

# Online Scheduling for Energy Minimization in Wireless Powered Mobile Edge Computing

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**Abstract**—The integration of Mobile Edge Computing (MEC) and Wireless Power Transfer (WPT), which is usually referred to as Wireless Powered Mobile Edge Computing (WP-MEC), has been recognized as a promising technique to enhance the lifetime and computation capacity of wireless devices (WDs). Compared to the conventional battery-powered MEC networks, WP-MEC brings new challenges to the computation scheduling problem because we have to jointly optimize the resource allocation in WPT and computation offloading. In this paper, we consider the energy minimization problem for WP-MEC networks with multiple WDs and multiple access points. We design an online algorithm by transforming the original problem into a series of deterministic optimization problems based on the Lyapunov optimization theory. To reduce the time complexity of our algorithm, the optimization problem is relaxed and decomposed into several independent subproblems. After solving each subproblem, we adjust the computed values of variables to obtain a feasible solution. Extensive simulations are conducted to validate the performance of the proposed algorithm.

**Index Terms**—wireless power transfer, mobile edge computing, Lyapunov optimization, energy minimization

## I. INTRODUCTION

With the rapid development in recent years, the Internet of Things (IoT) technology has played an important role in the intelligent and autonomous control of many industrial and commercial systems, such as smart grid and smart cities. Due to the stringent size constraint and production cost consideration, the ubiquitously deployed IoT devices usually have restricted computation capability and finite battery capacity, which severely degrades the quality of service experienced by users. To handle the two fundamental performance limitations, Wireless Powered Mobile Edge Computing (WP-MEC) has been proposed as a novel paradigm that combines the advantages of Wireless Power Transfer (WPT) and Mobile Edge Computing (MEC).

As a promising approach that provides sustainable energy supply for wireless devices (WDs), WPT utilizes dedicated energy transmitters to broadcast radio frequency (RF) signals. The received RF signals can be converted to electricity by energy harvesting circuits and used to charge WDs continuously. On the other hand, MEC is a newly emerged computing paradigm that enables WDs to offload their computation tasks to nearby edge servers located at the edge of radio access networks. As the integration of both techniques, WP-MEC charges WDs with WPT and alleviates WDs' computation workloads with MEC. As a result, the WDs' device lifetime

and computation capacity are simultaneously improved, which leads to significantly enhanced user experiences.

In this paper, we study the computation offloading and system resource allocation in WP-MEC networks. Compared with the computation scheduling in conventional battery-powered MEC networks, our problem is much more challenging because 1) the optimal control decisions depend on the remaining energy in the battery and 2) WPT and computation offloading need to share the same limited system resources, such as time and frequency.

## A. Prior Works

Computation scheduling in conventional MEC networks has been extensively studied and was systematically summarized in [1] and [2]. Recently, the advancements in WPT technology bring in the possibility of building *wireless powered* MEC networks. To the best of our knowledge, the works in [3] and [4] are the first that simultaneously study energy harvesting and computation offloading in MEC networks, but they only consider simple networks with only one WD and one access point (AP). Their model was extended by subsequent researches to incorporate more WDs. The works in [5] and [6] consider the WP-MEC networks with two near-far WDs and try to resolve the so-called “double-near-far” effect, which occurs because a farther device harvests less energy from the AP but spends more power to communicate in longer distances. The authors in [7] and [8] aim to maximize the overall computation rate of all WDs in the networks, where an unmanned aerial vehicle was utilized to transmit energy in [8]. To the best of our knowledge, [9] is the only work that considers WP-MEC networks with *multiple* APs, where an approximation algorithm is derived to maximize the ratio of computation tasks completed before their deadlines.

The researches described above generally focus on the one-shot optimization where the scheduling problem is only considered in a specific time interval. However, in practical settings, the WP-MEC networks are operated under sustainable manners and the control decisions at different times are mutually dependent. For example, the energy harvested in the current time frame, if not fully consumed, may be stored in the battery for later use. Inspired by this fact, many recent works try to solve the scheduling problem in online settings. A one-WD-one-AP model is considered in [10] where the energy consumption is minimized by optimizing the power of the energy transmitter and the offloading decisions of

WDs. The model is extended to include multiple WDs in [11] where the long-term system throughput is maximized. In [12], the authors designed an online algorithm based on the Lyapunov optimization theory and presented a theoretical tradeoff between energy efficiency and delay.

