Optimal Multi-User Computation Offloading Strategy for Wireless Powered Sensor Networks

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ABSTRACT Wireless sensors network (WSN) is widely used for environmental monitoring, surveillance, healthcare, and security services. One of the most critical challenges that WSN facing is the heavy computation requirements and limited energy storage. The recent development of radio frequency-based (RF) wireless power transfer (WPT) and mobile computation offloading to cloud provide a promising solution to overcome these shortcoming. In this paper, we consider a multi-user Mobile/Multi-Access edge computing (MEC) aided WSN powered by the WPT, where BSs are equipped with multiple antennas jointly service the whole sensors, the sensor node is powered by the WPT only. An optimal multi-user computation offloading strategy is proposed, where sensor nodes choose to operate in either the offloading or the local computing. In addition, perfect channel state information (CSI) and imperfect CSI are taken into account. We study the optimization of computation task offloading in MEC aided WSN under the conditions of perfect CSI and imperfect CSI. In particular, the optimal dynamic time division duplex (D-TDD) factor is investigated. Numerical results confirm the advantages of the proposed computation offloading strategy over the conventional local computation design in handing computationally heavy tasks.

INDEX TERMS Wireless sensor networks, wireless power transmitting, energy harvesting, computation offloading.

I. INTRODUCTION

Wireless sensors network (WSN) is widely used for environmental monitoring, surveillance, healthcare, and security services. With the gaining popularity of Internet-of-Things (IoT) in 5G and driven by smart applications, more intelligent applications such as target recongition (TR), environment perception based on WSN may meet a great opportunity to emerge. Those applications usually have a heavy computation requirements, which leads to powerful hardware equipment and high energy consumption in WSN. However, the contridiction is that WSN terminals are usually small size and small battery storage equiped, and in many cases of WSN, especially when massive amount of sensors are deployed, wired power supply is not economic and sometimes even

not feasible. Consequently, these facts lead to the challenges that WSN is facing (1) Convenient lifelong energy supply, (2) Continuously powerful computing capability.

Mobile/Multi-Access edge computing (MEC) aided WSN and wireless power transmitting (WPT) techniques provide two alternative ways to address the issue [1]–[5]. Wireless power transmission offers the possibility of not charging the terminals, reducing the size of the electronic device and improving its endurance reliability. With MEC aided WSN, the huge data generated by the distributed sensors can be offloaded to MEC platform, which can further improve the performance and reduce energy consumption in WSN. Therefore, academia and industry have great enthusiasm for the study of wireless powered transmission and MEC aided WSN.

The adoption of wireless power transmission and MEC capability faces the following two problems: i) Wireless

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energy transmission efficiency. Due to the physical characteristics of wireless channels, wireless transmission efficiency is not efficient, especially for omnidirectional antenna transmission. ii) Offloading strategy of cloud computing under the limitation of energy supply. Due to the limited energy of mobile nodes, how to design the optimal data scheduling and offloading strategy, guarantee the service quality and improve the energy efficiency has become an important research field.

Simultaneous wireless information and power transfer is an effective way to prolong the battery life of the battery equipped wireless devices [6], [7]. Recently, simultaneous wireless information and power transfer has attracted considerable research interests from wireless communication since it is identified as a promising approach to solve the energy scarcity problem in energy-constrained environments. In WPT design, with a base station continously broadcasting energy, the wireless sensors can harvest the energy with its antenna and power its functional modules. There are several taxonomies of WPT, including the "near-field" electromagnetic coupling, i.e. the inductive and capacitive coupling, and the "far-field" radiation in the form of microwaves or lasers. Due to the high efficiency of electromagnetic coupling and short distance between the energy source and destination, the "near-field" WPT can achieve a relative high end-to-end transmiting efficiency. In [8], the author implemented a WPT system to power a laptop with peak power consumption of 12W at a range of 0.7m, whose end-to-end efficiency is around 50%.

One the other side, far-field WPT techniques use radio-frequency (RF) signals to convey the energy, which may suffer the channel attenuation and scatter, degradating the transmitting efficiency. The fundamental tradeoff in far-field WPT is directionality and the transmission efficiency. According to the law of conservation of energy, the power density of an omnidirectional antenna decreases with $1/r^2$, resulting in the received power several magnitude less than the transmited power. The promising way to improve the end-to-end WPT efficiency is to adopt the directional antennas or energy beamforming techniques. In [9], the author proposed a scheme for simultaneous wireless information and power transfer in MIMO boardcasting networks. Optimal energy beamforming in MIMO system is derived and the tradeoff between energy and rate is explored. In [10], the author proposed an adaptive directional WPT scheme, the aggregate received power of a typically node is analyzed and the optimal charging radius is derived by exploiting the tradeoff between the power intensity of the energy beam and the number of nodes.

From the aspect of the way to harvest energy from wireless signals, it can be also divided into two categories. Generally speaking, there are two representative protocols for simultaneous wireless information and power transfer systems: 1) time switching protocol [11]; and 2) power splitting protocol [12]–[15]. For power splitting, the received signal at each antenna is splited into two separate streams with difference power levels for energy harvester and information decoder.

While for time splitting, each antenna periodically switches between energy harvester and information receiver, which could also be call time division duplex (TDD).

With the target of improve the energy efficiency of WSN, MEC enabled approaches are also studies in current researches. The combination of wireless power transmission and MEC aided is an effective means to solve the insufficient computing amount and energy supply of mobile nodes [10], [16]–[19]. In [16], the authors propose a user cooperative scheme in which the near user can forward the far user's tasks to the edge cloud utilizing its more harvested energy. In [17], a distributed unloading decision-making algorithm is proposed, which USES the potential game to solve the unloading equilibrium solution by determining whether the node is the unloading revenue node. Reference [18] proposes a problem of integrated node computing power scheduling and cloud computing unloading in mobile cloud computing to optimize the probability of successful completion of calculated data. And in [19], a mixed-timescale joint computational offloading and wireless resource allocation algorithm for latency-critical applications is proposed, aiming at minimizing the total energy consumption.

Even though with WPT and MEC aided, there are still several critical issues that need to be addressed in WSN: 1) the harvested energy by sensor nodes is still scarce. Few works have considered the large asymmetry between uplink and downlink in WSN, which means the data transmission in UL and DL are quite different, and usually are dynamic. 2) The radio link is limited compared to the data generated by hunderds of sensors. It's critical to design a offloading profile to maximize the total amount of prossed data. 3) The imperfect CSI knowledge between the distributed sensors and the base stations (BSs) may affect the overall performance and should be quantified. However, most of state-of-art works mainly focus on perfect CSI scenario.

