, where p_{min}^u and p_{max}^u are the lower and upper limits of p_i^u.

According to the received signal at the BS, we can calculate the received signal power as follows.

$$\begin{aligned} P_i^u &= tr\{\boldsymbol{y}_i^u(\boldsymbol{y}_i^u)^H\} \\ &= p_i^u tr\{\boldsymbol{h}_i^u(\boldsymbol{h}_i^u)^H\} + p_j^d tr\{\boldsymbol{H}_0(\boldsymbol{H}_0)^H\} + \delta_{bs}^2 \end{aligned} \tag{2}$$

Based on equation (2), we can obtain the signal to interference plus noise ratio (SINR) and the uplink rate accroding to the Shannon Theorem at the BS.

$$SINR_{max,i}^u = \frac{p_i^u tr\{\boldsymbol{h}_i^u(\boldsymbol{h}_i^u)^H\}}{p_j^d tr\{\boldsymbol{H}_0(\boldsymbol{H}_0)^H\} + \delta_{bs}^2} \tag{3}$$

$$R_{max,i}^u = Blog(1 + SINR_{max,i}^u) \tag{4}$$

As we known, the actual uplink transmission rate is no more than the theoretical maximal transmission rate, i.e.,

$$R_i^u \le R_{max,i}^u \tag{5}$$

Hence, the offloading time t_i^u of each user U_i and the total energy comsuption of all users as shown below

$$t_i^u = \frac{D_i^{off}}{R_i^u} \tag{6}$$

$$E_{us} = \sum_{i=1}^{N} p_i^u \frac{D_i^{off}}{R_i^u} \tag{7}$$

In addition, the local computing time of each user satisfies [40]

$$t_i^{lo} = \sum_{i=1}^{C(D_i - D_i^{off})} \frac{1}{f_i^n} \tag{8}$$

where C represents the CPU cycles of U_i required for computing 1-bit of data, and f_i^n is the CPU frequency of U_i required for the n-th CPU cycles ($0 \le f_i^n \le f_i^{max}$, f_i^{max} is the maximum CPU frequency).

The total energy comsuption of all users is as follows [40]

$$E_{lo} = \sum_{i=1}^{N} \sum_{n=1}^{C(D_i - D_i^{off})} \kappa (f_i^n)^2 \tag{9}$$

where κ represents the effective capacitance coefficient based on the chip architecture of user's [41].

We assume that users have enough energy to offload computation tasks and execute local computation tasks by harvesting energy from the BS. Thus, the energy consumption of users both in computation tasks' offloading and local computing should satisfy

$$E_{us} + E_{lo} \le E_{uh} \tag{10}$$

B. COMMUNICATION OF BS

In downlink communication, U_j transmits the RF (radio frequency) signal from the BS to the PS receiver which can separate the computation task and energy. Similar to uplink communication, the received signal at the U_j as follows

$$y_j^d = \sqrt{p_j^d}(\boldsymbol{h}_j^d)^T \boldsymbol{s}_j^d + n_j^d \tag{11}$$

where the first component of y_j^d is the received RF signal of U_j from the BS while the second component is the AWGN at U_j.

The signal power at U_j can be expressed as

$$P_j^d = p_j^d tr\{(\boldsymbol{h}_j^d)^T (\boldsymbol{h}_j^d)^{TH}\} \tag{12}$$

Due to the information conversion coefficient of PS receiver is β, therefore, the energy conversion coefficient is $1-\beta$. Correspondingly, the information is βy_j^d while the energy is $(1-\beta)y_j^d$.

Hence, the SNR and the downlink rate can be formed as

$$SNR_j^d = \frac{\beta p_j^d tr\{(\boldsymbol{h}_j^d)^T (\boldsymbol{h}_j^d)^{TH}\}}{\delta_j^2} \tag{13}$$

$$R_j^d = Blog(1 + SNR_j^d) \tag{14}$$

where we ignore the co-channel interference from the uplink user U_i to the downlink user U_j, since the BS power is much higher than that of U_i.