### B. Our Contributions

In this paper, we study the computation scheduling problem in WP-MEC networks with multiple WDs and multiple APs. Different from [9], we formulate our problem under an online setting where both channel states and computation data arrivals fluctuate over time. This brings new challenges in algorithm design as decision variables are coupled along the timeline. To facilitate the process of tasks, the partial offloading mode is adopted in our model, where tasks can be divided into smaller parts and executed on WDs and APs concurrently. In consideration of green computing, our objective is to minimize the long-term energy consumption in the system by jointly optimizing the resource allocation in WPT and wireless communication stages. To avoid the mutual interference of concurrently emitted energy waves [13], only one AP is allowed to broadcast RF energy at the same time. Our main contributions are summarized as follows.

- We formulate the energy minimization problem for WP-MEC networks with partial offloading. To the best of our knowledge, this is the first work that considers multiple WDs and multiple APs under online settings.
- We design an online algorithm by transforming the original problem into a series of deterministic optimization problems in each time slot based on the Lyapunov optimization theory. To reduce the time complexity of our algorithm, we propose a relax-then-adjust technique where the optimization problem is first relaxed and decomposed into several independent subproblems. After solving each subproblem, we adjust the computed values of variables to obtain a feasible solution.
- To solve the non-convex computation offloading subproblem obtained in the previous step, we propose an iterative algorithm based on the Alternating Minimization method. We demonstrate that each iterative step can be solved in polynomial time and the algorithm converges to local optima.
- Extensive simulations are conducted to validate the performance of our algorithm. Numerical results show that the total energy consumption is significantly reduced under various settings.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider a WP-MEC network consisting of  $N$  WDs and  $M$  APs, where each AP is integrated with an RF energy transmitter and a MEC server. APs are assumed to have a stable power supply and broadcast RF energy to WDs. The energy harvested by each WD is stored in a rechargeable battery, which is used to power its computing and communication operations. Similar to [9], we assume that WPT and wireless communications (for offloading) of the

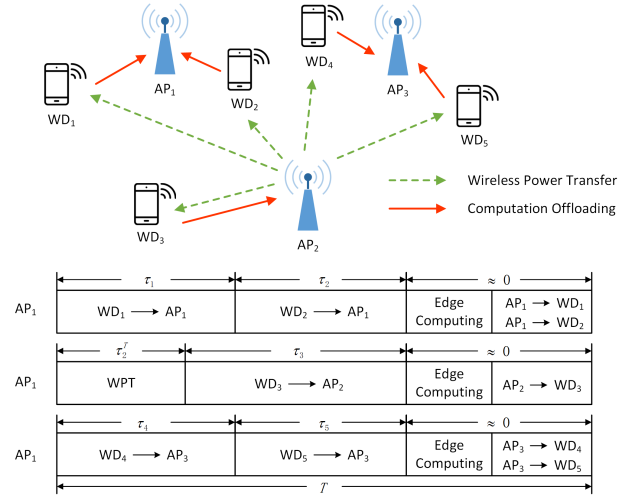


Fig. 1. An example of system model and time allocation.

same AP cannot be performed simultaneously and the TDMA protocol is applied to avoid mutual interference, but WPT and wireless communications of different APs can be operated simultaneously over orthogonal frequency bands.

The time horizon is divided into slots with equal length  $T$ , where each slot consists of four phases, i.e., WPT, computation offloading, edge computing, and result downloading, as illustrated in Fig. 1. Note that we have assumed WDs have simultaneous wireless information and power transfer (SWIPT) abilities, as shown in [14]. However, our model can be easily tailored for WDs without SWIPT capabilities. Since MEC servers have strong computation capacities compared with WDs and the computation results are of small data sizes, the time consumption for edge computing and result downloading is negligible [9], [11], [12], [15]. Therefore, we only consider the duration of the first two phases in our model. Let  $h_{ij}^D(t)$  and  $h_{ij}^U(t)$  denote the downlink and uplink channel gain between WD  $i$  and AP  $j$  on slot  $t$ . As in [10]–[12], we assume all channels follow quasi-static flat-fading, i.e., the channel state remains constant within each time slot, but may vary across different slots. Our goal is to minimize the total energy consumption for processing the data of WDs.