Hence, in this paper we consider an MEC aided and wireless powered WSN, aiming to provide a battery-free WSN solution. In WSN, sensors are mostly in idle state, only small period is in transmission state. Therefore, the TDD energy harvesting mode is more suitable for WSN. So, in our scenario we firstly design dynamic TDD (D-TDD) energy harvesting mechanism which can adapt to the dynamic and asymmetric features of uplink and downlink transmission in wireless sensor networks. And then a joint optimization between D-TDD energy harvesting and computing offloading approach is investigated. The main results and contributions of this paper are as followings:

- An MEC aided WSN is proposed, where WPT is considered to address the problem of limited energy storage. The wireless sensors can harvest the energy with its antenna and power its functional modules.
- We propose an optimal offloading algorithm to maximize the total numbers of computed bits under the condition of perfect CSI. In particular, the optimal D-TDD factor is investigated.
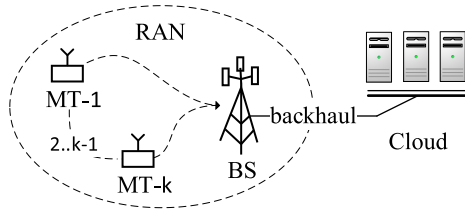
FIGURE 1. Overview of the WSN offloading. The MTs can offload its computation task to the mobile edge cloud through wireless RAN.

FIGURE 2. Centralized MEC aided offloading protocol.

- Then a more realistic scenario with imperfect CSI estimation is considered. The sub-optimal offloading algorithm is studied to maximize the total numbers of computed bits under the condition of imperfect CSI.

II. SYSTEM MODEL

Considering a system consists of K low-power mobile terminals (MT) denoted as $\mathcal{K} = \{1, 2, \ldots, k\}$, which are powered by energy radiated from the BSs. M BSs denoted as $\mathcal{M} = \{1, 2, \cdots, m\}$ jointly serve all the terminal users, which are worked as the distributed MIMO style. MEC is empolyed in WSN for cloud computing, as illustrated in Fig. 1. Each MT has a single transmit antenna to harvest energy or data transmitting. The backhaul capacity between the BS and MEC is assumed large enough. The MTs are randomly distributed in the coverage area. With the harvested energy, the MT can process the data it collected. This is a typically scenario of the internet of things (IoT), which consists hundreds of sensors or even more in a limited area and powering the devices and processing their data can be a tough task.

The total available bandwidth of the radio access network (RAN) is ω which can be used by all the MTs. The MTs charge and process with a periodic T in a time division duplex mode. T is less than the coherent time of the channel. Within each period T, a D-TDD scheme is adopted for the downlink and uplink. In the downlink channel, each MT harvests energy and receive information from the BS, and it is powered only by the harvested energy. As IoT is usually used for data collecting or situation surveillance, uplink data can be much more than downlink data. Therefore, we mainly focus on the energy harvesting of downlink and data transmission of the uplink. For the downlink information transmission, the power-splitting scheme can be cooperated in this paper.

If there is a job prepared to be processed, the MT can either compute it locally with its own Mirco Processing Unit (MCU) or offload it to the cloud servers. We denote the decision set of all MTs as the offloading profile, i.e.

$$S_K = \{s_1, s_2, \ldots, s_k\}, \quad s_i = \{0, 1\} \quad (1)$$

where $s_i = 0$ means the ith MT decides to compute the date locally, and $s_i = 1$ means the ith MT decides to offload the date to the cloud servers.

Typically the computation ability of cloud servers is much more powerful than the local MCU. Both the local computing (LC) and the remote computing (RC) will consume the energy
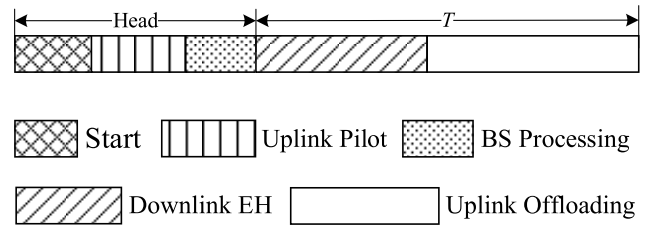
it harvested. With the diversity of all the channels fadings, it is critical to design the offloading profile and the optimal TDD factor to maximize the processing performance. In this work, with the aid of MTs periodically feedback their channel state information (CSI) to the BS, we propose a centralized offloading scheme for the MTs to achieve the maximal system throughput.

In this paper, quality of service (QoS) can be considered as the amount of data that can be processed per unit time. According to weber-Fechner law, the larger the value, the shorter the processing time, the better the user experience. Since in this system, the time processing period T is fixed, we further optimize the system throughput within time period T.

A. OFFLOADING PROTOCOL FOR MTs

The protocol for the centralized MEC aided offloading protocol is illustrated in Fig. 2. First the BSs broadcast a start signal to all the MTs, then the MTs begin to send their corresponding pilots to BSs. State-of-the-art research works have shown that the minimum number of pilots symbols is equal to the number of terminals. With the feedback pilots, the BSs calculate the channel matrix **H** and length of T according to the channel coherence time, together with the optimal α and the offloading profile S_k, then begin to radiated power and control information in the downlink. The MTs can extract the control information with a power splitting technology, which is not considered in this context.

We assume the MTs are sychronized perfectly. The main factor that may degrade the performance lies on the imperfect CSI estimation at BS side. For multiuser MIMO systems, precoding in the downlink and detection in the uplink require CSI at the BS. The resource, time or frequency required for channel estimation in a MIMO system is proportion to the number of MTs. In the proposed D-TDD system, based on the assumption of channel reciprocity, only CSI for the uplink needs to be estimated. When the MTs received the start signal from the BSs, they send uplink pilots. The BSs use these pilot sequences to estimate CSI of the MTs. Then the BSs use the estimated CSI to generate beamforming vectors for the energy beamforming and multiuser detection.

B. ENERGY AND COMMUNICATION MODEL

The process of energy harvesting and task offloading is illustrated in Fig.3. Every period T is splitted into 2 slots,
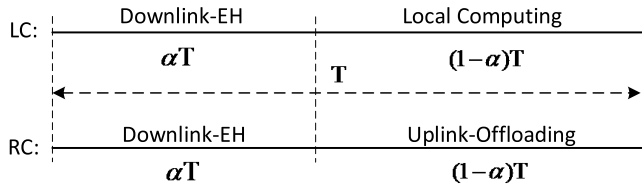
FIGURE 3. D-TDD scheme for the energy harvesting and data offloading. The downlink power splitting for information transmission is neglected.

i.e. αT and $(1-\alpha)T$ with $\alpha \in (0, 1)$ being the D-TDD factor. In the first αT time, all the MTs harvest energy from the downlink received signal and save it in its battery, and in the rest $(1-\alpha)T$ time, part of the MTs proccess its data locally while the others offload the data accroding to the offload profile S_K^T. When there are MTs offloading, the BS stops radiating signals and begins to receive and forward the data to the remote cloud. The T-TDD factor α is identical cross all the MTs in T. No energy harvested in the current T is retained to the next T. The optimal α will be disccused later.

Downlink EH: For the downlink energy broadcasting, let x be the energy symbol, $\mathbf{w}^{dl} = [\mathbf{w}_1^{dl}, \mathbf{w}_2^{dl}, \cdots, \mathbf{w}_M^{dl}] \in \mathbb{R}^{MN_t}$ is downlink energy beamforming vector, where $\mathbf{w}_i \in \mathbb{R}^{N_t}$ is the corresponding BF vector at BS i. The receive signal can be written as:

$$Y = \sqrt{P_{dl}}\mathbf{H}\mathbf{w}^{dl}x + \mathbf{n}_k \tag{2}$$

where $\mathbf{H} \in \mathbb{C}^{k \times MN_t}$ is the channel matrix, P_{dl} is the transmit power of BS, which is assumed to be identical across all BSs.