Thus, we have the downlink time duration in which the BS transmits the computation task to U_j as shown below

$$t_j^d = \frac{\alpha D_j^{off}}{R_j^d} \tag{15}$$

Ultimately, the energy harvesting of U_j can be denoted as

$$E_{uh} = \sum_{j=1}^{N} (1-\beta) P_j^d t_j^d \tag{16}$$

C. PROBLEM FORMULATION

Based on the above analysis, we aim to minimize the uplink energy consumption of users since the downlink energy transmitted by the BS is considered as infinite which ensuring each user has enough energy to complete local computation task and offload computation task to the BS. The mathematical model is shown in problem $(P1)$.

$$(P1) \quad \min_{\boldsymbol{f}^n, \boldsymbol{p}^u, \boldsymbol{D}^u, \boldsymbol{R}^u} E_{us} + E_{lo}$$
$$s.t. \begin{cases} E_{us} + E_{lo} \le E_{uh} \\ 0 \le D_i^u \le D_i \\ 0 \le R_i^u \le R_{i,max}^u \\ p_{min}^u \le p_i^u \le p_{max}^u \\ 0 \le t_i^u, t_j^d \le T \\ 0 \le t_i^{lo} \le t_i^u \\ 0 \le f_i^n \le f_i^{max} \end{cases} \tag{17}$$

where $\boldsymbol{f}^n = [f_1^n, \ldots, f_N^n]^T$, $\boldsymbol{p}^u = [p_1^u, \ldots, p_N^u]^T$, $\boldsymbol{D}^{off} = [D_1^{off}, \ldots, D_N^{off}]^T$, $\boldsymbol{R}^u = [R_1^u, \ldots, R_N^u]^T$.

III. OPTIMAL SOLUTION

Due to the cost function and the constraint $E_{us} + E_{lo} \le E_{uh}$ are non-convex in problem $(P1)$, we decouple the problem into two subproblems.

Subproblem 1: we obtain the optimal closed-form solution of the CPU frequency $\boldsymbol{f}^n$ through the theoretical derivation while the rest varibles $\{\boldsymbol{p}^u, \boldsymbol{D}^{off}, \boldsymbol{R}^u\}$ are fixed. And then the optimal solution of $\boldsymbol{f}^n$ is denoted as $\boldsymbol{f}^{opt}$.

Subproblem 2: replacing the $\boldsymbol{f}^n$ with the optimal solution $\boldsymbol{f}^{opt}$, we have the new problem. Since the new problem is also non-convex, we first transform it into a convex problem and then use classical interior algorithm to solve this convex optimization problem.

A. LOCAL COMPUTING OPTIMIZATION

Based on [41], the optimal CPU frequency of n-th ($n \in \{1, \ldots, C(D_i - D_i^{off})\}$) CPU cycles satisfies

$$f_i^1 = \ldots = f_i^n = \ldots = f_i^{C(D_i - D_i^{off})} = \bar{f}_i \tag{18}$$

where $\bar{f}_i$ is the average CPU frequency. Bring the $\bar{f}_i$ into the problem $(P1)$, we obtain the following problem $(P2)$

$$(P2) \quad \min_{\bar{f}} \quad E_{us} + \sum_{i=1}^{N} \sum_{n=1}^{C(D_i - D_i^{off})} \kappa (\bar{f}_i)^2$$
$$s.t. \begin{cases} E_{us} + \sum_{i=1}^{N} \sum_{n=1}^{C(D_i - D_i^{off})} \kappa (\bar{f}_i)^2 \le E_{uh} \\ 0 \le D_i^u \le D_i \\ 0 \le R_i^u \le R_{i,max}^u \\ p_{min}^u \le p_i^u \le p_{max}^u \\ 0 \le t_i^u, t_j^d \le T \\ 0 \le \dfrac{C(D_i - D_i^{off})}{f_i} \le t_i^u \\ 0 \le \bar{f}_i \le f_i^{max} \end{cases} \tag{19}$$

where the variables $\{\boldsymbol{p}^u, \boldsymbol{D}^{off}, \boldsymbol{R}^u\}$ are fixed and meet the constraints meanwhile.

In order to minimize the objective function of $(P2)$, we hope the $\bar{f}_i$ to be as small as possible. Hence, according to the constraint $0 \le \frac{C(D_i - D_i^{off})}{f_i} \le t_i^u$ of $(P2)$, we get the lower limit of $\bar{f}_i$, namely

$$\bar{f}_i = \frac{C(D_i - D_i^{off})}{t_i^u} \tag{20}$$

So far, we have the optimal closed-form solution of CPU frequency, namely $f_i^{opt} = f_i^n = \bar{f}_i = \frac{C(D_i - D_i^{off})}{t_i^u}$. Substituting this optimal solution into equation (8) and (9), these two equations can be transformed as follows

$$t_i^{lo} = t_i^u \tag{21}$$

$$E_{lo} = \sum_{i=1}^{N} \frac{\kappa C^3 (D_i - D_i^{off})^3}{(t_i^u)^2} \tag{22}$$

