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Wireless Powered Multi-Access Edge Computing with Slotted ALOHA

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***Abstract*—In this work, the integration of multi-access edge computing (MEC) with wireless power transfer (WPT) and slotted-ALOHA (SA) is investigated. All aforementioned technologies are considered key enablers for future Internet of Things networks, therefore, their interaction is of great significance. To that end, an energy efficient medium access protocol is designed, where each wireless powered device (WPD) harvests energy in order to either locally process a task or to offload it to the MEC server, by using SA. A non-convex energy minimization problem is formulated, which with the aid of proper transformations and successive convex approximation (SCA) is transformed to an equivalent convex one. Finally, simulation results are presented which aid to extract various insights for the proposed architecture.**

***Index Terms*—multi-access edge computing, wireless power transfer, Internet of Things, slotted-ALOHA.**

I. Introduction

The development of Internet of Things (IoT) networks, has been inentified as of of paramount importance in improving autonomy, scalability, and intelligence of smart grids, manufacturing, transportation, smart cities and communities, smart food and farming, and healthcare applications, all of which will need to support the activity of numerous wireless connected sensors. Due to the use of massive number of wireless devices and the corresponding cost limitations, future IoT networks cannot rely on fixed supply energy sources [1]. As a consequence, wireless power transfer (WPT), which enables energy harvesting from radio frequency signals, emerges as a feasible alternative to the fixed energy supply of low powered devices [1]. Also, due to its broadcasting nature, WPT is particularly suitable for powering closely-located wireless powered devices (WPDs), like those deployed in IoT networks.

Generally, WPDs' data requirements are low, while their computational capabilities are be suited for complex channel access methods [2]. Therefore, contention-based protocols, can be more practical access method choices compared to contention-free ones. Among the available contention based protocols, slotted-ALOHA (SA) is considered a prominent candidate for IoT applications. SA is based on probabilistic transmissions during separated time slots and compared to other random access schemes, it offers a reduced number of collisions while keeping the computational complexity low.

Furthermore, central cloud architectures are gradually to be substituted by distributed and flexible ones. To that end, multi-access edge computing (MEC) has been proposed, which provides computation capabilities to the edge, and thus, closer to the end users [3], [4]. That can significantly improve the end-to-end latency of the networks, while it can also increase their reliability, especially for users who repeatedly tend to offload intensive tasks to the server.

The integration of the aforementioned technologies in the future wireless communication networks is of paramount importance and several papers have worked on it. In [5], a SA network with WPT was examined and the proportional fairness of the users was maximized, under statistical channel information. In [6], a zero-energy devices network was investigated through WPT and SA, while an energy efficient communication scheme was proposed. Regarding the integration of MEC with WPT, in [7] a single user WPT-aided MEC architecture with partial offloading was investigated with dynamic task arrivals. Also, in [8] a multi-user MEC-WPT network was adopted, in which the harvested energy was maximized under orthogonal multiple access. In addition, in [9] a non-orthogonal multiple access WPT-aided MEC system model was proposed, which was shown to outperform its orthogonal counterpart. Moreover, in [10] and [11] the weighted sum rate of a MEC network with WPT was maximized under binary and partial offloading in respect. Finally, wireless powered MEC with SA was identified as a promising technology for the IoT [12]. However, the optimal resource allocation for a wireless powered MEC with SA has not yet been investigated in the existing literature.

To this end, in this work, we introduce a novel and practical medium access control (MAC) protocol for wireless powered MEC networks based on SA transmissions. Specifically, the WPDs operate under either local computing or full offloading by utilizing SA transmissions. Thus, each timeslot is divided in different phases, the duration of which, similarly to the rest communication and computation resources, can be dynamically controlled. For this purpose, an energy minimization problem is formulated subject to quality of service (QoS) constraints, which is solved by a centralized MAC scheduler. It is highlighted that for the implementation of the proposed MAC protocol, the scheduler solely needs to be aware of the knowledge of the channel statistics, instead of the instantaneous channel gains. However, mainly due to this practical requirement, the formulated energy minimization problem is non-convex. Thus, in order to be optimally solved, it is first transformed to an equivalent convex one, which can then be solved with acceptable complexity.