The received signal y_k at the kth MT can be written as:

$$y_k = \sqrt{P_{dl}}\sum_{i=1}^{MN_t}\mathbf{h}_{k,i}w_i^{dl}x + n_k^{dl} \tag{3}$$

where $\mathbf{h}_{k,i}$ is the complex channel response from the ith BS to kth MT. $n_k^{dl} \sim \mathcal{CN}(0, 1)$ is the additive white noise. With $\mathbb{E}\{x^\dagger x\} = 1$, the receive power of MT k can be written as:

$$P_k = P_{dl}\sum_{m=1}^{M}||\mathbf{h}_{k,m}\mathbf{w}_m^{dl}||^2 \tag{4}$$

where $\mathbf{h}_{k,m} \in \mathbb{C}^{1 \times N_t}$, is the channel matrix from BS m to MT k respectively. The power of white noise is neglectable compared with the aptitude of the received signals.

(4) indicates that the power received at a MT is the sum of the power received from each BS. Compared with the information beamforming, the constraints of energy beamforming is more relax. Its reason is that for the WPT the interference can be harvested by the MT, but for wireless information transfer (WIT), the interference needs to be eliminated with proper beamforming matrix.

Uplink offloading: Based on the uplink-downlink reciprocity, the received signal $\mathbf{r}_m \in \mathbb{C}^{N_t}$ at the mth BS is expressed as:

$$\mathbf{r}_m = \sqrt{P_{ul}}\sum_{k=1}^{K}\mathbf{h}_{k,m}^H s_k + \mathbf{n}_m^{ul} \tag{5}$$

where P_{ul} is the transmit power of the MT, $\mathbf{h}_{k,m}^H \in \mathbb{C}^{N_t}$ is the uplink matrix. s_k is the transmit symbol of kth MT on subchannel n. $\mathbf{n}_m^{dl} \sim \mathcal{CN}^{N_t}(0, 1)$ is the additive white noise. Assuming linear processing by BSs, the estimation of s_k at the BS can be written as:

$$\begin{aligned}\hat{s}_k &= \sqrt{P_{ul}}\sum_{m=1}^{M}\mathbf{w}_{k,m}^H\mathbf{r}_m \\ &= \sqrt{P_{ul}}\sum_{m=1}^{M}(\mathbf{w}_{k,m}^H\mathbf{h}_{k,m}s_k \\ &\quad + \sum_{i=1,i\neq k}^{K}\mathbf{w}_{k,m}^H\mathbf{h}_{i,m}s_i + \mathbf{w}_{k,m}^H n_m^{ul})\end{aligned} \tag{6}$$

where

$$\mathbf{W} = \begin{bmatrix} \mathbf{w}_{1,1} & \mathbf{w}_{1,2} & \cdots & \mathbf{w}_{1,m} \\ \mathbf{w}_{2,1} & \mathbf{w}_{2,2} & \cdots & \mathbf{w}_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{w}_{k,1} & \mathbf{w}_{k,2} & \cdots & \mathbf{w}_{k,m} \end{bmatrix} \in \mathbb{C}^{k \times MN_t}$$

with $\mathbf{w}_{k,m} \in \mathbb{C}^{N_t}$ is the receiving beamforming vector. Then the signal to interference-plus-noise ratio (SINR) of kth MT can be denoted as:

$$\gamma_k = \frac{P_{ul}|\sum_{m=1}^{M}\mathbf{w}_{k,m}^H\mathbf{h}_{k,m}|^2}{\sum_{i\neq k}|\sum_{m=1}^{M}\mathbf{w}_{k,m}^H\mathbf{h}_{i,m}|^2 P_{ul} + \sum_{m=1}^{M}||\mathbf{w}_{k,m}||^2} \tag{7}$$

As a consequence, the uplink capacity of MT k on the nth subchannel can be expressed as:

$$R_k = \omega\log_2(1 + \gamma_k) \tag{8}$$

Here ω is the bandwidth of the subchannel. From the communication model in (7) (8), we see that the offloading data rate is correlated with the interference. If there are too many MTs choose to offload the computation simultaneously during a period, they may incur severe interference, leading to low data rates.

C. COMPUTATION MODEL
A two-tuple is used to denoted the computation job prepared at the begining of each T, i.e.

$$J = (b, d) \tag{9}$$

where b denote the total bits of the the job, and d denote the total MCU cycles needed to finish the job. For the LC, we denote the energy consumption per CPU cycle as τ joul per cycle. Then total number of bits can be processed with the harvested energy within T for the kth MT can be derived as:

$$\mathcal{B}_k^{lc} = \frac{\eta P_k\alpha T}{\tau d}, (bit) \tag{10}$$

where $\eta \in (0.1\ 0.8)$ is the energy transition efficiency from RF to DC. It is noted that in (10) we neglect other insignificant energy loss such as in peripheral circuits.

For the RC, the total number of bits is bounded both by the energy and tranmission time. If the available harvested energy dominants, the total number of bits can be offloaded with the harvested energy can be denoted as:

$$\mathcal{B}_k = \frac{\eta P_k \alpha T}{\sigma P_{ul} + P_0} R_k \quad (11)$$

where σ is the RF efficiency and P_0 is the energy consumption apart from the RF front end. At last the total offloaded number of bits for kth MT can be wiritten as:

$$\mathcal{B}_k^{rc} = \min(\frac{\eta P_k \alpha T}{\sigma P_{ul} + P_0} \omega \log_2(1 + \gamma_k), \ R_k(1 - \alpha)T) \quad (12)$$

III. PROBLEM FORMULATION

According to weber-fechner law, QoS can be expressed as a function of the service processing rate. Combined with the actual application scenarios in this paper, the QoS of WSN can be expressed as the data that can be processed in unit time. Optimizing the amount of data processed per unit time means optimizing the QoS. Therefore, the main objective of offloading is maximize the total number of computed bits within each T. With the offloading scheme defined in (1), the total computed number of bits can be written as:

$$U_T = \sum_{k=1}^{K} s_k \mathcal{B}_k^{rc} + \sum_{k=1}^{K} (1 - s_k) \mathcal{B}_k^{lc}, \ (bits) \quad (13)$$

The problem can be expressed as:

$$\max_{S_K, \mathbf{w}^{dl}, \mathbf{W}, \alpha} U_T \quad (14a)$$

$$s.t. \ s_k \in \{0, \ 1\} \quad (14b)$$

$$\alpha \in (0, \ 1) \quad (14c)$$

$$||\mathbf{w}_m^{dl}|| \le 1, \quad \forall m \quad (14d)$$

$$||\mathbf{w}_{k,m}|| \le 1, \quad \forall k, m \quad (14e)$$

where (14b) follows from (1), (14c) is boudary of the D-TDD factor, (14d) is the power constraints at the BS. (14e) is the uplink beamforming matrix defined in section II-B.