### A. Wireless Power Transfer and Energy Harvesting Model

According to [13], when multiple APs transfer RF power simultaneously, their energy waves may interfere with each other and lead to a possible energy cancellation. To improve the efficiency of RF energy transfer, we select only one AP to broadcast RF energy during each time slot. We use  $a_j^T(t) \in \{0, 1\}$  to indicate whether AP  $j$  broadcasts RF energy in slot  $t$  and let  $P_j^T(t)$  and  $\tau_j^T(t)$  be the corresponding transmission power and transmission time. Then we have the following constraint

$$\sum_{j=1}^M a_j^T(t) \leq 1 \quad (1)$$

and the energy consumption of AP  $j$  during the WPT is

$$E_j^T(t) = a_j^T(t) P_j^T(t) \tau_j^T(t). \quad (2)$$

As in [12], we adopt a linear model to characterize the energy harvesting circuit of WDs. In particular, the energy harvested by WD  $i$  during the  $t$ -th time slot is

$$E_i^H(t) = \sum_{j=1}^M \mu_i a_{ij}^T(t) P_j^T(t) h_{ij}^D(t) \tau_j^T(t) \quad (3)$$

where  $\mu_j \in (0, 1)$  is the energy conversion efficiency of WD  $i$ . The harvested energy is stored in the battery of WDs. Let  $B_i^{max}$  and  $B_i(t)$  be the capacity and remaining power of the battery in WD  $i$ , then the update rule of  $B_i(t)$  is

$$B_i(t+1) = \min [B_i(t) - E_i^L(t) - E_i^O(t) + E_i^H(t), B_i^{max}]$$

where  $E_i^L(t)$  and  $E_i^O(t)$  are the energy consumption for local computation and wireless communication, as explained in the next subsection. Due to the energy causality constraint, the energy consumption cannot exceed the available energy in the battery, so we must ensure

$$E_i^L(t) + E_i^O(t) \leq B_i(t). \quad (4)$$

### B. Computation Scheduling Model

In each time slot  $t$ , let  $A_i(t)$  be the amount of computation data arrived at WD  $i$ . Without loss of generality, we assume  $A_i(t)$  is i.i.d. with average rate  $\mathbb{E}[A_i(t)] = \lambda_i$ . The arrived data can be either processed locally or offloaded to the APs. The length of queueing data  $Q_i(t)$  at WD  $i$  evolves according to the following equation

$$Q_i(t+1) = Q_i(t) - D_i^L(t) - D_i^O(t) + A_i(t)$$

where  $D_i^L(t)$  and  $D_i^O(t)$  are the amount of locally processed data and offloaded data, respectively. Note that the new data may arrive at the end of slot  $t$  and cannot be processed until the beginning of next slot, so  $D_i^L(t)$  and  $D_i^O(t)$  must satisfy

$$D_i^L(t) + D_i^O(t) \leq Q_i(t). \quad (5)$$

1) *Local Computation*: As in previous researches, we assume the local computation and WPT can be performed simultaneously and each WD  $i$  adopts the Dynamic Voltage and Frequency Scaling technique to control its CPU frequency  $f_i(t)$ . Let  $\tau_i^L(t)$  be the local computation time of WD  $i$  in slot  $t$ , then we can express  $D_i^L(t)$  as

$$D_i^L(t) = \frac{f_i(t) \tau_i^L(t)}{\phi_i} \quad (6)$$

where  $\phi_i$  is the number of CPU cycles required to process one bit of computation data. According to [5], the energy consumption for the local computation of WD  $i$  is