II. System Model

We consider a wireless powered network which consists of K WPDs and a base station (BS) integrated with a MEC

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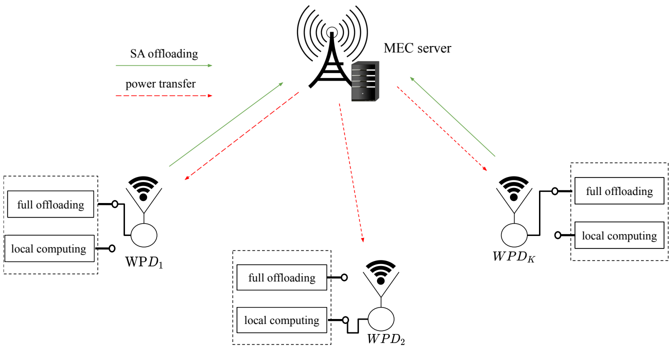

Fig. 1: Proposed architecture

server, as shown in Fig. 1. Also, it is assumed that the BS acts as a power beacon while the MEC server acts as the MAC scheduler of the network, due to its computing capabilities. All devices are capable of performing both local computing and full offloading, nonetheless partial offloading is not supported. The communication time T between the BS and the devices is separated into two distinct phases, one phase of energy harvesting and one phase of data offloading. During the first phase, of $(1-\tau_0)T$ duration, where τ_0 is a time-sharing parameter, the BS transmits power in order to charge the devices. WPDs lifetime is envisioned to last for more than a decade [13], without the need to substitute their batteries. WPT can increase that margin, since the energy consumed from the WPDs can be replaced by the energy harvested. Also, WPDs are characterized by extremely low energy consumption, while WPT also provides limited energy. Thus it can be assumed that the WPDs' battery capacity is modelled as an infinity queue [4], since the battery capacity of the WPDs' is large enough to accumulate all the available harvested energy. Therefore, from [5], the average energy arrival at the devices is denoted as

$$\eta_k P_0(1-\tau_0)\Omega_k. \tag{1}$$

The parameter η_k represents the energy conversion efficiency of a WPD, P_0 is the broadcast power of the BS and Ω_k is the path loss of the k-th WPD.

In the remaining time, $\tau_0 T$, of the second phase, a SA communication protocol is adopted for data offloading to the MEC server. The transmission probability, i.e., the probability with which a WPD will transmit data at the beginning of the transmission phase, and the transmit power of the k-th WPD are denoted as q_k and $P_{tr,k}$ respectively. Moreover, the uplink communication channel between the WPDs and the BS, is considered to be quasi-static and its instantaneous values follow a Rayleigh distribution. With this assumption, the average data rate (bps) of the k-th WPD is given as [5]

$$\overline{R}_{0,k} = T\frac{\tau_0 R_{0,k}}{u} B \exp\left(-\frac{(2^{R_{0,k}}-1)N_0 B}{\Omega_k P_{tr,k}}\right) q_k \prod_{\substack{i\neq k\\ i\in\mathcal{O}}}(1-q_i), \tag{2}$$

where $\mathcal{O}$ is the set containing all devices which choose to offload data and $R_{0,k}$ denotes the fixed spectral efficiency (bps/Hz) of transmission. Moreover, u stands for the communication overhead in task offloading, such as packet header, N_0 is the spectral density of additive white Gaussian noise (AWGN) and B denotes the communication bandwidth (Hz). For convenience, and without loss of generality, we set $T=1$. Furthermore, the exponential term describes the outage probability when transmitting under Rayleigh channel conditions. Since, during the offloading phase, partial offloading is not supported, a task has to be offloaded as whole during a successful transmission. Therefore, for the fixed transmission rate, the following needs to hold

$$R_{0,k}B \geq u\frac{L_k}{\tau_0}, \tag{3}$$

where $u \geq 1$ accounts for additional bits to the packet transmitted due to header overheads, etc. Note that (3) forces that the delay of a packet which is transmitted successfully, without collisions, has to be less than the data transmission phase duration. Moreover, the average power consumption of offloading a task is given as

$$P_{\mathrm{of},k} = \tau_0 q_k P_{tr,k} \tag{4}$$

On the other hand, the power consumption of the WPDs' CPUs during local computing is estimated by [3] as

$$P_{L,k} = k_k f_k^3, \tag{5}$$

while the achievable computation rate of the k-th WPD is given as

$$R_{L,k} = \frac{f_k}{\phi}, \tag{6}$$

where ϕ_k denotes the number of CPU cycles required for process of one bit, f_k represents the processor's CPU cycles per second and k_k denotes the computation energy efficiency coefficient.