IV. OPTIMAL OFFLOADING WITH PERFECT CSI

Due to the non-convexity and integer programming properties of (14), it's hard to directly solve the problem. In this section, we propose to solve the problem by 3 steps. First, by fixing $\alpha = \hat{\alpha}$ and $S_K = \hat{S_K}$, the problem (14) can be reduced to the following energy beamforming and uplink beamforming problem:

$$Q_1 : \max_{\mathbf{w}_{dl}, \mathbf{W}} U_T \quad (15a)$$

$$s.t. \ ||\mathbf{w}_m^{dl}|| \le 1 \quad \forall m \quad (15b)$$

$$||\mathbf{w}_{k,m}|| \le 1 \quad \forall k, \forall m \quad (15c)$$

With the α and S_K been defined, problem (Q_1) can be solved analytically. Then with $\alpha = \hat{\alpha}$ being fixed, the offloading problem can be reduced as:

$$Q_2 : \max_{S_K} U_T \quad (16a)$$

$$s.t. \ s_k \in \{0, 1\}, \quad \forall k \in \mathcal{K} \quad (16b)$$

Problem (Q_2) can be regard as a cooperative game. With S_K, $\mathbf{w}_{dl}$ and $\mathbf{W}$ been defined, the probem (14) can be reduced to:

$$Q_3 : \max_{\alpha} U_T \quad (17a)$$

$$s.t. \ \alpha \in [0, \ 1] \quad (17b)$$

The optimal α in Q_3 can be found by a one dimension search. With some predifined region, the search efficiency can be improved.

A. OPTIMAL DOWNLINK BEAMFORMING FOR ENERGY HARVESTING

The main purpose of downlink beamforming is to maximize the receiving signal energy for each MT. Due to the independence of downlink energy harvest and uplink offloading, the optimal downlink beamforming can be solved equavilantly to maximize the received power, i.e. :

$$\max_{\mathbf{w}^{dl}} P_{dl} \mathrm{tr}[(\mathbf{H}\mathbf{w}^{dl})(\mathbf{H}\mathbf{w}^{dl})^H] \quad (18a)$$

$$s.t. \ \mathrm{tr}(\mathbf{w}_m^{dl}(\mathbf{w}_m^{dl})^H) \le 1, \quad \forall m \quad (18b)$$

where $\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_m]^1 \in \mathbb{C}^{K \times MN_t}$ is the downlink channel matrix, $\mathbf{w}^{dl} = [\mathbf{w}_1^{dl}, \mathbf{w}_2^{dl}, \ldots, \mathbf{w}_M^{dl}] \in \mathbb{C}^{MN_t}$ is the beamforming matrix.

B. UPLINK MULTIUSER DETECTION AND OFFLOADING CAPACITY

There are three conventional linear detectors minimum square error (MMSE), zero forcing (ZF), maximal ratio combination (MRC), i.e.

$$\mathbf{W} = \begin{cases} \mathbf{H}^H & \text{for MRC} \\ (\mathbf{H}^H \mathbf{H})^{-1} \mathbf{H}^H & \text{for ZF} \\ (\mathbf{H}^H \mathbf{H} + \frac{1}{P_{ul}} \mathbf{I}_K)^{-1} \mathbf{H}^H & \text{for MMSE} \end{cases} \quad (19)$$

Typically MRC performs worse than the other two. With the perfect knowledge of CSI for the BS, the offloading rate of MT k can be determined according to (8)(9).

C. OFFLOADING COALITION FORMATION GAME

With the downlink energy beamforming and uplink multiuser detection been defined, the problem of the offloading decision can be formulated as a dynamic coalition formulation game denoted by $(\mathcal{K}, v)$, where $\mathcal{K}$ is the set of all MTs and v is the value of each coalition. We define v as the system data processing throughput in this paper.

Initially we assume there are $K + 1$ coalitions with each MT being an independent LC coalition and an empty RC coalition.

The ultimate goal of the game is to organize all the terminals into two coalitions through the formation process of the coalitions, namely, the terminal set S representing LC and the terminal set representing RC. According to the following

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[1] Here we use the MATLAB notation, the comma defines a block matrix and $\mathbf{H}_m \in \mathbb{C}^{k \times N_t}$ is the channel fading between the MTs and BS m. So does the following $\mathbf{w}_{k,m}^{dl}$.

rules, for two sets of coalitions $\overline{\mathcal{S}} = \{\overline{S_1}, \cdots, \overline{S_k}\}$ and $\mathcal{S} = \{S_1, \cdots, S_l\}$, if it satisfies:

$$\sum_{i=1}^{k} v(\overline{S_i}) > \sum_{i=1}^{l} v(S_i) \qquad (20)$$

where v been defined as the total bits processed in period T, (20) means the utility of new coalition partition is better than the previous one, the system performance is higher than the previous one, so it will move from an old alliance organization to a new one.

There, for every MT (coalition), there are three options: (i) stay in the current coalition, i.e., LC coalitions; (ii) merge with the RC coalition, separated from the local computing alliance and joined the remote unloading alliance; (iii) split from the RC coalition, there may be too many unloading terminals. The newly added terminals reduce the system utility of the old alliance terminals and make them leave the remote unloading alliance.

We use a merge and split process to formulate the offloading coalition illustrated as follows:

Let $\{s_i\}$ denotes the coalition formulated by a single MT i, S_{lc}, S_{rc} denote the LC coalition and RC coalition respectively, S_{-i} denotes the collection of LC coalitions except $\{s_i\}$, i.e. $S_{lc} = \{s_i\} \cup S_{-i}$. A partition of the players is denoted as (*LC coalitions, RC coalition*), i.e. (S_{lc}, S_{rc}).

Merge: For a given LC coalition $\{s_i\}$, if the value of the partitions satisfies

$$v(S_{-i}, \{s_i\} \cup S_{rc}) > v(\{s_i\} \cup S_{-i}, S_{rc}), \qquad (21)$$

then merge $\{s_i\}$ into S_{rc}.

Split: For a given RC MT $s_i \in S_{rc}$, if the value of the partition satisfies

$$v(S_{lc} \cup \{s_i\}, S_{rc}/\{s_i\}) > v(S_{lc}, S_{rc}), \qquad (22)$$

then s_i splits from S_{rc}.

It is noted that in (21), the increase of value is equivalent to that for MT i, the offloading is beneficial to local computing, which will process more bits subject to the harvested energy in T. While in (22), with some new MT offloading their computation in wireless channels, the multiuser interference may become severe and some MTs in S_{rc} may not be beneficial to offloading any more. The process of merge and split is illustrated in Algorithm 1.

As illustrated in Algorithm 1, there are two loops in the merge and split process. When a merge process happens, a new MT is added to the RC coalition. However it may degrade the utility of existing RC players, and a scan is needed to split these unbeneficial players from the RC coalition. After all, suppose there are K MTs in the system, the complexity of the merge and split algorithm is $1 + 2 + \cdots + K = \mathcal{O}(K^2)$.

