BINARY VS PARTIAL OFFLOADING IN WIRELESS POWERED MOBILE EDGE COMPUTING SYSTEMS WITH FAIRNESS GUARANTEES

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Abstract – *Mobile Edge Computing (MEC) has recently emerged as a new communications/computing concept that amends the limited computing of IoT devices by completely or partially offloading the computational tasks to the MEC servers at the network edge (typically co-located with the base stations). Because IoT devices are typically power limited, the potential of the MEC is further enhanced by its integration with wireless power transfer technology, especially for those IoT devices with a high duty cycle that requires frequent battery replacement. This paper develops fairness-aware resource allocation schemes for a WPT-assisted MEC system whose Energy Harvesting Users (EHUs) employ either binary or partial offloading. Specifically, the proposed schemes optimize the computational speeds and the energy harvesting and offloading durations of the EHUs with the aim to maximize the minimum of their computed bits (sum of locally and remotely processed bits of each EHU), subject to the RF energy harvested from the base station. When EHUs are concentrated closer to the base station, remote processing is preferred over local processing, as local processing consumes more energy than the Radio Frequency (RF) power for offloading data to the MEC server, but this effect diminishes for lower values of the computational effort needed for the processing of a single bit. Interestingly, in terms of the sum computation rate, the partial offloading scheme only slightly outperforms the binary offloading scheme, but only when the EHUs are moderately away from the base station.*

Keywords – Internet of Things (IoT), mobile edge computing (MEC), wireless powered communication network (WPCN)

1. INTRODUCTION

MEC has appeared as a promising technological concept that enables large scale deployment of IoT devices (e.g. sensors) with a small power supply and limited processing capabilities. It is achieved by the introduction of MEC servers close to the network edge and used for the processing of data offloaded from the wireless devices in their vicinity. MEC offers storage and processing capabilities at the edge of the mobile network, i.e. Base Station (BS), but within the Radio Access Network (RAN) [2]. Namely, wireless devices can offload their computational tasks (data) to the BS that has integrated MEC server, and then the MEC server facilitates the real-time implementation of computation-intensive tasks. Offloading can be implemented in two ways, partial offloading and binary offloading. In the partial offloading, data is partitioned in two parts, one part is computed locally at wireless devices and the other part is offloaded to the MEC server and computed there. In the binary offloading case, data is not partitioned, and the data is either locally computed at wireless devices, or offloaded to the MEC server, as a whole. Since the MEC servers are located close to the end users, the latency is significantly reduced, while the bandwidth is increased, which makes it applicable in latency-critical applications and sets it apart as one of the crucial elements of 5G/6G [4]–[7]. As a result of all that has been said, MEC is really prone to combining and integrating with other technologies, such as intelligent reflective surfaces [8] and Wireless Powered Transfer (WPT) [11]-[14]

To enhance energy efficiency even more, Radio Frequency (RF)-based Wireless Powered Transfer (WPT) is found as a suitable and promising technology that complements MEC, providing a feasible solution by deploying a dedicated energy transmitter to wirelessly broadcast energy [10]. Thus, wireless devices are provided with cost-effective and sustainable energy supply that facilitates perpetual operation. WPT-assisted MEC systems are studied in several existing works [11]-[14]. Authors in [11] first considered a wireless powered MEC system consisting of single user and co-located MEC BS with the objective of maximizing the probability of successfully computing given tasks at the user. The work presented in studies multi-user wireless powered MEC systems under a time division multiple access with the objective to minimize the overall energy consumption in the system. Furthermore, authors in [13] propose maximizing the sum computation rate in a multi-user WPT assisted MEC system employing binary offloading, while authors in [14] propose maximizing the computational efficiency for wireless powered MEC systems under both binary and partial offloading, considering a non-linear energy harvesting model.

Previous work has focused on the maximization of the system's sum rate while disregarding fair resource allocation. In [15], we focus on fairness-aware resource allocation of a MEC system using Time Division Multiple Access (TDMA), binary offloading and wireless powered

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Energy Harvesting Users (EHUs). This paper extends [15] by developing a novel resource allocation scheme based on partial offloading. Specifically, we maximize the mini- mum computation rate of binary offloading and partial of- floading schemes, and then compare their performances expressed in terms of the system's sum computation rate and fairness index. In the special case of equal EHUs' distances from the base station, we derive analytical expressions for calculating the optimal values of the resource allocation parameters, the durations of EH and offload- ing phases, and the EHUs' processing speeds and output powers. To the best of the authors' knowledge, this is the first work that proposes the design of fairness-aware re- source allocation schemes of wireless powered MEC sys- tems with binary and partial offloading.

The rest of the paper is organized as follows. In Section 2, we introduce the system model of the wireless powered MEC system. Sections 3 and 4 present the optimization problems for devising fairness-aware resource allocation schemes for binary and partial offloading, respectively. Section 5 presents the numerical analysis for the performance comparison between the binary and the partial of- floading schemes. Finally, we conclude the paper in Section 6.

2. SYSTEM MODEL

We consider wireless powered MEC systems consisting of a base station and K energy harvesting users (Fig. 1). All EHUs are equipped with a single antenna. The base station integrates the following functionalities:

1. Communication transmitter/receiver (i.e. receives the uplink information transmissions from the EHUs and transmits downlink information to the EHUs);
2. RF power beacon (i.e. broadcasts RF energy via wireless link to the EHUs);
3. MEC server (i.e. processes/compute offloaded data by the EHUs).