III. Optimal Resource Allocation

In this section, the energy minimization of the power beacon will be formulated, subject to QoS constraints for the WPDs. Efficient wireless power transfer is of significant importance for next generation IoT networks, since fixed energy supply may not be a viable solution. The optimization problem is then formulated as follows:

$$\begin{aligned}
&\min_{\mathbf{x}} \quad \sum_{k=1}^{K} P_0(1-\tau_0)\\
&\textbf{s.t.} \quad \mathrm{C}_1: \quad m_k\overline{R}_{0,k} + (1-m_k)R_{L,k} \geq R_{\mathrm{th,k}}\\
&\qquad \mathrm{C}_2: \quad R_{0,k}B \geq m_k u\frac{L_k}{\tau_0}\\
&\qquad \mathrm{C}_3: \quad k_k f_k^3 + q_k\tau_0 P_{tr,k} \leq P_{\mathrm{har,k}}\\
&\qquad \mathrm{C}_4: \quad P_{\mathrm{har,k}} \leq \eta_k P_0(1-\tau_0)\Omega_k\\
&\qquad \mathrm{C}_5: \quad 0 \leq f_k \leq f_{\max}, \quad \text{and} \quad 0 \leq q_k \leq 1\\
&\qquad \mathrm{C}_6: \quad 0 \leq \tau_0 \leq 1, \quad \text{and} \quad 0 \leq m_k \leq 1
\end{aligned} \tag{7}$$

where $\mathbf{x} = \left[\mathbf{m}, \mathbf{R_0}, \mathbf{f}, \mathbf{P_{tr}}, \mathbf{q}, \mathbf{P_{har}}, \tau_\mathbf{0}\right]$. Since, variable m which indicates whether a WPD will choose to offload data to the MEC server ($m=1$), or to perform local computation ($m=0$), is a binary variable the problem is NP-hard. As such, variable m will be relaxed to a continuous variable $\in [0,1]$, which represents the case of partial offloading. Thus, solving problem (7) also provides a tractable solution to the partial offloading resource allocation problem. Due to the limited energy provided by WPT and the poor computing capabilities of the WPDs, problem (7) might be infeasible for a certain combination of parameters and QoS thresholds. Thus, a proper choice of parameters is necessary, to ensure that the available energy offered from the BS is sufficient for the WPDs to satisfy their QoS. Regarding the constraints of the problem, C_1 ensures that the average QoS of the WPDs is satisfied, while C_2 ensures that the offloading of the tasks is completed within the data transmission phase. The time needed for the MEC server to process the offloaded tasks is ignored, due to the MEC server possessing superior computation capabilities compared to the WPDs [3]. Furthermore, constraints C_3 and C_4 are energy constraints, according to which, the average energy consumed by the devices for both full offloading and local computing must be less than the average energy harvested. Furthermore, in [14], it was proven that for the steady state of a wireless powered network, if a WPD with unlimited energy storage capacity employs a power allocation policy for which the average harvested energy is larger than or equal to the average amount of energy desired to be extracted from the battery, then this device can extract its desired output power in almost all time slots. It should also be noticed that the MAC scheduler needs knowledge of only the channel statistics, instead of the instantaneous channel gains. Therefore, for a static IoT scenario the proposed algorithm needs to run only once, while for a mobile scenario it needs to run only when the path loss coefficients have changed sufficiently due to the WPDs' movement.

Moreover, the optimization problem in (7) is non-convex due to the product of multiple optimization variables in every constraint except C_5 and C_6 and due to $\overline{R}_{0,k}$ containing the product of multiple optimization variables. To overcome this, a simple solution is to logarithmize each constraint. However, the summation to the left side of the inequalities of constraints C_1 and C_2 would make those constraints rather impossible to transform to a convex form. To that end, constraints C_1 and C_2 will be split into two constraints by introducing variables $R^L_{\mathrm{th,k}}$, $R^O_{\mathrm{th,k}}$, $P^L_{\mathrm{har,k}}$, and $P^O_{har,k}$, for which will hold that

$$R^L_{\mathrm{th,k}} + R^O_{\mathrm{th,k}} \geq R_{\mathrm{th,k}}, \quad \text{and} \quad P^L_{\mathrm{har,k}} + P^O_{har,k} \leq P_{\mathrm{har,k}}. \tag{8}$$