Finally, the problem ($P2$) can be rewritten as

$$(P3)\quad \min_{\boldsymbol{p}^u,\boldsymbol{D}^{off},\boldsymbol{R}^u} E_{us}+\sum_{i=1}^{N}\frac{\kappa C^3(D_i-D_i^{off})^3}{(t_i^u)^2}$$
$$s.t.\begin{cases} E^{uo}+\sum_{i=1}^{K}\frac{\kappa C^3(D_i-D_i^{off})^3}{(t_i^u)^2}\le E^{uh}\\ 0\le D_i^{off}\le D_i\\ 0\le R_i^u\le R_{i,max}^u\\ p_{min}^u\le p_i^u\le p_{max}^u\\ 0\le t_i^u,t_j^d\le T\end{cases}\tag{23}$$

The algorithm of subproblem ($P2$) is described in **Algorithm 1**.

Algorithm 1 Local Computing Optimization

Input: $N, M, B, \boldsymbol{h}_i^u, \boldsymbol{h}_j^d, \boldsymbol{H}_0, T, C, \kappa, \beta, \alpha, \boldsymbol{D}, \delta_j^2, \delta_{bs}^2, \boldsymbol{s}^u, \boldsymbol{s}^d, p_{min}^u, p_{max}^u, p_{min}^d, p_{max}^d, \boldsymbol{D}^{off}, \boldsymbol{p}^u, \boldsymbol{R}^u$

1: According to ($P2$), get the optimal CPU frequency $f_i^{opt}=\frac{C(D_i-D_i^{off})}{t_i^u}$, and $t_i^{lo}=t_i^u$

2: Convert ($P2$) into ($P3$) by putting $f_i^{opt}=\frac{C(D_i-D_i^{off})}{t_i^u}$ and $t_i^{lo}=t_i^u$ into ($P2$)

Output: $\boldsymbol{f}^{opt}$

B. COMMUNICATION OPTIMIZATION

The equivalent problem of ($P3$) is shown below.

$$(P4)\quad \min_{\boldsymbol{p}^u,\boldsymbol{D}^{off},\boldsymbol{R}^u}\sum_{i=1}^{N}D_i^{off}\frac{p_i^u}{R_i^u}+\sum_{i=1}^{N}\frac{\kappa C^3(D_i-D_i^{off})^3}{(\frac{D_i^{off}}{R_i^u})^2}$$
$$s.t.\begin{cases}\sum_{i=1}^{N}D_i^{off}\frac{p_i^u}{R_i^u}+\sum_{i=1}^{N}\frac{\kappa C^3(D_i-D_i^{off})^3}{(\frac{D_i^{off}}{R_i^u})^2}\\ \le\sum_{j=1}^{N}(1-\beta)P_j^d\frac{\alpha D_j^{off}}{R_j^d}\\ p_{min}^u\le p_i^u\le p_{max}^u\\ 0\le R_i^u\le R_{max,i}^u\\ 0\le\frac{D_i^{off}}{R_i^u}\le T\\ 0\le\frac{\alpha D_j^{off}}{R_j^d}\le T\end{cases}\tag{24}$$

Since the problem ($P4$) is also non-convex, we first transform ($P4$) into three convex problems. Concretely, problem ($P4$) is convex with variable $\boldsymbol{p}^u$ while the other two variables $\boldsymbol{D}^{off}$, $\boldsymbol{R}^u$ are fixed. Analogously, problem ($P4$) is convex with variable $\boldsymbol{D}^{off}$ and $\boldsymbol{R}^u$ respectively, while the other two corresponding variables are fixed. Based on this theory, we can obtain three convex problems as below.

$$(P4.1)\quad \min_{\boldsymbol{p}^u}\sum_{i=1}^{N}v_ip_i^u+E_{lo}$$
$$s.t.\begin{cases}\sum_{i=1}^{N}v_ip_i^u+E_{lo}\le E_{uh}\\ p_{min}^u\le p_i^u\le p_{max}^u\\ 0\le R_i^u\le R_{max,i}^u\\ 0\le\frac{D_i^{off}}{R_i^u}\le T\\ 0\le\frac{\alpha D_j^{off}}{R_j^d}\le T\end{cases}\tag{25}$$

where $v_i=\frac{D_i^{off}}{R_i^u}$, and all parameters are fixed except for $\boldsymbol{p}^u$.