The BS is connected to a stable power supply, and at the same time broadcasts RF energy to all EHUs. Every end device has an energy harvesting circuit and rechargeable battery used to collect the harvested energy to power its functions. Each device, including the BS and EHUs go through different communication blocks. In order to avoid interference, the phases dedicated to WPT and wireless communication are separated in time, i.e. they use TDMA frames with duration T. Within one TDMA frame, the channel between the BS and the ith EHU is denoted by $h_i = \Omega_i$, that is assumed to be reciprocal.

2.1 Communication model

Each TDMA frame of duration T consists of a energy harvesting phase (WPT phase) of duration τ_0, followed by successive phases for information transmission of duration $\tau_1, \tau_2, \cdots, \tau_K$, respectively. During the WPT phase, the base station broadcasts RF signals with power P_0 dedicated to power all EHUs. During the ith information transmission phase, ith EHU offloads its information to the BS for further processing in the MEC server. Therefore, the duration of all information transmission phases should satisfy following equation:

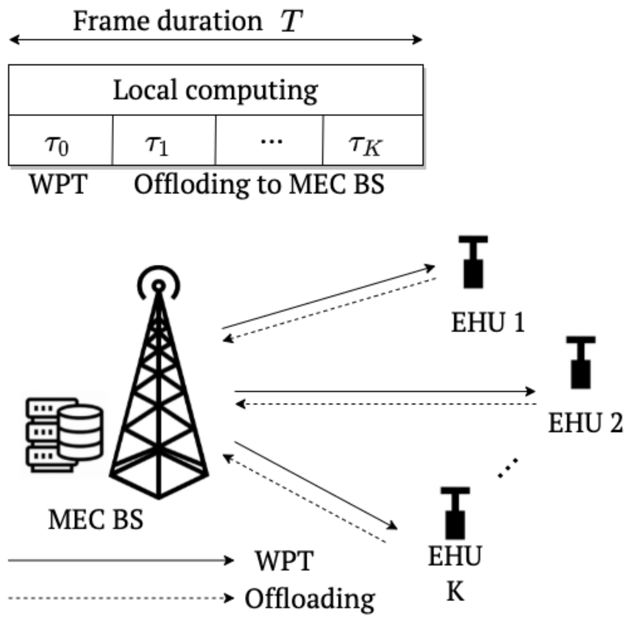

Fig. 1 – Multi-user MEC assisted WPT network.

$$\tau_0 + \tau_1 + \tau_2 + \cdots \tau_K = T \tag{1}$$

If some of the EHUs (e.g. jth EHU) perform only local computing, it does not offload any data and correspondingly the duration of information transmission phase is zero (e.g. $\tau_j = 0$), while the local computing is performed over the entire duration of the TDMA frame.

Within each TDMA frame, we assume that each EHU should perform a specific computation task based on its local data. The computational task of an EHU station can be performed on a local processor, which usually has low computational capacity due to limited power. Alternatively, the EHU can offload the data to the MEC server/BS that has much more processing power,so the calculations can be performed efficiently and the result can be sent back to the EHU. We consider two mechanisms for MEC calculations:

1. Partial offloading
2. Binary offloading

The partial offloading mechanism means that one part of the useful data is transferred over the wireless channel from the EHU to the MEC server, and the other part is kept for computing by the EHU itself.

When the binary offloading mechanism is used, the wireless station either computes all the data independently using its own processing resources (the so-called local computing mode), or transmits the data to the MEC server for further processing.

2.2 Energy-harvesting model

In WPT phase, the BS transmits RF energy, during which each EHU harvests energy the amount of which is decreasing with increasing distance from the BS. Thus, energy harvested by the jth EHU during its energy-harvesting phase is:

$$E_j^{EH} = \eta\tau_0 P_0 \Omega_j \tag{2}$$

where P_0 is BS transmit power, and $\eta \in (0, 1)$ is energy-conversion efficiency coefficient of the EH circuit. This equation is applicable in case when the circuit that performs energy harvesting at the EHU is modeled according to the linear model, which assumes that the energy harvested at the EHU is directly proportional to the RF energy before the antenna of the EHU.

If we assume that the wireless channel h_j in *(2)* is static, then its value depends only on path loss and can be determined depending on the distance. We assume a path loss exponent of 3 and attenuation of 30dB at referent distance of 1 meter, then channel gain h_j is calculated according to:

$$h_j = \Omega_j = \frac{10^{-3}}{r_j^3}. \tag{3}$$

2.3 Data offloading model

In this paper we assume that all EHUs employ a binary or partial offloading method. In the former method, the computational data is not partitioned and should be offloaded to the MEC BS (mode-1) or computed locally at the EHUs' side (mode-0), as whole, while the in latter method data is partitioned into two parts, one is computed locally at the EHUs, while the remaining part is offloaded for edge computing to the MEC BS via wireless links. In the second part of the TDMA frame with duration $T - \tau_0$, EHUs transfer their data to the BS. To avoid interference, it is assumed that EHUs send information successively, where the information transmission time of the ith EHU is τ_i, so that $0 \leq \tau_i \leq T$. The operation of the EHU stations depending on the operation mode (either local computing or offloading) is explained below.