D. OPTIMAL D-TDD FACTOR SEARCH

With the $\mathbf{W}_{dl}$, $\mathbf{W}$ and S_K being derived, the optimal D-TDD factor α can be computed with one-dimension search in $(0, 1)$,

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Algorithm 1 Merge and Split Algorithm for Offloading

Data: the channel matrix $\mathbf{H}$, MT set $\mathbf{S}_K = \{s_1, \cdots, s_k\}$, MT energy set $\mathbf{E}_K = \{E_1, \cdots, E_k\}$;

Result: S_{lc}, S_{rc}

begin

  Initilization: $S_{lc} = \mathbf{S}_K$, $S_{rc} = \emptyset$

  for s_k *in* S_{lc} **do**

    For $s_k \in S_{lc}$, compute U_1 according to (13);

    For $s_k \in S_{rc}$, compute U_2 according to (13);

    if $U_2 > U_1$ **then**   /* merge */

      $S_{lc} = S_{lc}/\{s_k\}$;

      $S_{rc} = S_{rc} \cup \{s_k\}$;

      for s_i *in* $S_{rc}/\{s_k\}$ **do**

        For $s_i \in S_{rc}$, compute U_3 according to (13);

        For $s_i \in S_{lc}$, compute U_4 according to (13);

        if $U_4 > U_3$ **then**   /* split */

          $S_{lc} = S_{lc} \cup \{s_i\}$;

          $S_{rc} = S_{rc}/\{s_i\}$;

  return S_{lc}, S_{rc};

---

and the search region can be futher optimized according to offloading proccess. The α is a fundermental tradeoff between harvest energy and offloading data. If α is too small, the MTs may not harvest enough energy for local computing or offloading for the rest $(1 - \alpha)T$ time; and with the boundary of T, if α is too large, the MTs will harvest more energy, but the time left and the channel capacity will limit the energy consumption.

The lower boundary of α should satisfy for the MT harvested minimum energy $\alpha T P_k^*$, if it choose offloading, then at the end of T, the harvested energy just runs out, i.e. :

$$(\sigma P_{ul} + P_0)(1 - \alpha)T = \alpha T \eta P_k^* \qquad (23)$$

Then the optimal D-TDD factor located in:

$$\alpha \in \left[\frac{\sigma P_{ul} + P_0}{1 + \eta P_k^*}, \; 1\right] \qquad (24)$$

The analysis in this section considered perfect CSI to be available at the sensor nodes. However, in practical scenarios, the CSI is obtained via channel estimation, which leads to errors in the estimated CSI. The next section analyze offloading scheme considering imperfect CSI.

V. OFFLOADING SCHEME WITH IMPERFECT CSI

We now consider the more realistic scenario with imperfect CSI estimation. In practice, obtaining perfect CSI is of great challenge, the common way is that the channel $\mathbf{h}_{k,i}$ is estimated by using linear minimum mean-square error (LMMSE) [20]. The channel estimated channel can be expressed as $\mathbf{h}_{k,i} = \hat{\mathbf{h}}_{k,i} + e$, where the channel estimation error is distributed as $e \sim \mathcal{CN}\left(0, \sigma_e^2\right)$, the estimate channel

$\hat{\mathbf{h}}_{k,i}$ is independent of e. Note that σ_e^2 is a function of average transmit SNR, which is

Therefore, the receive signal for downlink EH can be rewritten as:

$$Y = \sqrt{P_{dl}} \left(\hat{\mathbf{H}} + \mathbf{e} \right) \mathbf{w}^{dl} x + \mathbf{n}_k \tag{25}$$

where $\hat{\mathbf{H}} \in \mathbb{C}^{k \times MN_t}$ is the estimated channel matrix, $\mathbf{e}$ is the channel estimation error.

For imperfect CSI scenario, the received signal y_k at the kth MT can be rewritten as:

$$y_k = \sqrt{P_{dl}} \sum_{i=1}^{MN_t} \left(\hat{h}_{k,m} + e \right) w_i^{dl} x + n_k^{dl} \tag{26}$$

where $\hat{\mathbf{h}}_{k,i}$ is the estimated channel response from the ith BS to kth MT. With $\mathbb{E}\{x^\dagger x\} = 1$, the receive power of MT k can be written as:

$$P_k = P_{dl} \sum_{m=1}^{M} \left\| \left(\hat{h}_{k,m} + e \right) w_m^{dl} \right\|^2 \tag{27}$$

where $\mathbf{h}_{k,m} \in \mathbb{C}^{1 \times N_t}$, is the estimated channel matrix from BS m to MT k respectively.

For uplink offloading, the receive signal $\mathbf{r}_m \in \mathbb{C}^{N_t}$ at the mth BS is expressed as:

$$r_m = \sqrt{P_{ul}} \sum_{k=1}^{K} \left(h_{k,m}^H + e \right) s_k + n_m^{ul} \tag{28}$$

we consider a representative type of channel estimation error model, i.e., the variance of the error, σ_e^2, is fixed and independent of the average transmit SNR. Therefore, under the condition of imperfect CSI scenario, we employ a similar offloading scheme for the perfect CSI scenario.

VI. NUMERICAL ANALYSIS

In this section, we analyze the performance of the centralized computing offloading scheme with energy harvest by numerical studies, including receiving power analysis of terminals in the coverage area, offloading model, determination of optimal dynamic time division factor, and comparison of offloading algorithms. We first consider the scenario where the RAN has a coverage of 100×100 meters. Initially there are 5 BSs and 60 MTs located in the area, the communication of BSs with the help of the traditional way and work with distributed MIMO [21], [22]. As illustrated in Fig. 4, the BSs are uniformly distributed along the two axises and MTs are randomly distributed.

We consider a flat-fading channel model illustrated as:

$$h_{m,k,i} = ||h_{m,k,i}|| L_0 (\max(||\mathbf{x}||_{k,m}, d))^{-a} \tag{29}$$

where $h_{m,k,i}$ is the channel fading from i-th antenna of BS m to MT K, which follows from Rayleigh distribution, L_0 is the path loss function for a reference distance $r_0 = 1$, a is the path loss factor, x is the distance between MT K and BS m, d is used to avoid singularity caused by proximity between BSs and MTs, we set $d = 3$ in this paper.
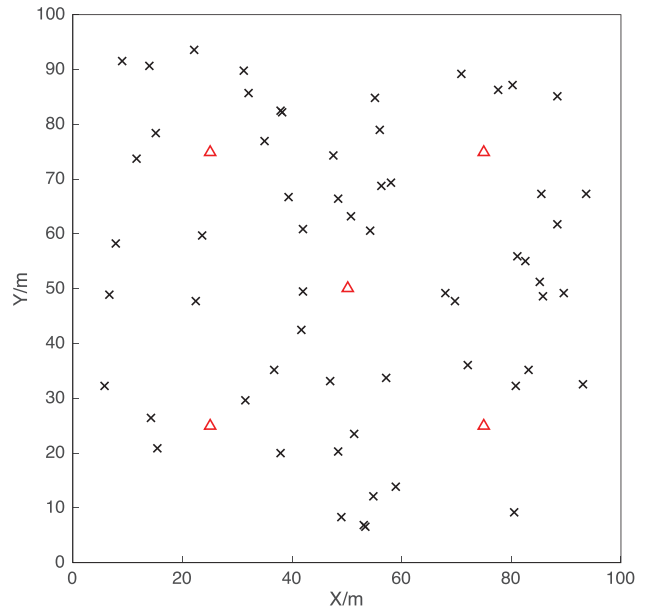