$$(P4.2)\quad \min_{\boldsymbol{D}^{off}}\sum_{i=1}^{N}D_i^{off}q_i+\sum_{i=1}^{N}\frac{\kappa C^3(D_i-D_i^{off})^3}{(\frac{D_i^{off}}{R_i^u})^2}$$
$$s.t.\begin{cases}\sum_{i=1}^{N}D_i^{off}q_i+\sum_{i=1}^{N}\frac{\kappa C^3(D_i-D_i^{off})^3}{(\frac{D_i^{off}}{R_i^u})^2}\\ \le\sum_{j=1}^{N}\alpha D_j^{off}x_i\\ p_{min}^u\le p_i^u\le p_{max}^u\\ 0\le R_i^u\le R_{max,i}^u\\ 0\le\frac{D_i^{off}}{R_i^u}\le T\\ 0\le\frac{\alpha D_j^{off}}{R_j^d}\le T\end{cases}\tag{26}$$

where $q_i=\frac{p_i^u}{R_i^u}$, $x_i=\frac{(1-\beta)P_j^d}{R_j^d}$, and all parameters are fixed except for $\boldsymbol{D}^{off}$.

$$(P4.3)\quad \min_{\boldsymbol{R}^u}\sum_{i=1}^{N}\frac{m_i}{R_i^u}+\sum_{i=1}^{N}r_i(R_i^u)^2$$
$$s.t.\begin{cases}\sum_{i=1}^{N}\frac{m_i}{R_i^u}+\sum_{i=1}^{N}r_i(R_i^u)^2\le E_{uh}\\ p_{min}^u\le p_i^u\le p_{max}^u\\ 0\le R_i^u\le R_{max,i}^u\\ 0\le\frac{D_i^{off}}{R_i^u}\le T\\ 0\le\frac{\alpha D_j^{off}}{R_j^d}\le T\end{cases}\tag{27}$$

where $m_i=D_i^{off}p_i^u$, $r_i=\frac{\kappa C^3(D_i-D_i^{off})^3}{(D_i^{off})^2}$, and all parameters are fixed except for $\boldsymbol{R}^u$.

In each iteration, we obtain the optimal solution $\boldsymbol{p}^{u(iter)}, \boldsymbol{D}^{off(iter)}, \boldsymbol{R}^{u(iter)}$. Until the algorithm converges, the final optimal solution is $\boldsymbol{p}^{u(opt)}, \boldsymbol{D}^{off(opt)}, \boldsymbol{R}^{u(opt)}$. Where, "iter" represents iteration number.

The algorithm of subproblem ($P3$) is described in **Algorithm 2**.

Algorithm 2 Multi-Step Optimization

Input: $N, M, B, \boldsymbol{h}_i^u, \boldsymbol{h}_j^d, \boldsymbol{H}_0, T, C, \kappa, \beta, \alpha, \boldsymbol{D}, \delta_j^2, \delta_{bs}^2, \boldsymbol{s}^u, \boldsymbol{s}^d, p_{min}^u, p_{max}^u, p_{min}^d, p_{max}^d, \boldsymbol{D}^{off(0)}, \boldsymbol{p}^{u(0)}, \boldsymbol{R}^{u(0)}$

1: Set the initial value $\boldsymbol{p}_{ini}^u = \boldsymbol{p}^{u(0)}, \boldsymbol{D}_{ini}^{off} = \boldsymbol{D}^{off(0)}, \boldsymbol{R}_{ini}^u = \boldsymbol{R}^{u(0)}$, and iteration number $n = 1$

2: **repeat**

3: Solve problem $(P4.1)$ with fixed $\boldsymbol{D}^{off(n-1)}, \boldsymbol{R}^{u(n-1)}$, while $\boldsymbol{p}_{ini}^u = \boldsymbol{p}^{u(n-1)}$, to achieve the optimal $\boldsymbol{p}^{u(n)}$;

4: Solve problem $(P4.2)$ with fixed $\boldsymbol{p}^{u(n-1)}, \boldsymbol{R}^{u(n-1)}$, while $\boldsymbol{D}_{ini}^{off} = \boldsymbol{D}^{off(n-1)}$, to achieve the optimal $\boldsymbol{D}^{off(n)}$;

5: Solve problem $(P4.3)$ with fixed $\boldsymbol{D}^{off(n-1)}, \boldsymbol{p}^{u(n-1)}$, while $\boldsymbol{R}_{ini}^u = \boldsymbol{R}^{u(n-1)}$, to achieve the optimal $\boldsymbol{R}^{u(n)}$;

6: Set $n = n + 1$;

7: **until** the cost function of problem $(P4)$ converges.