2.3.1 Local computing mode (mode-0)

When operating in local computing mode, the computation is performed for the entire frame duration T. Let the parameter f_i denote the computing speed of the ith EHU, expressed in number of CPU cycles per unit time. Let the parameter L denote the computational load required by the CPU to compute one bit of raw data, which is expressed in the number of CPU cycles required to process one bit of data by the corresponding EHU. Let the parameter α indicate the energy efficiency coefficient of the processor of the EHU, and it depends on its processor's architecture. In that case, the number of locally computed bits by the ith EHU station is calculated according to the expression $(1 \leq i \leq K)$:

$$d_i^{mode-0} = \frac{Tf_i}{L}. \tag{4}$$

Thereby, the energy consumption for local computing at the ith EHU is calculated as:

$$E_i^{mode-0} = \alpha T f_i^3. \tag{5}$$

2.3.2 Offloading mode (mode-1)

When operating in mode-1, an EHU can transfer its computational task to the MEC server at the BS. Let the number of bits that the ith EHU can offload be denoted by d_i^k, which represents the amount of "raw" data transmitted from the ith EHU to the MEC server. Let P_i denote the output power of the ith EHU. The number of bits that can be offloaded corresponds to the capacity of the wireless link between the respective EHU and the BS,

$$d_i^{mode-1} = B\tau_i \log_2\left(1 + \frac{P_i\Omega_i}{N_0}\right), \tag{6}$$

where B represents the bandwidth of the communication channel between the EHU and the BS. Thereby, the energy consumed for offloading data from the EHU to the BS is calculated according to the expression:

$$E_i^{mode-1} = \tau_i P_i. \tag{7}$$

Since EHUs employ harvest-then-transmit scheme [16], an EHU during a single TDMA frame spends energy stored during the preceding WPT phase of that frame, regardless of whether it uses a partial or binary offloading. Therefore, that energy can be consumed: (1) either for offloading or for local calculation (binary offloading), or (2) part for offloading and the remaining part for local computing (partial offloading). Therefore, according to the law on energy conservation, the ith EHU must satisfy the following constraint $(1 \leq i \leq K)$:

$$\alpha T f_i^3 + \tau_i P_i \leq \eta\tau_0 P_0 \Omega_i \tag{8}$$

3. RESOURCE ALLOCATION WITH PARTIAL OFFLOADING

The resource allocation schemes for MEC systems are usually designed to maximize the system's sum computation rate. The criterion for maximizing the sum computation rate leads to unfair resource sharing, as EHU stations closer to the base station receive a disproportionately high share of the system's resources. To deal with this problem, we propose resource sharing according to the max-min criterion [17]. Therefore, for the considered system model, we propose the following optimization problem that maximizes the number of computed

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bits at the EHU that has minimal number of computed bits:

$$\underset{\tau_0,\tau_i,P_i,f_i}{\text{Maximize}} \min_{1\le i\le K}\left\{\frac{Tf_i}{L}+B\tau_i\log_2\left(1+\frac{P_i\Omega_i}{N_0}\right)\right\}$$

subject to:

$$\begin{aligned}&C1:\textstyle\sum_{i=1}^{K}\tau_i+\tau_0=T\\&C2:\alpha T f_i^3+\tau_i P_i\le\eta\tau_0P_0\Omega_i,\forall i\\&C3:\tau_i\ge 0,\tau_0\ge 0,P_i\ge 0,f_i\ge 0,\forall i\end{aligned}\tag{9}$$

where $C1$ refers to the total duration of all phases within a TDMA frame, $C2$ refers to the law of conservation of energy, whereas constraint $C3$ naturally requires all optimization variables to have a non-negative value. The optimization problem is convex and can be solved numerically using various software tools, for example, CVX.

3.1 Special case solution: Equal EHUs' distances from BS

The optimization problem *(9)* can be solved even analytically in an idealized case when all EHU stations are at the same distance from the base station, where $\Omega_1=\Omega_2=\cdots=\Omega_K$, $\tau_1=\tau_2=\cdots=\tau_K$, $f_1=f_2=\cdots=f_K$ and $P_1=P_2=\cdots=P_K$ whose solutions are given by the following expressions: The optimal EHU transmit power P_1^* satisfies:

$$P_1^*=\frac{1}{\Omega}\left[\frac{K\eta P_0\Omega^2-N_0}{W\left(\frac{K\eta P_0\Omega^2-N_0}{N_0e}\right)}-N_0\right]\tag{10}$$

where $W(\cdot)$ is the Lambert W function [18].
The optimal local computation speed f_1^* is:

$$f_1^*=\left(\frac{\ln 2\left(N_0+P_1^*\Omega\right)}{3B\Omega\alpha L}\right)^{1/2}.\tag{11}$$

The optimal offloading time denoted by τ_1^* is:

$$\tau_1^*=T\frac{\eta P_0\Omega-\alpha(f_1^*)^3}{K\eta P_0\Omega+P_1^*}.\tag{12}$$

The optimal energy harvesting time τ_0^* is:

$$\tau_0^*=T-K\tau_1^*\tag{13}$$

The details of how the equations *(10)*-*(13)* are obtained are given in Appendix A.