FIGURE 4. Scenario of the system (Red triangles denote the 5 BSs, black crosses denote the 60 MTs).
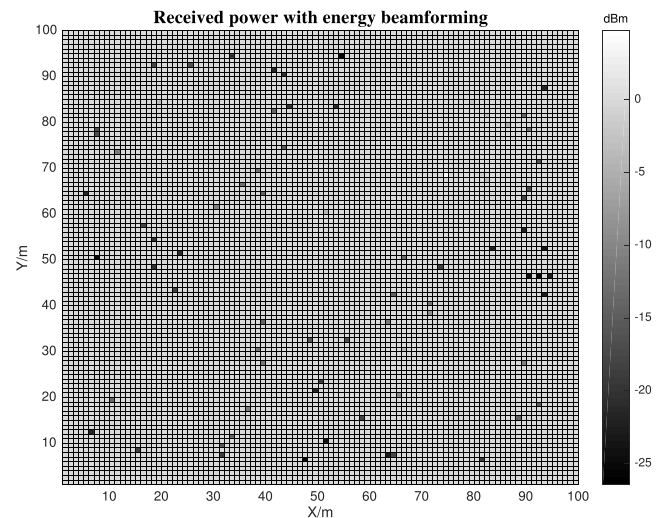

FIGURE 5. The received power with energy beamforming.

In the simulation, it is assumed that the transmitting power of the BS is adjustable. Then we will analyze the influence on the terminal energy collection under the premise of different transmitting power of the BS. When the terminal carries out uplink information transmission, the transmitting power is 50mW and the system bandwidth is 1 MHz.

When 80 terminal nodes are included in the coverage area, the transmitting power is 20W and the path loss factor is 2.5. Fig. 5 shows the received power of corresponding node when downlink energy beamforming is adopted. In Fig. 5, the location of the BS is not marked. The grayscale bar on the right, represents the power value corresponding to the color, and the unit is dBm. The lighter the color, and the higher the corresponding power value. The darker the color, the smaller the power received. Meanwhile, for the position coordinates in Fig. 5, in order to facilitate the display in the grid of lxl m^2,
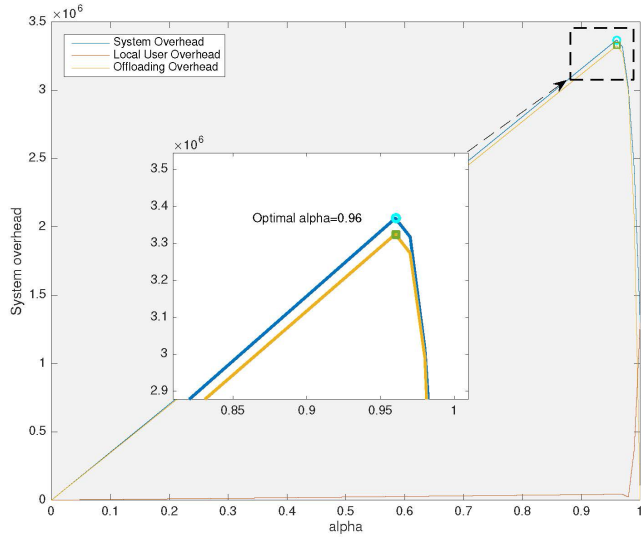
FIGURE 6. The offloading users versus α.

FIGURE 7. Through versus total user number with $a = 2.5$ under the condition of perfect CSI.

FIGURE 8. Through versus total user number with $a = 3.5$ under the condition of perfect CSI.

we round the position coordinates in Fig. 5. It can be seen from Fig. 5 that the receiving power of the node located near the Bs is significantly higher than that of the node at the edge of the BS, which indicates that when energy beamforming is adopted, the power of the node in the coverage area can be effectively improved. The node that is far from the BS and whose channel is in deep fading has limited improvement in energy transmission efficiency. The difference in receiving power leads to a large difference in the energy collected by nodes in the region with in the same amount of time. In order to complete the computation tasks of each node under the premise of unbalanced energy and great difference, a set of task splitting algorithm needs to be designed effectively.

Fig. 6 shows the system overhead versus α. We set that the transmit power at BS is $20W$, the path loss factor is 2.5, the coverage area includes 80 nodes. Where the horizontal coordinate represents the charging time for downlink; the vertical coordinate represents the throughput; blue, red and orange among the three lines represent the throughput of the system, the sum of the throughput of all RC users and the sum of the throughput of all LC users. When α is small, the system throughput is limited due to insufficient available energy. As the charging time increases, the total available energy of the system increases, the total throughput of the system, the throughput of RC users and the throughput of LC increase linearly. When α closes to 1, as shown in Fig. 6 into the most, because for offloading users, its due to the limitation of period T, with a maximum throughput, more than the maximum value corresponding to the α, because to uninstall user information transmission time is not enough, lead to collect energy cannot all used to transmit data in the limited time, makes the throughput degradation. At the same time, as the system aims to maximize the total throughput, after exceeding the optimal α, some RC users select LC, which rapidly increases the throughput of LC users, as shown in the red line in the Fig. 6. In the most extreme case, the whole cycle is used for power transmission, and no user chooses
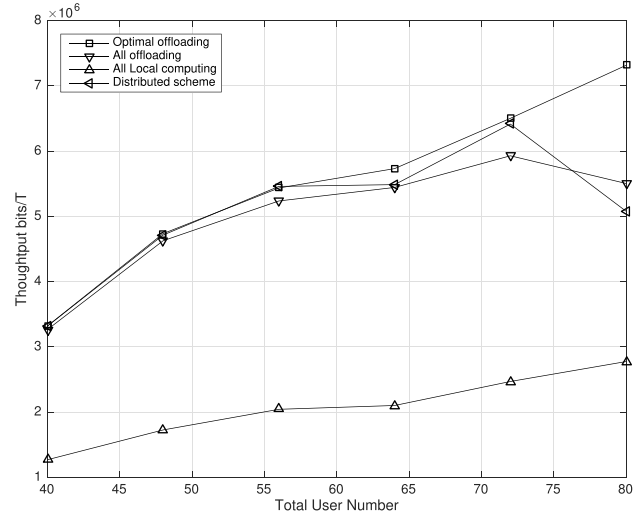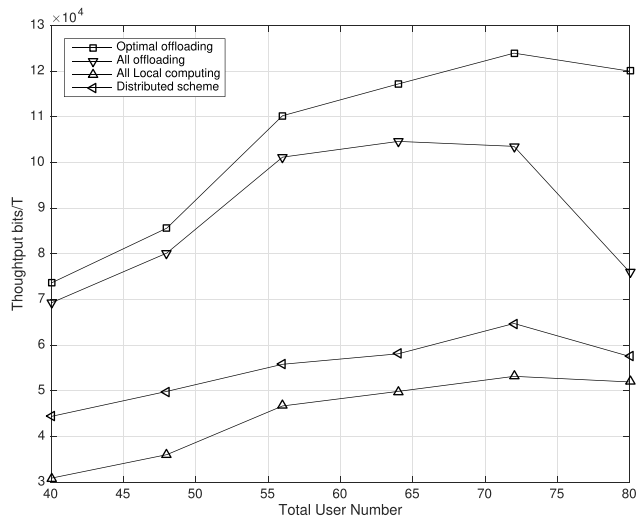
remote unloading, corresponding to $\alpha = 1$. When $\alpha = 1$, the system throughput equals the LC throughput, while the RC throughput decreases to zero. At the same time, it can be seen from Fig. 6 that, when the energy is sufficient, the data processing capacity of RC is far greater than the LC, which is the main contribution to the overall throughput of the system. While LC is an effective supplement to RC. When the remaining available time of RC is insufficient, the throughput provided by background computing can be rapidly increased to maintain the total throughput of the system.