Output: $\boldsymbol{p}^{u(opt)}, \boldsymbol{D}^{off(opt)}, \boldsymbol{R}^{u(opt)}$

TABLE 2. Simulation parameters.

Parameter	Value
N	$2 \sim 6$
M	$3 \sim 7$
$\boldsymbol{h}^u, \boldsymbol{h}^d, \boldsymbol{H}_0$	Modeled as Random Raylaigh Fading channel$\sim \mathcal{CN}(0, 0.1)$
p_{min}^u	$1W$
p_{max}^u	$5W$
p_j^d	$5W \sim 25W$
$\delta_{bs}^2 = \delta_j^2$	$10^{-7}W$ [40]
B	2MHz
β	0.2
κ	10^{-33}
C	$10^3 cycles/bit$
α	0.8

IV. NUMERICAL RESULTS

In this section, we show numerical simulations for tested schemes, where two benchmark schemes from [40] are presented, i.e.,

- Fixed-variable scheme: all variables are fixed.
- Full-offloading scheme: users offload all computation tasks to the BS, which indicates the local computation tasks equal zero, and the CPU frequency $\boldsymbol{f}^n = 0$.

The simulation parameters have been shown in Table. 2. In Fig. 2 $\sim$ Fig. 5, $\beta = 0.2, \alpha = 0.8$.

In order to fully reflect the impact of the total computation tasks on the number of iterations, we analyze and record the number of iterations under each computation task, and select three typical cases for drawing, as shown in Fig. 2. It demonstrates that the proposed algorithm converges within a few iteration numbers under varying computation task sizes, which demonstrates the effectiveness of the proposed algorithm.

Fig. 3 shows the energy comsuption versus different computation tasks. Both in Fig. 3 (a) and Fig. 3 (b), the uplink energy consumption increases with the computation task growing up. Meanwhile, the proposed algorithm has the lowest uplink energy consuption comparing with the other two schemes. On contrary, while the transmitting power of the BS decreasing, the uplink energy consumption of the proposed algorithm and the full-offloading scheme increase, which indicates that the energy harvesting of users from the BS decline. In addition, although the energy consumption of the fixed-variables scheme decreases, the performance of the other two schemes still outperform the fixed-scheme'.

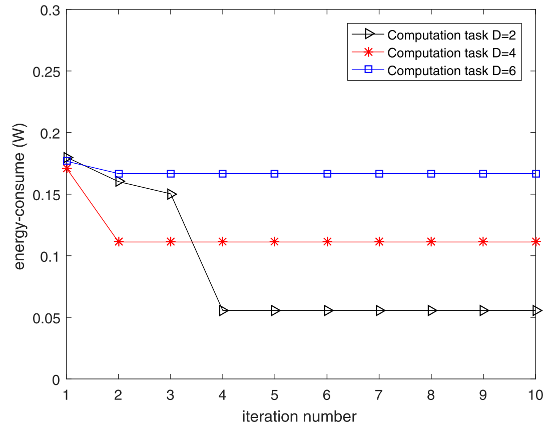
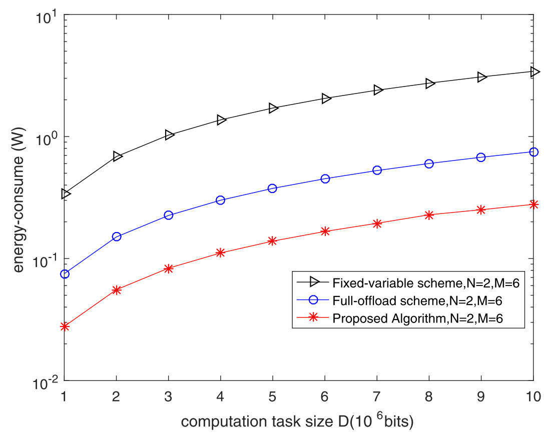
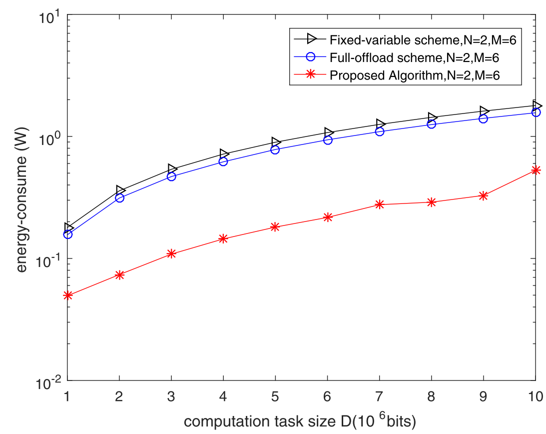


FIGURE 2. Convergence of the proposed algorithm.