Utilizing the above formulations, the optimization problem (7) can be rewritten as

$$\begin{aligned}
&\min_{\mathbf{x}} \quad 1-\tau_0\\
\textbf{s.t.}\quad &\mathrm{C}_1: \quad m_k \overline{R}_{0,k} \geq R_{\mathrm{th,k}}\\
&\mathrm{C}_2: \quad (1-m_k)R_{L,k} \geq R^L_{\mathrm{th,k}}\\
&\mathrm{C}_3: \quad R_{0,k}B \geq m_k u \frac{L_k}{\tau_0}\\
&\mathrm{C}_4: \quad k_k f_k^3 \leq P^L_{\mathrm{har,k}}\\
&\mathrm{C}_5: \quad q_k \tau_0 P_{tr,k} \leq P^O_{har,k}\\
&\mathrm{C}_6: \quad P^L_{\mathrm{har,k}} + P^O_{har,k} \leq P_{\mathrm{har,k}}\\
&\mathrm{C}_7: \quad R^L_{\mathrm{th,k}} + R^O_{\mathrm{th,k}} \geq R_{\mathrm{th,k}}\\
&\mathrm{C}_8: \quad P_{\mathrm{har,k}} \leq \eta_k P_0 (1-\tau_0)\Omega_k\\
&\mathrm{C}_9: \quad 0 \leq f_k \leq f_{\max}, \quad \text{and} \quad 0 \leq q_k \leq 1\\
&\mathrm{C}_{10}: \quad 0 \leq \tau_0 \leq 1, \quad \text{and} \quad 0 \leq m_k \leq 1,
\end{aligned} \tag{9}$$

where $\mathbf{x} = \left[\mathbf{m}, \mathbf{R_0}, \mathbf{f}, \mathbf{P_{tr}}, \mathbf{q}, \mathbf{R^L_{th}}, \mathbf{R^O_{th}}, \mathbf{P_{har}}, \mathbf{P^L_{har}}, \mathbf{P^O_{har}}, \boldsymbol{\tau_0}\right]$. The problem remains non-convex. Therefore, the logarithm of both sides of C_1-C_5 and C_8 will now be taken. Also, by substituting $\overline{R}_{0,k}$ and $R_{L,k}$ from their respective expressions relations, the optimization problem can be equivalently expressed as follows

$$\begin{aligned}
&\min_{\mathbf{x}} \quad 1-\tau_0\\
\textbf{s.t.}\quad &\mathrm{C}_1: -\log(\tau_0) - \log(R_{0,k}) - \log(m_k) + \frac{N_0 B}{\Omega_k}\frac{2^{R_{0,k}}-1}{P_{tr,k}}\\
&-\log(q_k) - \sum_{i\neq k, i=1}^{K} \log(1-q_i) - \log\left(\frac{B}{u}\right) + \log\left(R^O_{\mathrm{th,k}}\right) \leq 0\\
&\mathrm{C}_2: -\log(f_k) + \log(\phi) - \log(1-m_k) + \log\left(R^L_{\mathrm{th,k}}\right) \leq 0\\
&\mathrm{C}_3: \log\left(\frac{L_k}{B}\right) - \log(\tau_0) + \log(m_k u) - \log(R_{0,k}) \leq 0\\
&\mathrm{C}_4: -\log(P^L_{\mathrm{har,k}}) + 3\log(f_k) + \log(k_k) \leq 0\\
&\mathrm{C}_5: \log(q_k) + \log(\tau) + \log(P_{tr,k}) - \log(P^O_{har,k}) \leq 0\\
&\mathrm{C}_6: P^L_{\mathrm{har,k}} + P^O_{har,k} - P_{\mathrm{har,k}} \leq 0\\
&\mathrm{C}_7: R_{\mathrm{th,k}} - R^L_{\mathrm{th,k}} - R^O_{\mathrm{th,k}} \leq 0\\
&\mathrm{C}_8: \log(P_{\mathrm{har,k}}) - \log(\eta_k \Omega_k P_0) - \log(1-\tau_0) \leq 0\\
&(8).\mathrm{C}_9, \mathrm{C}_{10}.
\end{aligned} \tag{10}$$