Fig. 7 and Fig. 8 show the throughput versus total user number for $a = 2.5$ and $a = 3.5$, respectively. We set the transmit power at BS is $20W$. From Fig. 7 and Fig. 8, we can observe that the effect of different algorithms on the system throughput. The algorithms used for comparison include: (i) Users process their own tasks locally, that is, the terminal choose to LC using the energy collected form BS; (ii) Users offload their own task to cloud, terminals do

FIGURE 9. Through versus total user number with $a = 2.5$ under the condition of imperfect CSI.

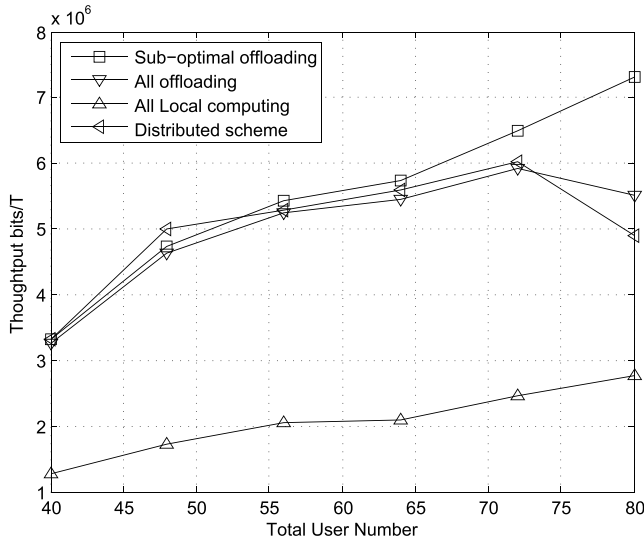**FIGURE 10.** Through versus total user number with $a = 3.5$ under the condition of imperfect CSI.

FIGURE 11. The offloading users versus total user number with different a.

not consider the wireless channel state information, it can offload all computing tasks to the cloud for processing; (iii) distributed computation offloading algorithm, the distributed computation offloading decision was proposed in [17], when RC is preferable to LC, RC is adopted, the system throughput performance is not considered. The optimal offloading is proposed in this paper.

From Fig. 8, we can observe that the proposed algorithm in this paper is obviously superior to the other three algorithms. When the optimal offloading algorithm is adopted, system throughput increases as the number of users increases. However, if each user chooses RC, system throughput will decreases. This is because that when the number of users exceeds a threshold, wireless channel interference intensifies, results in that uplink offloading capacity decreases. For distributed computation offloading algorithm, the total throughput is not stable. This is because that each node does not consider system throughput and uplink channel interference when deciding whether to offloading or not. As for the local computing strategy selected by all nodes, the charging process between each node is independent of the other, so the overall utility increases gradually with the increase of number of users in the coverage area. However, compared with offloading, the energy efficiency of local computing is low, making its performance worst.

When the channel state is worst, as shown in Fig. 8, its state is similar to Fig. 7, the difference is, compared to all the nodes choose RC, the system performance is low when all the nodes choose the distributed decision-making, this is due to the harvesting energy at nodes is limited, the performance of LC compared with RC is further reduced.

For the case of imperfect CSI, Fig. 9 shows the throughput versus total user number with $a = 2.5$. We set the variance of the channel estimation error is $\sigma = 0.5$. From Fig. 7 and Fig. 9, we can observe that the effect of channel estimation error on the system throughput. Similarly, the algorithms used
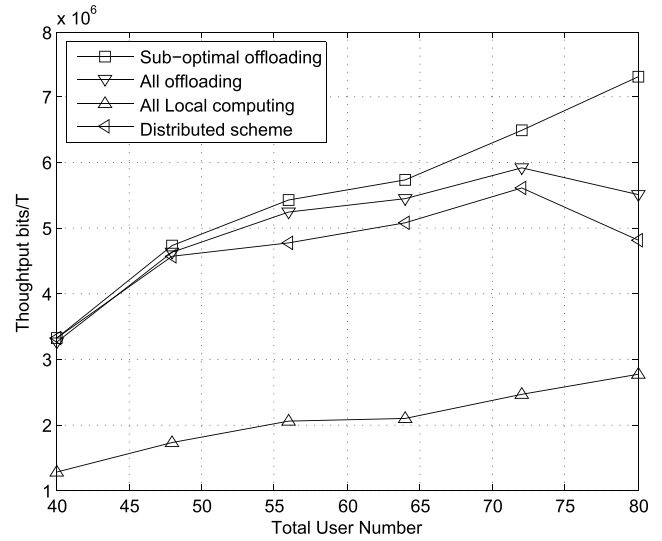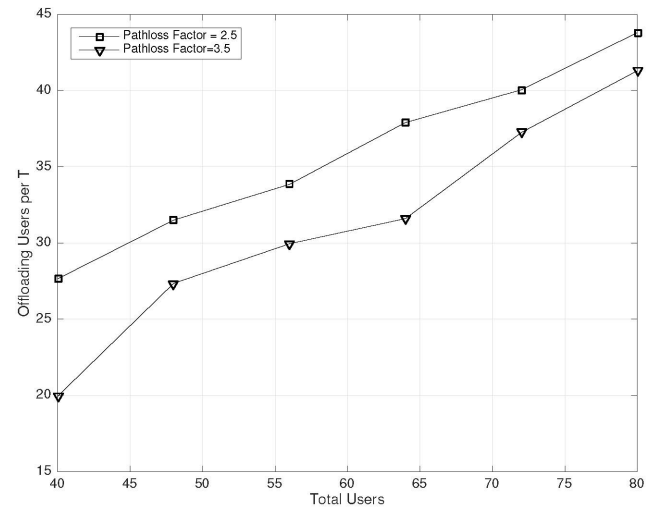
for comparison for the case of imperfect CSI align with the above settings. We can observe that the channel estimation error have small impact on the system throughput for the case of sub-optimal offloading, all offloading and all local computing, the channel estimation error have a larger effect on the system throughput for the distributed computation offloading algorithm. It can be also seen that the system throughput for the sub-optimal offloading algorithm increases with the increase of the number of terminal users.