4. RESOURCE ALLOCATION WITH BINARY OFFLOADING

In the case of binary offloading, the optimization problem *(9)* is adjusted to design an appropriate resource allocation scheme for mobile edge computing and wirelessly supplying the EHUs. For this purpose, we will use the following indicator variable:

$$I_i=\begin{cases}0, & i\text{th EHU in mode-0}\\1, & i\text{th EHU in mode-1}\end{cases}.\tag{14}$$

We now state the following max-min optimization problem:

$$\underset{\tau_0,\tau_i,P_i,f_i,I_i}{\text{Maximize}} \min_{1\le i\le K}\left\{(1-I_i)\tfrac{Tf_i}{L}+I_iB\tau_i\log_2\left(1+\tfrac{P_o\Omega_i}{N_0}\right)\right\}$$

subject to:

$$\begin{aligned}&C1:\textstyle\sum_{i=1}^{K}I_i\tau_i+\tau_0=T\\&C2:(1-I_i)\,\alpha T f_i^3+I_i\tau_iP_j\le\eta\tau_0P_0\Omega_i,\forall i\\&C3:I_i\in\{0,1\}\\&C4:\tau_0\ge 0,\tau_i\ge 0,P_i\ge 0,f_i\ge 0,\forall i\end{aligned}\tag{15}$$

The optimization problem *(15)* is not convex, because objective function and constraints contain products of two optimization variables. However, the optimization problem *(15)* can be solved for any possible combination of indicator variables $\{I_i\}_{i=1}^{K}$, where there are a total of 2^K possible combinations (starting from the case where all K EHUs stations are in mode 0, until the case when all K EHU stations are in mode 1). For each given set of indicator variables, $(I_1,I_2,\cdots,I_K)$, *(15)* is a convex optimization problem and can be solved numerically. Then, from all 2^K possible solutions, the optimal solution $(\tau_0^*,\tau_i^*,P_i^*,f_i^*)$, is the one that maximizes the objective function.

4.1 Special case solution: Equal EHUs' distances from BS

If we assume a symmetric-user case, where all EHUs are placed on a circle with radius r, then due to the symmetry all EHUs will either offload or compute locally ($I_1=I_2=\cdots=I_K$), compute the same number of bits, over the same offloading time ($\tau_1=\tau_2\cdots=\tau_K$), with the same computational speed ($f_1=f_2=\cdots=f_K$) and the same transmit power ($P_1=P_2=\cdots=P_K$). In this case, *(15)* is transformed as follows:

$$\underset{\tau_0,\tau_1,P_1,f_1,I_1}{\text{Maximize}}\ (1-I_1)\frac{Tf_1}{L}+I_1B\tau\log_2\left(1+\frac{P_1\Omega_1}{N_0}\right)$$

subject to:

$$\begin{aligned}&C1:KI_1\tau_1+\tau_0=T\\&C2:(1-I_1)\,\alpha Tf_1^3+I_1\tau_1P_1\le\eta\tau_0P_0\Omega_1\\&C3:I_1\in\{0,1\}\\&C4:\tau_0\ge 0,\tau_1\ge 0P_1\ge 0,f_1\ge 0\end{aligned}\tag{16}$$

Since the indicator variable I_1 can take two values, 1 and 0 (all EHUs are performing either offloading or local computing, respectively), we can represent the optimization problem given in *(16)* by two separate optimization problems, regarding the value of the indicator variable I_1. Therefore, two sets of optimal solutions will be derived and the solution that maximizes the objective function will be chosen.

1. *Case 1*: $I_1=1$, meaning all EHUs perform offloading. Since all EHUs perform data offloading, the optimization variable f_1 will disappear and the optimization problem will have the following form:

$$\underset{\tau_0,\tau_1}{\text{Maximize}}\ B\tau_1\log_2\left(1+\frac{A\tau_0}{\tau_1}\right)$$

subject to:

$$\begin{array}{l} C1: K\tau_1 + \tau_0 = T \\ C2: \tau_0 \geq 0, \tau \geq 0, \end{array} \quad (17)$$

where A is given by:

$$A = \frac{\eta P_0 \Omega_1^2}{N_0}. \quad (18)$$

2. *Case 2*: $I_1 = 0$, meaning all EHUs perform local computing. Since all EHUs perform local computing, the optimization variable τ_1 will disappear and local computing will be performed for the whole duration of the frame ($\tau_0 = T$), so we will optimize with respect to the variable f_1.

$$\underset{f_1}{\text{Maximize}} \frac{T f_1}{L}$$

subject to:

$$\begin{array}{l} C1: \alpha f_1^3 + \leq \eta P_0 \Omega_1, \\ C2: f_1 \geq 0, \end{array} \quad (19)$$

For a symmetric-user scenario, the optimal allocation scheme is as follows:

1. Case 1: EHUs operate in mode-1
   The optimal offloading time τ_1^* is found as a root of the following transcendental equation:

$$\frac{\tau_1^* + A\left(T - K\tau_1^*\right)}{AT} \ln\left(1 + A\frac{T - K\tau_1^*}{\tau_1^*}\right) = 0 \quad (20)$$

   The optimal energy harvesting time denoted by τ_0^* is:

$$\tau_0^* = T - K\tau_1^* \quad (21)$$

2. Case 2: EHUs operate in mode-0
   The optimal local computation speed denoted by f_1^* is:

$$f_1^* = \left(\frac{\eta P_0 \Omega_1}{\alpha}\right)^{1/3}. \quad (22)$$

Equations *(20)*-*(22)* are obtained following similar steps as in Appendix A.