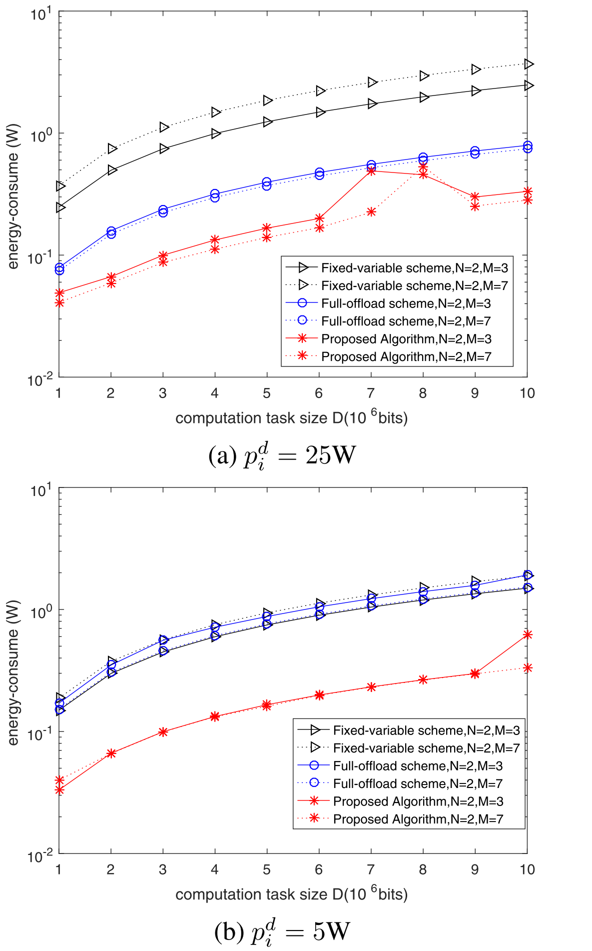


(a) $p_i^d = 25$W



(b) $p_i^d = 5$W

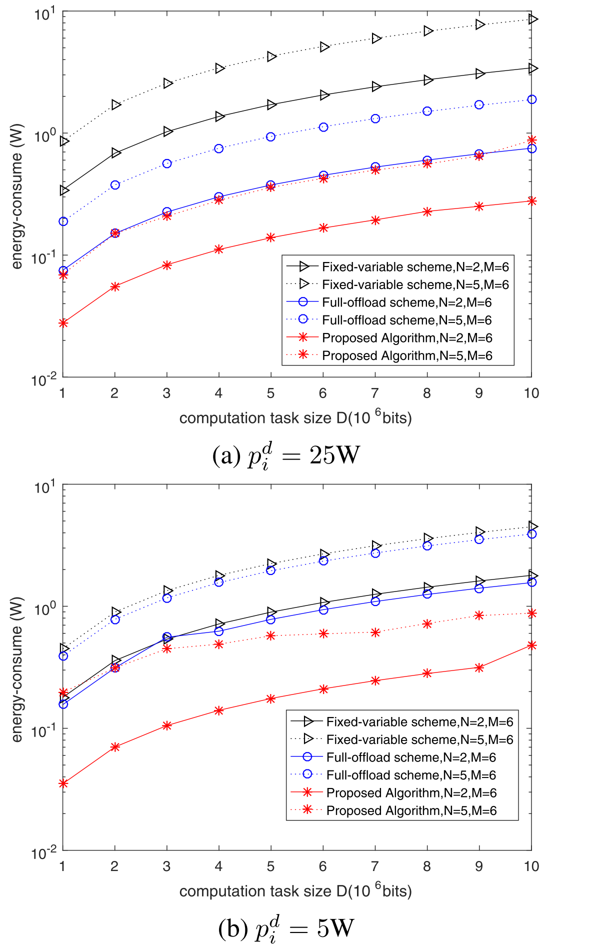
FIGURE 3. The energy consumption of the system versus the computation task size.



(a) $p_i^d = 25\text{W}$

(b) $p_i^d = 5\text{W}$

FIGURE 4. The energy consumption of the system versus the computation task size D under different number of BS antennas (*M*).