Notice that the problem still remains non-convex due to constraints C_1-C_5 and C_8 having positive $\log(\cdot)$ terms. To tackle this non-convexity, those positive $\log(\cdot)$ terms will be linearized by introducing another set of auxiliary variables, as shown

$$\begin{aligned}
&\exp(\tilde{P}^L_{\mathrm{har,k}}) = P^L_{\mathrm{har,k}}, \quad \exp(\tilde{P}^O_{har,k}) = P^O_{har,k},\\
&\exp(\tilde{P}_{\mathrm{har,k}}) = P_{\mathrm{har,k}}, \quad \exp(\tilde{m}_k) = m_k,\\
&\exp(\tilde{f}) = f, \quad 2^{R_{0,k}} - 1 = \exp(\tilde{R}_{0,k}),\\
&\exp(\tilde{P}_{\mathrm{tr,k}}) = P_{tr,k}, \quad \exp(\tilde{q}_k) = q_k, \quad \exp(\tilde{\tau}_0) = \tau_0.
\end{aligned} \tag{11}$$

Algorithm 1 Energy minimization algorithm with QoS requirements

1: Choose x_0, initial points $R^O_{\mathrm{th,SCA},0}$, $R^L_{\mathrm{th,SCA},0}$, tolerance e and c_{max}
2: **Start**
3: **while** $i \leq c_{max}$ and $\|x_i^* - x_{i-1}^*\| \leq e$ **do**
4: solve (13) and obtain optimal x_i^*
5: $R^O_{th,SCA} \leftarrow R^{O*}_{th}$, $R^L_{th,SCA} \leftarrow R^{L*}_{th}$
6: $x_0 \leftarrow x_i^*$
7: $i \leftarrow i+1$
8: **end while**
9: $m^*_{bin} \leftarrow \lfloor m^* \rceil$
10: Solve (13) for m^*_{bin} and obtain optimal allocation x_{bin},
11: $x_{bin} = \big[\tilde{R}_0, \tilde{f}, \tilde{P}_{tr}, \tilde{q}, R^L_{th}, R^O_{th}, \tilde{P}_{har},$
12: $P^{\tilde{L}}_{har}, P^{\tilde{O}}_{har}, \tau_0\big]^*$
13: **End**

However, the variables $R^L_{\mathrm{th,k}}$ and $R^O_{\mathrm{th,k}}$, will still produce non-convex terms. In order to cope with this, SCA will be exploited, specifically, each logarithmic term will be approximated by its first order Taylor approximation, which for a function $f(x)$ around an initial point γ is given by

$$f(x) \approx f(\gamma) + f'(\gamma)(x-\gamma) \tag{12}$$

The initial points, used for the SCA approximation will be denoted as $R^O_{th,k,SCA}$ and $R^L_{\mathrm{th,k,SCA}}$. Moreover, taking into account that $\exp(\cdot)$ is an increasing function, the optimization problem can be transformed as convex as follows,

$$\begin{aligned}
&\max_{\mathbf{x}} \quad \tilde{\tau}_0 \\
\textbf{s.t.} \quad & \mathrm{C}_1: -\tilde{\tau}_0 - \log\Big(\log_2\big(\exp(\tilde{R}_{0,k})+1\big)\Big) - \tilde{m}_k \\
& \frac{N_0 B}{\Omega_k}\exp\Big(\tilde{R}_{0,k} - \tilde{P}_{\mathrm{tr,k}}\Big) - \tilde{q}_k - \sum_{i\neq k, i=1}^{K}\log\left(1-\exp(\tilde{q}_i)\right) \\
& -\log\left(\frac{B}{u}\right) + \frac{R^O_{\mathrm{th,k}}}{R^O_{\mathrm{th,k,SCA}}} - 1 + \log\left(R^O_{\mathrm{th,k,SCA}}\right) \leq 0 \\
& \mathrm{C}_2: -\tilde{f}_k + \log\left(\frac{\phi}{f_{\max}}\right) + \frac{R^L_{\mathrm{th,k}}}{R^L_{\mathrm{th,k,SCA}}} \\
& \quad -\log(1-\exp(\tilde{m}_k)) - 1 + \log\left(R^L_{\mathrm{th,k,SCA}}\right) \leq 0 \\
& \mathrm{C}_3: \log\left(\frac{L_k}{B}\right) - \tilde{\tau}_0 + \tilde{m}_k + \log(u) \\
& -\log\Big(\log_2\big(\exp(\tilde{R}_{0,k})+1\big)\Big) \leq 0 \\
& \mathrm{C}_4: -\tilde{P}^L_{\mathrm{har,k}} + 3\tilde{f}_k + \log(k_k f^3_{max}) \leq 0 \\
& \mathrm{C}_5: \tilde{q}_k + \tilde{\tau}_0 + \tilde{P}_{\mathrm{tr,k}} - \tilde{P}^O_{har,k} \leq 0 \\
& \mathrm{C}_6: \log\Big(\exp(\tilde{P}^L_{\mathrm{har,k}}) + \exp(\tilde{P}^O_{har,k})\Big) - \tilde{P}_{\mathrm{har,k}} \leq 0 \\
& \mathrm{C}_7: R_{\mathrm{th,k}} - R^L_{\mathrm{th,k}} - R^O_{\mathrm{th,k}} \leq 0 \\
& \mathrm{C}_8: \tilde{P}_{\mathrm{har,k}} - \log\left(\eta_k \Omega_k P_0\right) - \log(1-\exp(\tilde{\tau}_0)) \leq 0 \\
& \mathrm{C}_9: \tilde{f}_k \leq 0, \quad \tilde{q}_k \leq 0, \quad \tilde{\tau}_0 \leq 0, \quad \tilde{m}_k \leq 0
\end{aligned} \tag{13}$$