5. NUMERICAL RESULTS

In addition, the performance of the two proposed resource allocation schemes for allocation of resources in a mobile edge computing system with wireless powered EHUs performing binary/partial offloading based on the max-min criterion, will be presented. The following two parameters are considered to evaluate the performance of the system:

- System's sum computation rate:

$$C = \sum_{i=1}^{K} C_i \quad (23)$$

where the computation rate of the ith EHU, C_i, is determined as the ratio between the amount of processed data of that EHU (i.e., the objective function of the considered optimization problem) and the duration of a single TDMA frame, i.e.,

$$C_i = \frac{f_i}{L} + \frac{B}{T}\tau_i \log_2\left(1 + \frac{P_i\Omega_i}{N_0}\right). \quad (24)$$

- System's fairness index [19]:

$$J = \frac{\left(\sum_{i=1}^{K} C_i\right)^2}{K\sum_{i=1}^{K} C_i^2}. \quad (25)$$

System parameters: The energy harvesting efficiency coefficient $\eta = 1$, while the computing efficiency coefficient is $\alpha = 10^{-28}$ Js. The duration of one frame is $T = 1$. The power of the thermal noise at the input of the receiver is $N_0 = 10^{-12}$ Watts/Hertz, while the bandwidth of the channel from one EHU station to the base station is $B = 10$ MHz. The number of EHU stations is $K = 10$.

5.1 EHUs placed along a single circle

Let us assume that all EHU stations are located at the same distance from the base station, i.e. along a circle of radius r around the base station. Fig. 2 shows the sum of the computation rate in the system as a function of radius r, while Fig. 3 shows the dependence of the percentage of offloaded data from EHU to the base station on radius r. The BS transmit power is set to $P_0 = 10$ Watts. Corresponding curves are shown for two different values of the computational load: $L = 100$ CPU cycles / bit (solid line) and $L = 1000$ CPU cycles / bit (dashed line). It is noted that for smaller values of r, it is better to transfer data to the MEC server, because local calculations consume more energy compared to wireless communication. For small values of radius r, the computational load has only a small effect on the sum computation rate, and so the curves for $L = 100$ and $L = 1000$ overlap in this region of r. However, as the radius r increases, the effect of the computational load on the sum computation rate is more significant. Specifically, for higher values of radius r, $L = 100$ leads to higher rates compared to the case of $L = 1000$, because ever more increasing percentage of the raw data are processed locally, in which case, the amount of processed bits is inversely proportional to L (c.f. *(24)*).

In case of binary offloading, above a given threshold distance to the base station, the EHUs perform offloading via the wireless channel to the base station. This threshold in Fig. 2 is easily identified at the knee of the curves, while in Fig. 3 identified at the "step" of the corresponding curves ($r \approx 30$ m for $L = 100$ and $r \approx 50$ m for $L = 1000$). When the radius exceeds that threshold, all EHUs utilize only local computing. The partial offloading scheme behaves similarly to the binary offloading scheme, except that, as the radius increases, the percentage of offloaded

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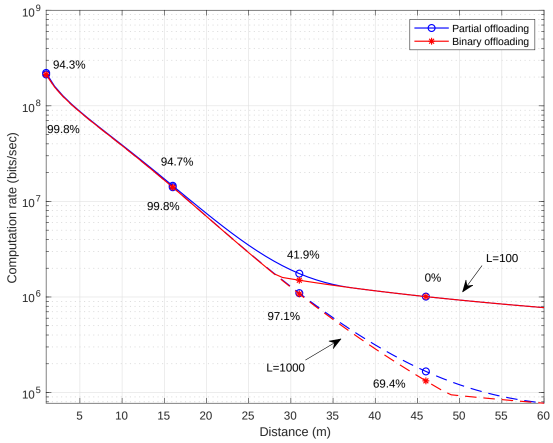

Fig. 2 – Impact of distance r on the number of computed bits ($P_0 = 10$ Watts, $K = 10$ EHUs).

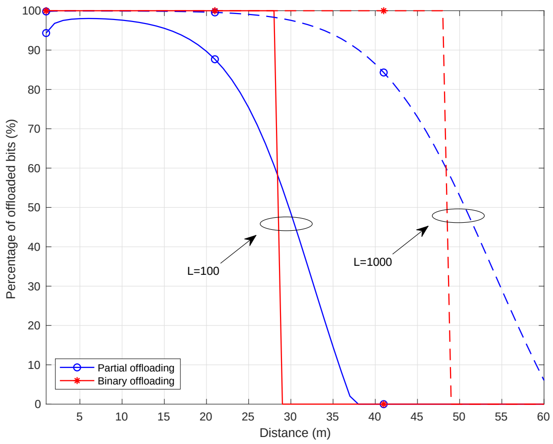

Fig. 3 – Impact of distance r on the number of offloaded bits ($P_0 = 10$ Watts, $K = 10$ EHUs).

bits gradually decreases from 100 percent to 0 percent. In this interval, the partial offloading scheme outperforms the binary offloading scheme, as the partial offloading scheme allows some optimal percentage of raw data (between 0 and 100 percent) to be processed remotely so as to maximize the system's sum computation rate.