$$E_i^L(t) = \kappa_i f_i^3(t) \tau_i^L(t) \quad (7)$$

where  $\kappa_i$  is the energy efficiency coefficient of the chip equipped with WD  $i$ . By substituting (7) into (6) we can obtain

$$D_i^L(t) = \sqrt[3]{\frac{E_i^L(t) \tau_i^L(t)^2}{\kappa_i}} \cdot \frac{1}{\phi_i}$$

which is an increasing function with respect to the computation time  $\tau_i^L(t)$  under fixed energy consumption  $E_i^L(t)$ . Therefore, we can simply set

$$\tau_i^L(t) = T$$

to maximize the computation data processed locally.

2) *Computation Offloading*: Let  $\tau_i(t)$  and  $P_i(t)$  denote the offloading time and the transmit power of WD  $i$ , respectively. Suppose each WD can only communicate with at most one AP within one time slot. We use the binary variable  $a_{ij}(t) \in \{0, 1\}$  to indicate whether WD  $i$  is communicating with AP  $j$ , then  $a_{ij}(t)$  should satisfy

$$\sum_{j=1}^M a_{ij}(t) \leq 1 \quad (8)$$

and the amount of computation data offloaded from WD  $i$  to APs can be expressed as

$$D_i^O = \sum_{j=1}^M \frac{a_{ij}(t) B \tau_i(t)}{v_i} \log_2 \left( 1 + \frac{P_i(t) h_{ij}^U(t)}{\sigma_j^2} \right)$$

where  $B$  is the spectrum bandwidth,  $\sigma_j^2$  is the noise power of AP  $j$ , and  $v_i > 1$  indicates the communication overhead induced by encryption and packet header [7]. The energy consumption for the computation offloading of WD  $i$  is

$$E_i^O = \sum_{j=1}^M a_{ij}(t) P_i(t) \tau_i(t) = P_i(t) \tau_i(t).$$

Similar to [15], we assume the energy consumption for the computation at AP  $j$  is proportional to the total data it received

$$E_j^C(t) = \sum_{i=1}^N \eta a_{ij}(t) \phi_i D_i^O(t)$$

where  $\eta$  is the energy consumption per CPU cycle of APs.

### C. Problem Formulation

To reduce the carbon footprint, in this paper, we aim to minimize the energy consumption for processing computation data arrived at WDs by jointly optimizing the control decisions for WPT, local computation, and data offloading. A similar objective is also considered in [4], [6], [12]. Based on our model, the considered problem can be formulated as follows.

$$\begin{aligned} \min \quad & \lim_{H \rightarrow \infty} \frac{1}{H} \sum_{t=0}^{H-1} \sum_{j=1}^M \mathbb{E} \{ E_j^T(t) + E_j^C(t) \} \\ \text{s.t.} \quad & (1), (4), (5), (8) \end{aligned}$$

$$a_j^T(t) \tau_j^T(t) + \sum_{i=1}^N a_{ij}(t) \tau_i(t) \leq T \quad \forall j, \forall t \quad (9)$$

$$0 \leq \tau_j^T(t) \leq T, 0 \leq P_j^T \leq P_j^{T, max} \quad \forall j, \forall t \quad (10)$$

$$0 \leq \tau_i(t) \leq T, 0 \leq P_i(t) \leq P_i^{max} \quad \forall i, \forall t \quad (11)$$

$$0 \leq f_i(t) \leq f_i^{max}, Q_i(t) \text{ is stable} \quad \forall i, \forall t \quad (12)$$

where  $P_i^{max}$  and  $f_i^{max}$  is the maximum offloading power and computation capacity of WD  $i$ . Constraint (9) ensures the time allocation is feasible under the TDMA protocol. Although the objective function only concerns energy consumption, our proposed algorithm actually achieves a trade-off between energy consumption and computation delay. Please see the next section and the numerical results for more details.

### III. AN ONLINE ALGORITHM FOR WIRELESS POWER TRANSFER AND COMPUTATION SCHEDULING

In this section, we design an online algorithm that jointly optimizes WPT and computation scheduling based on the Lyapunov optimization. A relax-then-adjust technique is proposed to decompose the original problem into smaller subproblems so that the algorithm's complexity is significantly reduced.