Fig. 10 shows the throughput versus total user number for $a = 3.5$ under the condition of imperfect CSI. The variance of the channel estimation error is set as $\sigma = 0.5$. From Fig. 8 and Fig. 10, we can observe that the channel estimation error have a smaller impact on the system throughput when $a = 3.5$. In addition, we can observe from the comparision between Fig. 9 and Fig. 10, the system throughput of the case for all offloading algorithm and all local computing algorithm have a serious effect when the value of a is from 2.5 to 3.5, for

the cases of sub-optimal offloading and distributed scheme, the system throughput have a small impact when *a* increase.

Fig. 11 shows the offloading users versus the number of the all users with different α. When the optimal offloading strategy is adopted, the number of nodes selected for RC under the condition of different path loss factors is provided. As can be seen from the Fig. 11, with the increase of the total users in the coverage area, the number of offloading nodes increases under the conditions of two different path loss. However, it can be also seen that the number of offloading nodes under the condition of worst channel is always less than that under the condition of better channel conditions, which also explains the differences in the performance of the four comparison algorithms mentioned above.

VII. CONCLUSION

Aiming at the scenario of downlink wireless power transmission and uplike task loading, we established a task processing strategy including uplink and downlink power-information dynamic time division, unlike remote unloading and local computation, and optimized the data processing capacity of the system in unit cycle under the scenario of downlink wireless power transmission. The strategy uses centralized control to calculate the downlink wireless power transmission energy beam matrix, node local calculation and uplinking offloading strategy. Due to the original problem is a decision problem of integer programming, it is difficult to directly to solve, we break it down into descending, the optimal power transmission, uplink uninstall decision-making, and dynamic factor in optimizing three sub-problems, by solving the three sub problems, to maximize the unit cycle system's ability to process the data. Simulation analysis shows that the downgoing energy beamforming can effectively improve the average received power of about 8-20 dBm in the region, and the up-down dynamic time division can effectively utilize the received energy in the time slot to maximize the throughput. The comparison of algorithm performance shows that, under different channel conditions, the dynamic time division factor centralized unloading decision-making algorithm adopted in this paper has better performance than existing distributed unloading decision-making, single local calculation and remote unloading algorithm. In particular, the optimal D-TDD factor was investigated.

REFERENCES

[1] S. Ulukus, A. Yener, E. Erkip, O. Simeone, M. Zorzi, P. Grover, and K. Huang, "Energy harvesting wireless communications: A review of recent advances," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 360–381, Mar. 2015.

[2] S. Bi, Y. Zeng, and R. Zhang, "Wireless powered communication networks: An overview," *IEEE Wireless Commun.*, vol. 23, no. 2, pp. 10–18, Apr. 2016.

[3] X. Chen, C. Yuen, and Z. Zhang, "Wireless energy and information transfer tradeoff for limited-feedback multiantenna systems with energy beamforming," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 407–412, Jan. 2014.

[4] D. Arnitz and M. S. Reynolds, "MIMO wireless power transfer for mobile devices," *IEEE Pervas. Computing*, vol. 15, no. 4, pp. 36–44, Oct. 2016.

[5] O. Galinina, H. Tabassum, K. Mikhaylov, S. Andreev, E. Hossain, and Y. Koucheryavy, "On feasibility of 5G-grade dedicated RF charging technology for wireless-powered wearables," *IEEE Wireless Commun.*, vol. 23, no. 2, pp. 28–37, Apr. 2016.

[6] L. Jiang, H. Tian, Z. Xing, K. Wang, K. Zhang, S. Maharjan, S. Gjessing, and Y. Zhang, "Social-aware energy harvesting device-to-device communications in 5G networks," *IEEE Wireless Commun.*, vol. 23, no. 4, pp. 20–27, Aug. 2016.

[7] Y. Liu, Z. Ding, M. Elkashlan, and H. V. Poor, "Cooperative non-orthogonal multiple access with simultaneous wireless information and power transfer," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 938–953, Apr. 2016.

[8] A. P. Sample, D. A. Meyer, and J. R. Smith, "Analysis, experimental results, and range adaptation of magnetically coupled resonators for wireless power transfer," *IEEE Trans. Ind. Electron.*, vol. 58, no. 2, pp. 544–554, Feb. 2011.

[9] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, May 2013.

[10] Z. Wang, L. Duan, and R. Zhang, "Adaptively directional wireless power transfer for large-scale sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1785–1800, May 2016.

[11] A.-N. Nguyen, V. N. Vo, C. So-In, D.-B. Ha, S. Sanguanpong, and Z. A. Baig, "On secure wireless sensor networks with cooperative energy harvesting relaying," *IEEE Access*, vol. 7, pp. 139212–139225, 2019.

[12] A. A. Nasir, X. Zhou, S. Durrani, and R. A. Kennedy, "Relaying protocols for wireless energy harvesting and information processing," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 3622–3636, Jul. 2013.

[13] O. S. Badarneh, "Energy harvesting in α - μ environment under different relaying protocols," *IEEE Wireless Commun. Lett.*, vol. 6, no. 6, pp. 814–817, Dec. 2017.

[14] A. Alsharoa, H. Ghazzai, A. E. Kamal, and A. Kadri, "Optimization of a power splitting protocol for two-way multiple energy harvesting relay system," *IEEE Trans. Green Commun. Netw.*, vol. 1, no. 4, pp. 444–457, Dec. 2017.

[15] 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, Sep. 2017.

[16] L. Ji and S. Guo, "Energy-efficient cooperative resource allocation in wireless powered mobile edge computing," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4744–4754, Jun. 2019.

[17] X. Chen, L. Jiao, W. Li, and X. Fu, "Efficient multi-user computation offloading for mobile-edge cloud computing," *IEEE/ACM Trans. Netw.*, vol. 24, no. 5, pp. 2795–2808, Oct. 2016.

[18] 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. 1757–1771, May 2016.

[19] Y. Teng, K. Cheng, Y. Zhang, and X. Wang, "Mixed-timescale joint computational offloading and wireless resource allocation strategy in energy harvesting multi-MEC server systems," *IEEE Access*, vol. 7, pp. 74640–74652, 2019.

[20] P. SinghParihar, R. Saraswat, and S. Maheshwari, "Energy and spectral efficiency of very large multiuser MIMO systems," *Int. J. Comput. Appl.*, vol. 111, no. 5, pp. 4–7, Feb. 2015.

[21] S. Biswas, K. Singh, O. Taghizadeh, and T. Ratnarajah, "Coexistence of MIMO radar and FD MIMO cellular systems with QoS considerations," *IEEE Trans. Wireless Commun.*, vol. 17, no. 11, pp. 7281–7294, Nov. 2018.

[22] S. Zhang, S. Jin, C. Wen, and Z. He, "Improving expectation propagation with lattice reduction for massive mimo detection," *China Commun.*, vol. 15, no. 12, pp. 49–54, Dec. 2018.

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