Fig. 4 shows the dependence of the sum computing rate on the BS transmit power, P_0, at two different radii of the circle along which all EHU stations are located, $r = 25$m and $r = 35$m. Curves for different numbers of EHU stations are presented, $K = 10$ (solid line) and $K = 20$ (dashed line). The computational load is fixed at $L = 1000$. The number above each marker indicates the percentage of offloaded bits in case of partial offloading. It is obvious that with the increase of P_0, the amount of energy harvested by the EHU stations increases, so the computation rate and the percentage of offloaded data increase. Also, due to the diffuse nature of the wireless channel, increasing the number of EHU stations proportionally increases the total amount of harvested energy, which leads to an increase in the sum computation rate at

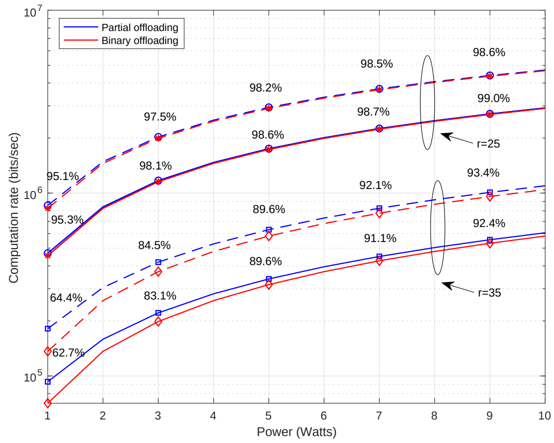

Fig. 4 – Impact of BS transmit power P_0 on the number of computed bits ($L = 1000$ CPU cycles/bit, solid line: $K = 10$EHUs, dashed line: $K = 20$ EHUs).

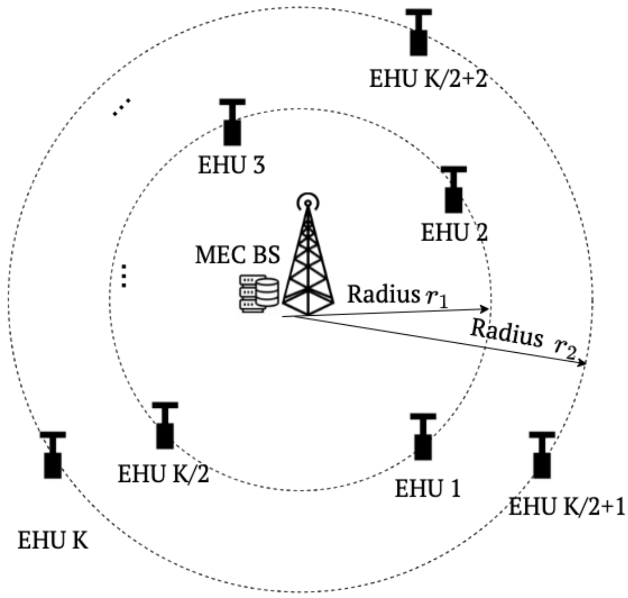

Fig. 5 – Asymmetric-user MEC assisted WPT network.

the same transmit power of the base station. At $r = 25$m, both offloading mechanisms reach the same sum computation rate (the corresponding curves match), while their computation rates differ at $r = 35$m. Namely, the partial offloading scheme at $r = 35$m outperforms the binary offloading scheme, because the number of bits to be offloaded is optimally chosen as a fraction of the total amount of raw data, contrary to the rigid choice between offloading only or local computing only offered by the binary offloading scheme.

5.2 EHUs placed along two concentric circles

In order to analyze the fairness level of the proposed resource allocation schemes, we assume that half of the EHU stations $(K/2)$ are located at a distance $r_1 = 5$m from the base stations, while the second half of the EHU stations $(K/2)$ are located at distance r_2 from the base station

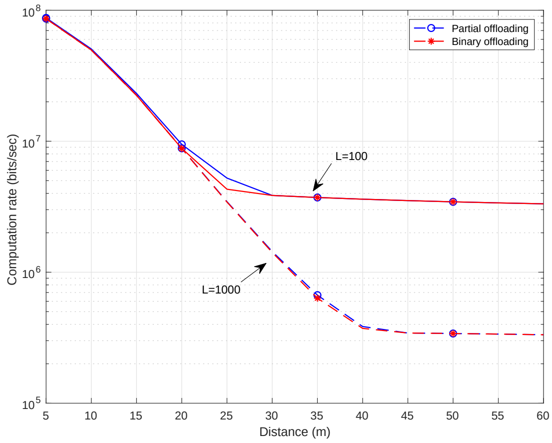

Fig. 6 – Impact of distance r_2 on the number of computed bits ($r_1 = 5$, $P_0 = 10$ Watts, $K = 10$ EHUs, $L = 1000$ (dashed line), $L = 100$ (solid line)).

(Fig. 5). Fig. 6 depicts the sum computation rate as a function of the distance r_2. We notice that the computation rate decreases with increasing r_2, because the max-min criterion adjusts the system to those EHUs at greater distances from the BS . Similar to the case of equal EHUs' distances, when the radius r_2 is less than some limit value, the sum computation rate of the MEC system overlaps for both offloading schemes (independently from the computation load L). Specifically, when $L = 1000$, the two offloading schemes have the same performance in the whole interval of the radius r_2 from 5 meters to 60 meters. When $L = 100$, the performance of the two offloading schemes also matches in the whole interval of radius r_2 from 5 meters to 60 meters, except up to the interval of 20 meters to 30 meters, when the partial offloading scheme reaches a higher computation rate. Again the reason is the choice of the appropriate optimal value of the percentage of offloaded data, while the binary offloading scheme employs either local computing or offloading.