#### A. Algorithm Design with Lyapunov Optimization

For convenience of description, we first define the battery shortage  $B_i^-(t)$  as

$$B_i^-(t) = B_i^{max} - B_i(t).$$

Let  $\Theta(t) = [Q(t), B^-(t)]$  be the combined queue vector. According to the Lyapunov optimization theory, we start by defining the quadratic Lyapunov function

$$L(t) = \frac{1}{2} \sum_{i=1}^N [Q_i(t)^2 + B_i^-(t)^2]$$

and the conditional Lyapunov drift

$$\Delta L(t) = \mathbb{E} \{L(t+1) - L(t) | \Theta(t)\}.$$

Next, we combine  $\Delta L(t)$  with the objective function and form the following drift-plus-penalty term

$$\Delta_V L(t) = \Delta L(t) + V \mathbb{E} \left\{ \sum_{j=1}^M (E_j^T(t) + E_j^C(t)) | \Theta(t) \right\}$$

where  $V$  is a tunable parameter that controls the trade-off between the energy consumption and the queueing delay of computation data. The following lemma provides an upper bound for  $\Delta_V L(t)$ .

**Lemma 1:** On every slot  $t$  and for any value of  $\Theta(t)$ , the drift-plus-penalty term always satisfies

$$\begin{aligned} \Delta_V L(t) \leq & C - \sum_{i=1}^N Q_i(t) \mathbb{E} \{D_i^L(t) + D_i^O(t) - A_i(t) | \Theta(t)\} \\ & - \sum_{i=1}^N B_i^-(t) \mathbb{E} \{E_i^H(t) - E_i^L(t) - E_i^O(t) | \Theta(t)\} \\ & + V \mathbb{E} \left\{ \sum_{j=1}^M (E_j^T(t) + E_j^C(t)) | \Theta(t) \right\} \end{aligned} \quad (13)$$

where  $C$  is a constant defined in the proof.

The proof follows a standard procedure [16] and is omitted for brevity. Based on the Lyapunov optimization theory, we can obtain an approximately optimal algorithm of our problem by minimizing the right-hand side of (13) in every slot  $t$ . The resulting time-average energy consumption decreases at the rate of  $O(1/V)$  and the time-average queueing delay increases at the rate of  $O(V)$ , presenting a  $O(1/V)$ - $O(V)$  tradeoff between the two metrics. As a result, we can approach the optimal energy consumption arbitrarily close by increasing the value of  $V$ . However, in our problem, directly solving the minimization problem is difficult because the decision variables are coupled in constraints such as (4) and (5). To reduce the complexity of our algorithm, we propose a relax-then-adjust

technique to decompose the original minimization problem into independent subproblems. The details are presented in the next subsection.

#### B. Relax-Then-Adjust

In our problem, the objective is to minimize the system energy consumption used to process the computation data of WDs. When the amount of arrived workload is fixed, this is equivalent to maximizing the energy efficiency, which is defined as the ratio of total energy consumption to the corresponding aggregate accomplished computation data. Inspired by this interpretation, we define the *marginal energy efficiency* of local computation and computation offloading, denoted by  $\epsilon_i^L(t)$  and  $\epsilon_i^O(t)$  respectively, as follows

$$\begin{aligned} \epsilon_i^L(t) &= \frac{\partial E_i^L(t)}{\partial D_i^L(t)} = 3\kappa_i \phi_i f_i^2(t) \\ \epsilon_i^O(t) &= \frac{\partial (E_i^O(t) + \eta \phi_i D_i^O(t))}{\partial D_i^O(t)} \\ &= \sum_{j=1}^M \frac{a_{ij}(t) v_i \ln 2}{B} \cdot \left( \frac{\sigma_j^2}{h_{ij}^U(t)} + P_i(t) \right) + \eta \phi_i \end{aligned} \quad (14)$$