(a) $p_i^d = 25\text{W}$

(b) $p_i^d = 5\text{W}$

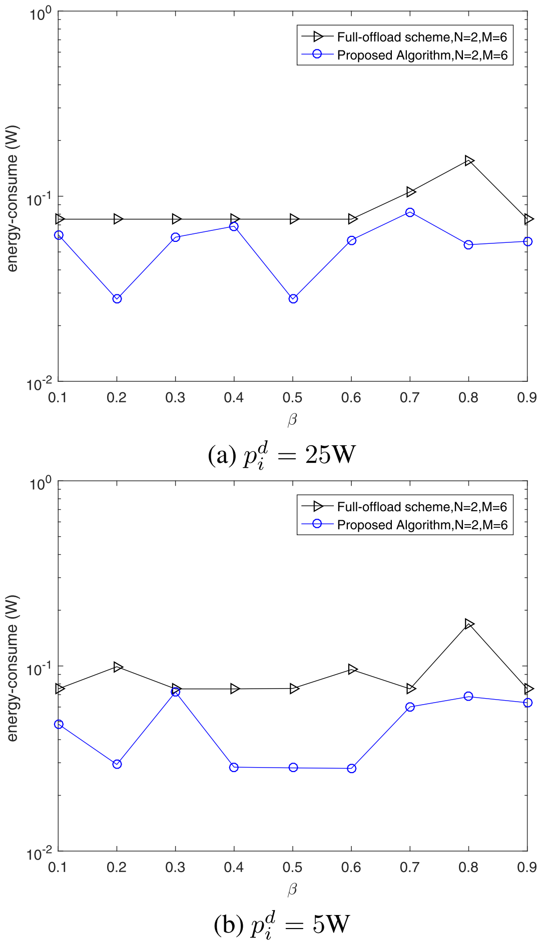
FIGURE 5. The energy consumption of the system versus the computation task size D under different number of users (*N*).

Fig. 4 compares the uplink energy consumption under different antennas versus varying computation tasks. The uplink energy consumption of the fixed-variables scheme decents with the antenna increasing while the other two schemes' energy consumption decrease. Thus, the MIMO technology can improve the system performance. What's more, the energy consumption of the proposed algorithm and the fixed-variables scheme decrease while the antenna number increases and the transmitting power of the BS decreases. On the other hand, the energy consumption of the full-ofloading scheme increases while the transmitting power of the BS decreases. In addition, the energy consumption of all these three schemes change small under different antennas, while the transmitting power of the BS decreases. Since the lower tansmitting power of BS leads to lower downlink rate while the number of antenna affects the channel gain only, which has the less impact than the former. In any case, the proposed algorithm is superior to the comparison schemes.

Fig. 5 shows that more users consume more energy whatever which schemes. And the performance of the proposed algorithm almost outperforms the other comparision schemes'. Comparing (a) and (b), we find that the influence of the fixed scheme and the full-offloading scheme on the system is very close when the power transmitting of the base station is small, which shows that the advantage difference between these two schemes is no longer obvious in the case of small power transmitting of the base station. However, the proposed algorithm still has obvious advantages in the case of low power transmitting compared with the other two schemes. It shows that the proposed algorithm has more adaptability.

Fig. 6 shows the uplink energy consumption with different PS receiver coefficient β. Both in Fig. 6 (a) and (b), energy consumption of the proposed algorithm changes dynamically with β. And the energy consumption of the proposed algorithm reaches maximum when $\beta = 0.7$ in Fig. 6 (a) and $\beta = 0.3$ in Fig. 6 (b) with $\alpha = 0.8$, respectively. Meanwhile, the energy consumption of the full-offloading scheme reaches maximum when $\beta = 0.8$ both in Fig. 6 (a) and (b) with $\alpha = 0.8$. Comparing (a) with (b), β has the same effect on the system performance under different transmitting powers of the BS. Certainly, the proposed algorithm is superior to the full-offloading scheme.