Fig. 7 shows computation rate vs. MEC BS's transmit power P_0, where $K = 10$, $r_1 = 15$m, $r_2 = 30$m, $L = 100$ CPU cycles/bit (solid line), and $L = 1000$ CPU cycles/bit (dashed line). Simulation shows that both offloading schemes gain from increasing the BS transmit power, as the computation rate increases. Additionally, the sum computation rate increases with increasing L because more bits can be computed locally. Both partial and binary offloading schemes perform similarly when $L = 1000$ CPU cycles/bit, but when $L = 100$ CPU cycles/bit, the partial offloading scheme outperforms the binary offloading scheme for larger BS transmit power P_0 as a result of the ability to harvest more energy which increases the amount of offloaded and locally processed data.

Fig. 8 illustrates Jain's fairness index vs. the distance r_2, when $r_1 = 15$ meters. We notice that the fairness index decreases with increasing r_2, because the minimum computation rate is attained by EHUs at a higher distance

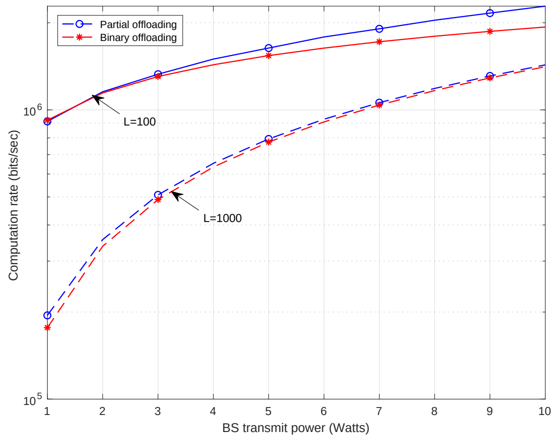

Fig. 7 – Impact of BS transmit power P_0 on the number of computed bits ($r_1 = 15$, $r_2 = 30$, $K = 10$ EHUs, $L = 1000$ (dashed line), $L = 100$ (solid line)).

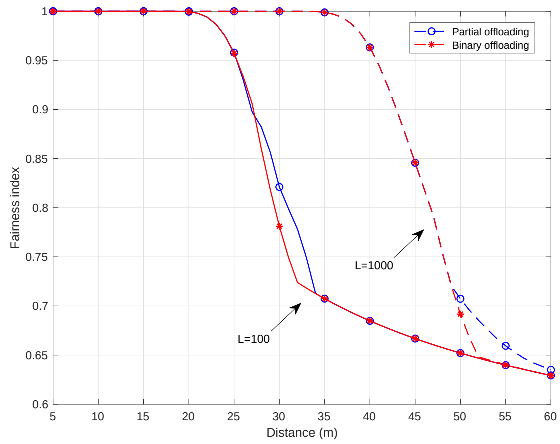

Fig. 8 – Impact of distance r_2 on the fairness index ($r_1 = 15$, $K = 10$ EHUs, $P_0 = 10$ Watts, $L = 1000$ (dashed line), $L = 100$ (solid line)).

from the BS, whereas the computation rate of the closer EHUs are much higher. Namely, when $L = 1000$ the two offloading schemes achieve the same values for the fairness index in the whole interval of radius r_2, while when $L = 100$, the partial offloading scheme reaches a higher fairness index in the interval form 20 meters to 30 meters. Moreover, both schemes achieve maximum value for the fairness index, when the radius r_2 is less than some limit value, as all EHUs perform offloading only.

The dependence of the Jain's fairness index on the BS transmit power P_0 is shown in Fig. 9. The number of EHUs is set to 10, half of which are placed on the circle with radius $r_1 = 15$ meters, and the other half are placed on the concentric circle with radius $r_2 = 30$ meters. When $L = 1000$, both offloading schemes guarantee an ideal level of fairness ($J = 1$). For $L = 100$, both offloading schemes reach close to the ideal level of fairness ($0.95 < J < 1$), with partial offloading slightly exceeding binary offloading with increasing P_0, which coincides with the behavior of the sum computation rate (c.f.

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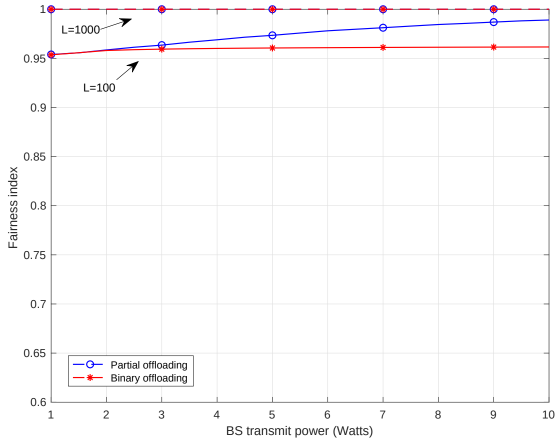

Fig. 9 – Impact of transmit power P_0 on the fairness index ($r_1 = 15$, $r_2 = 30$, $K = 10$ EHUs, $L = 1000$(dashed line), $L = 100$ (solid line)).