where we have assumed the time allocation  $\tau_i(t)$  is given in deriving (14). According to the optimality conditions, the two marginal energy efficiency should be equal when the overall energy efficiency is maximized. Based on this fact, we can first relax constraint (4) and (5) and then adjust the values of  $f_i(t)$  and  $P_i(t)$  to obtain a feasible solution that makes  $\epsilon_i^L(t) = \epsilon_i^O(t)$ . A similar technique is also used to decouple the WPT and computation offloading variables in constraint (9). After relaxing constraints (4), (5), and (9), the optimization problem of minimizing the right-hand side of (13) can be decomposed into three subproblems by classifying variables into independent groups. In our algorithm, we first compute solutions for these subproblems and then adjust their values according to the optimality conditions. The details of our algorithm are described as follows.

1) **WPT:** We compute the WPT-related control variables by solving the following subproblem

$$\min \sum_{j=1}^M \left( V - \sum_{i=1}^N B_i^-(t) \mu_i h_{ij}^D(t) \right) a_j^T(t) P_j^T(t) \tau_j^T(t) \quad (15)$$

subject to constraints (1) and (10). Note that we have relaxed the time allocation constraint (9). This problem is derived by substituting (2) and (3) into (13) and group WPT-related terms together. The next two subproblems are derived in a similar way. The optimization problem (15) is linear and can be solved analytically. Let  $c_j^T(t) = V - \sum_{i=1}^N B_i^-(t) \mu_i h_{ij}^D(t)$  be the coefficient of  $a_j^T(t) P_j^T(t) \tau_j^T(t)$ . If  $c_j^T(t) \geq 0$  for all  $j$ , then the optimal value is obtained by setting all  $a_j^T(t)$  to 0. Otherwise, find  $j^* = \arg \min c_j^T(t) P_j^{T,max}$  and the solution is  $a_{j^*}^T(t) = 1$ ,  $P_{j^*}^T(t) = P_{j^*}^{T,max}$ ,  $\tau_{j^*}^T(t) = T$ .

2) **Local Computation:** The only variable for local computation is the CPU frequency of WDs. By relaxing constraints

(4) and (5), we get the following subproblem

$$\min \sum_{i=1}^N B_i^-(t) \kappa_i f_i^3(t) T - \sum_{i=1}^N Q_i(t) \frac{f_i(t) T}{\phi_i} \quad (16)$$

where  $f_i(t)$  is subject to constraint (12). This problem can be further divided into  $N$  subproblems because the variable  $f_i(t)$  is independent with each other. As a result, the problem can be solved analytically and the optimal value of  $f_i(t)$  is obtained at either the boundary points or the stationary point of (16), which is given by

$$f_i(t) = \min \left\{ f_i^{max}, \sqrt{\frac{Q_i(t)}{3\kappa_i \phi_i B_i^-(t)}} \right\}.$$

3) *Computation Offloading*: The optimal time allocation of computation offloading can be derived by solving

$$\min \sum_{j=1}^M \sum_{i=1}^N V \eta a_{ij}(t) \phi_i D_i^O(t) - \sum_{i=1}^N Q_i(t) D_i^O(t) + \sum_{i=1}^N B_i^-(t) P_i(t) \tau_i(t) \quad (17)$$

s.t. (8), (11)

$$\sum_{i=1}^N a_{ij}(t) \tau_i(t) \leq T \quad \forall j, \forall t \quad (18)$$

where we have used a relaxed time allocation constraint (18) instead of (9). This mixed integer programming problem is non-convex and has no efficient algorithms in general. To solve this problem efficiently, we devised an iterative heuristic algorithm based on the Alternating Minimization method and Hungarian algorithm. We showed the computed solution converges to local minima. Due to space limitation, please see our technical report [17] for more detailed description.

4) *Adjust Variable Values*: If the variable values computed in previous steps satisfy constraint (4), (5), and (9), then we can skip this step. Otherwise, we have to adjust their values to obtain a feasible solution. As described earlier, our intuition is to equalize the marginal benefits of variables constrained by the same resource.