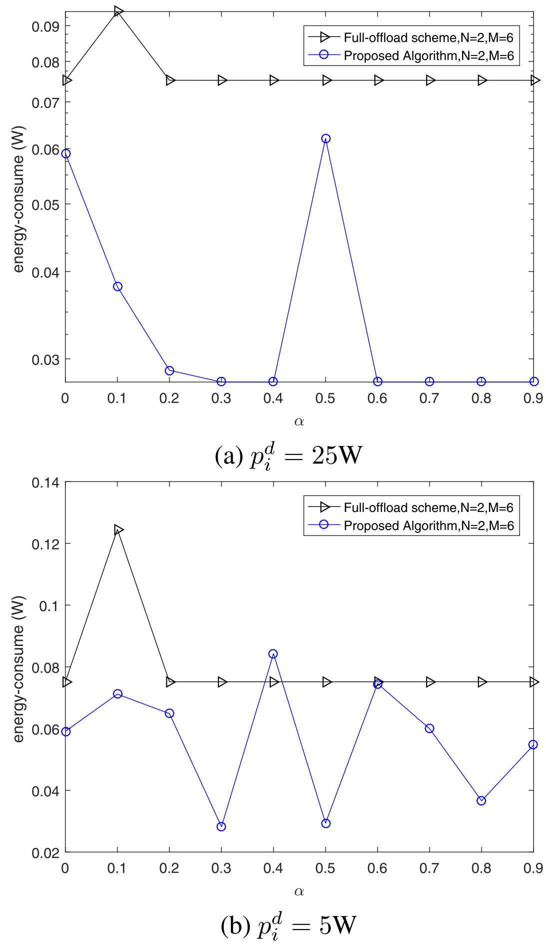
Fig. 7 compares the energy consumption versus different α. Similar to β, energy consumption of the proposed algorithm changes dynamically with α. As shown in Fig. 7, the energy



(a) $p_i^d = 25$W

(b) $p_i^d = 5$W

FIGURE 6. The energy consumption of the system versus PS receiver coefficient β.



(a) $p_i^d = 25$W

(b) $p_i^d = 5$W

FIGURE 7. The energy consumption of the protion coefficient α.

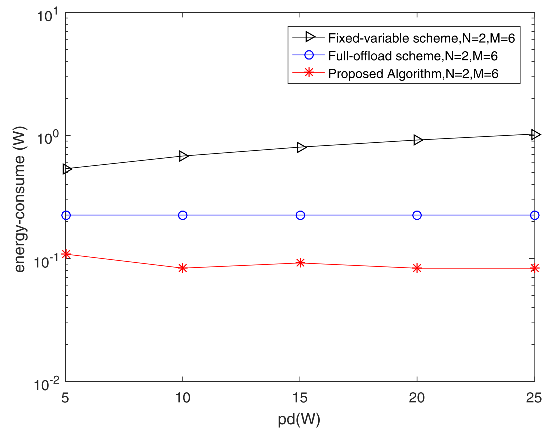


FIGURE 8. The energy consumption of the system versus transmitting power of the BS.

consumption of the proposed algorithm reaches maximum when $\alpha = 0.5$ in Fig. 7 (a) and $\alpha = 0.4$ in Fig. 7 (b) with $\beta = 0.2$, respectively. Analogously, energy consumption of the full-offloading scheme reaches maximum when $\alpha = 0.1$ both in Fig. 7 (a) and (b) with $\beta = 0.2$. Comparing (a) with (b), α has the same effect on the system performance under different transmitting powers of the BS. In addition, β and α change in the same direction in full-offloading scheme comparing Fig. 6 and Fig. 7, where full-offloading scheme reaches the maximal energy consumption at ($\beta = 0.8$, $\alpha = 0.8$) and ($\beta = 0.2$, $\alpha = 0.1$), respectively. Obviously, system performance of the proposed algorithm almost outperforms that of the full-offloading scheme. What's more, we find that curve (b) fluctuates more than curve (a), since the proportion (α) of the completed computation tasks in the uploaded computation tasks affects the constraint of energy collection. When the downlink transmitting power of the base station is reduced, this constraint may not be tight and the optimization effect may not be good enough.

Fig. 8 shows that the energy consumption of the proposed algorithm has a slight drop, while the fixed-variable scheme rises up slightly with the transmitting power of the BS increases. Between the proposed algorithm and the fixed-variables scheme, the full-offloading scheme is almost invariable. Due to more energy transmitted by the BS, more energy harvested by users, which leads to less uplink energy consumption.

V. CONCLUSION

In this paper, we formulate a MEC design framwork with joint optimization of the CPU frequency, the uplink transmitting power, the uplink rate and computation task in a MEC-based multi-user FD-SWIPT system. Ensuring the computation task be completed, we aim to minimize the uplink energy consumption of mobile terminals. Numerical results illustrate the superiority of the proposed algorithm comparing with other two schemes.

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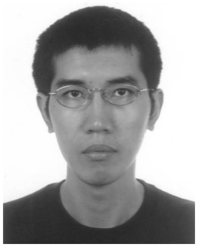

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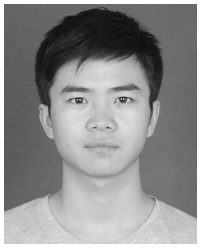

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