Fig. 7). Note, in order to attain convexity of the resource allocation problem *(9)*, the local computing at each EHU is assumed to cover the entire frame duration T. In this case, ith EHU computing speed, f_i, is unaffected by the constraint $C1$ and its local computing rate, f_i/L, is thus independent of τ_0 (c.f. *(12)*), which yields unequal EHUs' computation rates as the solution of *(9)*.

6. CONCLUSION

MEC is a promising concept that can extend the computational capabilities of resource-constrained wireless devices. The incorporation of the WPT technology further strengthens the MEC concept due to practical feasibility of the end devices with prolonged lifespans. We have specifically focused on the fusion between WPT and MEC concepts by proposing an effective resource allocation scheme with binary and partial offloading, which facilitates the practical feasibility of end devices without conventional batteries and yet sufficiently high computing rates.

The proposed system design maximizes the minimum of the end device's computing rate, defined as the sum between the local computing speed and the achievable rate of communications between the EHUs and the base station (and co-located MEC server). It has been found that if the EHUs are located close to the base station, then it is better to transfer the data from the EHU to the MEC server, because the local computing consumes more energy than the energy needed to transmit the raw data from the end device to the base station over the wireless channel. This perceived effect is even smaller if the computational load required to process one bit of information in the end users is reduced, which in turn depends on the architecture of their processors. It was also concluded that, contrary to expectations, the partial offloading mechanism only slightly outperforms the binary reloading mechanism in terms of the sum computation rate, and only in the case where the end devices are moderately away from the base station.

APPENDIX A

By inserting the substitution $U_k = P_k\tau_k$ in the optimization problem *(9)*, we obtain :

$$\underset{\tau_0,\tau_k,U_k,f_k}{\text{Maximize}} \ \min_{1\le k\le K} \left\{ \frac{Tf_k}{L} + B\tau_k \log_2\left(1+\frac{U_k\Omega_k}{\tau_k N_0}\right)\right\}$$

subject to:

$$\begin{aligned} &C1: \textstyle\sum_{k=1}^{K} \tau_k + \tau_0 \le T \\ &C2: \alpha T f_k^3 + U_k \le \eta\tau_0 P_0 \Omega_k, \forall k \\ &C3: \tau_k \ge 0, \tau_0 \ge 0, P_k \ge 0, f_k \ge 0, \forall k \end{aligned} \tag{26}$$

If we assume a symmetric-user scenario, where all EHUs are placed on one circle with radius r, the optimization problem *(26)* can be simplified as:

$$\underset{\tau_0,\tau_1,U_1,f_1}{\text{Maximize}} \ \frac{Tf_1}{L} + B\tau_1 \log_2\left(1+\frac{U_1\Omega_1}{\tau_1 N_0}\right)$$

subject to:

$$\begin{aligned} &C1: K\tau_1 + \tau_0 = T \\ &C2: \alpha T f_1^3 + U_1 \le \eta\tau_0 P_0 \Omega_1 \end{aligned} \tag{27}$$

In order to solve the optimization problem given in *(27)*, the objective function is transformed introducing Lagrange multipliers and Lagrange function $\mathcal{L}(\tau_0, \tau_1, U_1, f_1)$:

$$\begin{aligned} \mathcal{L}(\tau_0,\tau_1,U_1,f_1) &= \frac{Tf_1}{L} + B\tau_1\log_2\left(1+\frac{U_1\Omega_1}{\tau_1 N_0}\right) - \\ &- \lambda_1(K\tau_1+\tau_0-T) - \lambda_2(\alpha T f_1^3 + U_1 - \eta\tau_0 P_0\Omega_1) \end{aligned} \tag{28}$$

where λ_1 and λ_2 are the corresponding Lagrange multipliers. Taking the partial derivative of *(28)* with respect to τ_0, τ_1, U_1 and f_1 and equating them to zero, we have:

$$\lambda_1 = \lambda_2\eta P_0\Omega_1, \tag{29a}$$

$$K\lambda_1 = B\log_2\left(1+\frac{U_1\Omega}{\tau_1 N_0}\right) - B\frac{U_1\Omega_1}{\ln 2\,(\tau_1 N_0 + U_1\Omega)}, \tag{29b}$$

$$\lambda_2 = B\tau_1\frac{\Omega_1}{\ln 2\,(\tau_1 N_0 + U_1\Omega)}, \tag{29c}$$

$$f_1 = \left(\frac{1}{3\lambda_2\alpha L}\right)^{1/2}, \tag{29d}$$

$$K\tau_1 + \tau_0 = T, \tag{29e}$$

$$\alpha T f_1^3 + U_1 = \eta\tau_0 P_0.\Omega_1, \tag{29f}$$

By combining *(29)*a, *(29)*b and *(29)*c, we come up with:

$$\frac{K\eta P_0\Omega_1^2}{\ln 2\,(N_0 + P_1^*\Omega_1)} + \frac{P_1^*\Omega_1}{\ln 2\,(N_0+P_1^*\Omega_1)} - \log_2\left(1+\frac{P_1^*\Omega_1}{N_0}\right) = 0. \tag{30}$$

We obtain *(10)* by applying the definition of Lambert W function [18] to *(30)*. By inserting the optimal transmit power P_1^* calculated in *(10)* into *(29)*c, we can calculate the optimal value of Lagrange multiplier λ_2 and substitute it in *(29)*d, so we derive *(11)*. Then, by using the optimal values P_1^* and f_1^* and by combining *(29)*e and *(29)*f, we arrive at *(12)*.

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