Due to its convexity, problem (13) can be solved by any general purpose convex optimization method, following Algorithm 1. To obtain a binary policy for the network, in line 9 of Algorithm 1, the values of all m are rounded to their nearest integer and the problem is then solved again to obtain a sub-optimal and tractable, resource allocation strategy for the original problem (7). As such, the proposed solution will be called a partial binary strategy. In line 6 of Algorithm 1 the initial point of the SCA procedure is updated by the optimal solution obtained from solving problem (13). Therefore, at each iteration, the Taylor approximation is more accurate, since the approximation is closer to the optimal point of (13). Also, it should be mentioned that the complexity of Algorithm 1 is related to the complexity of solving (13). Thus, in the case where an interior-point method is used to solve (13) the complexity of Algorithm 1 is roughly $O(c_{\max}N^3)$, where N is the number of optimization variables.

IV. Numerical Results and Discussion

In this section, numerical results are presented for a wireless powered MEC network. Unless otherwise stated, the parameters of the simulation set-up are given in Table 1. The distance of the i-th WPD from the BS is given from $d_i = (i/K)r$ while the path loss will be estimated as $\Omega_i = \frac{1}{(1+d_i)^\alpha}$. All results have been acquired by exploiting Algorithm 1.

Parameters	Values
K	12 users
L	1 kbit
u	1.1
r	100 m
d	distance: $(i/K)r$ m, $i = 1\dots K$
α	2.0
η	0.51
ϕ	280 CPU cycles per bit
k	10^{-29}
$\mathrm{f_{max}}$	1 GHz
$\mathrm{P_0}$	10 W
$\mathrm{R_{th}}$	0.1 Mbps
$\mathrm{N_0}$	10^{-18} W/Hz
B	1 MHz
e	10^{-3}

TABLE I: Simulation parameters.

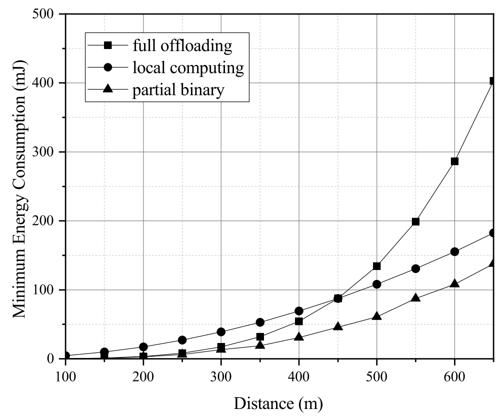

Fig. 2: BS's energy consumption vs distance r from BS

In Fig. 2, the optimized energy consumption of the WPT phase is plotted against the maximum distance r from the BS. A greater value of r indicates that the WPDs are distributed in greater distances from the BS. First, it is noticed that for small distances around the BS, full offloading offers more energy efficiency compared to local computing. However, as

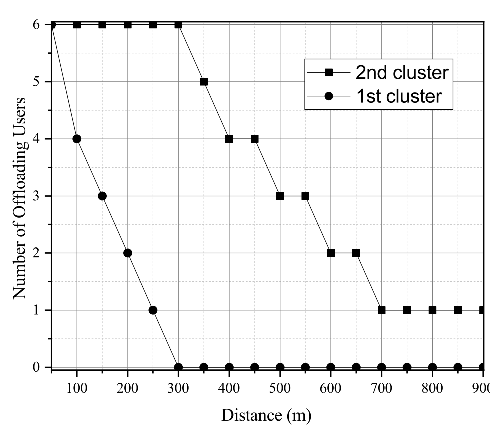

Fig. 3: Number of offloading WPDs vs distance r from BS

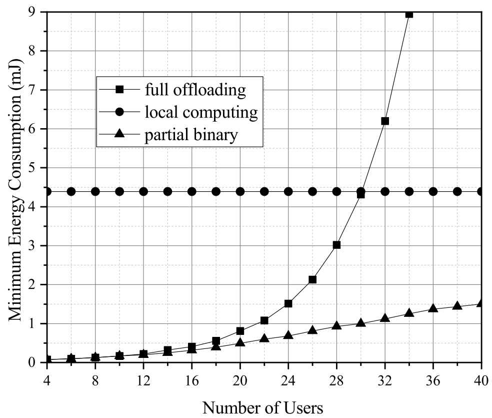

Fig. 4: BS's energy Consumption vs number of WPDs

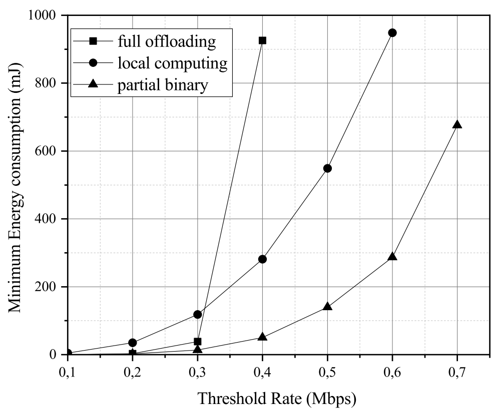

Fig. 5: BS's energy consumption vs QoS

the distance from the BS increases the situation is reversed, and the energy efficiency of full offloading rapidly worsens. This can be attributed to the doubly near-far effect since as the distance from the BS increases, the WPDs receive less energy during the WPT phase but they also need to cope with greater distance-based path losses during task offloading. On the other hand, the proposed partial binary strategy is much more energy efficient compared to both its counterparts. This is attributed to the fact that WPDs with problematic path losses prefer to locally compute their tasks, while for WPDs near to the BS, full offloading can be exploited.

In Fig. 3, the number of users, which choose to offload their data, is illustrated against the distance from the BS. The number of WPDs are separated into two clusters based on their path loss. It can be observed that for smaller distances from the BS, about 100m, the great majority of WPDs choose to perform full offloading, which is in accordance to the insights of Fig. 2. As distance from the BS increases, it is observed that the number of devices which offload data rapidly diminishes to the point that only one WPD performs full offloading. Notably, every 50m, one or two WPDs replace full offloading by local computing, since due to the double near-far effect full offloading is much more energy consuming than local computing. Nonetheless, that transition from full offloading to local computing can in some cases cause the original problem to be infeasible, since WPDs have poor computational capabilities and may not be able to satisfy their QoS.

In Fig. 4, the optimized energy consumption of the BS is plotted against the number of the WPDs. As expected, local computing is not affected by the number of WPDs. As the network's connected devices increases, it is observed that full offloading performs worse than local computing, which is attributed to the increased number of collisions among the offloading users. Furthermore, the proposed partial binary scheme is shown to be much more efficient compared to both binary schemes, since for fewer WPDs full offloading can be utilized, while for a greater number of WPDs, a combination of local computing and full offloading is exploited. That combination allows the MEC server to control the frequency of collisions, since a number of WPDs locally compute their tasks, thus, providing the network with the ability to adapt to multi-WPDs scenarios. Finally, in Fig. 5, the optimized energy consumption of the BS is plotted against the WPDs' QoS, where the partial binary strategy once again greatly outperforms both schemes in terms of energy efficiency, due to its ability to utilize the advantages of both local computing and full offloading.

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