Let us first consider the case where WDs have sufficient queueing data so constraint (5) is redundant. Without loss of generality, we can assume the energy causality constraint (4) is tight. Let  $\epsilon_i^L(t) = \epsilon_i^O(t)$ , we can express the local CPU frequency  $f_i(t)$  with respect to the offloading power  $P_i(t)$

$$f_i(t) = \sqrt{\sum_{j=1}^M \frac{a_{ij}(t) v_i \ln 2}{3\kappa_i \phi_i B} \cdot \left( \frac{\sigma_j^2}{h_{ij}^U(t)} + P_i(t) \right)} + \frac{\eta}{3\kappa_i}. \quad (19)$$

Suppose AP  $j^*$  is the one that broadcasts RF energy in time slot  $t$  and let  $\mathcal{N}^*(t)$  denote the set of WDs that offload data to AP  $j^*$ , i.e.,  $a_{ij^*}(t) = 1$  and  $\tau_i(t) > 0$  for all  $i \in \mathcal{N}^*(t)$ . If WD  $i$  does not belong to  $\mathcal{N}^*(t)$ , which means it communicates with some other AP  $j$  such that  $a_j^T = 0$ , then the time allocation constraint (9) of  $\tau_i(t)$  reduces to (18). Therefore, the time allocation computed in Section III-B3 is feasible and no need for adjustment. Thus, we only need to adjust the values of

$f_i(t)$  and  $P_i(t)$  by solving

$$E_i^L(t) + E_i^O(t) = B_i(t), \quad (20)$$

which results in

$$P_i(t) = \frac{B_i(t) - \kappa_i f_i^3(t) T}{\tau_i(t)}. \quad (21)$$

For WDs in  $\mathcal{N}^*(t)$ , we first re-allocate the WPT time  $\tau_{j^*}^T(t)$  and offloading time  $\tau_i(t)$ ,  $i \in \mathcal{N}^*(t)$ . According to (15) and (17), the marginal cost of  $\tau_{j^*}^T(t)$  is  $c_{j^*}^T(t) P_{j^*}^{T,max}$  and the marginal cost of  $\tau_i(t)$  for all  $i \in \mathcal{N}^*(t)$  is

$$\begin{aligned} & \frac{\partial (V \eta \phi_i D_i^O(t) - Q_i(t) D_i^O(t) + B_i^-(t) P_i(t) \tau_i(t))}{\partial \tau_i(t)} \\ &= \frac{(V \eta \phi_i - Q_i(t)) B}{v_i} \log_2 \left( 1 + \frac{P_i(t) h_{ij^*}^U(t)}{\sigma_{j^*}^2} \right) + B_i^-(t) P_i(t). \end{aligned} \quad (22)$$

By substituting (21) into (22), the marginal cost of  $\tau_i(t)$  is a function of itself. Due to the optimality condition, we can compute the new time allocation by equalizing the marginal cost of  $\tau_i(t)$  and  $\tau_{j^*}^T(t)$ . After that, the values of  $P_i(t)$  and  $f_i(t)$  for WDs in  $\mathcal{N}^*(t)$  are adjusted just like other WDs.

For cases where the remaining energy in the battery is adequate to handle all the queueing data in WDs, the data constraint (5) is tight and the energy constraint (4) is redundant. As a result, we can repeat the above procedures by replacing (20) with  $D_i^L(t) + D_i^O(t) = Q_i(t)$ .

#### IV. SIMULATION RESULTS

In this section, we evaluate the proposed algorithm through simulations and compare its performance with the following two benchmark schemes:

- *Local Computation Only (LCO) scheme*: the computation data of WDs are processed locally;
- *Fully Offloading (FO) scheme*: the computation data of WDs are fully offloaded to the APs.

Similar to our algorithm, we optimize the control decisions for these two schemes based on the Lyapunov optimization, so their performance is also associated with the parameter  $V$ .

We consider a WP-MEC network with  $N = 30$  WDs and  $M = 5$  APs. The simulation settings are selected based on the works in [12] and [9]. The duration of each slot is  $T = 100ms$  and  $\lambda_i = 30kb$  (kilobits). The maximum WPT power for each AP is  $P_j^{T,max} = 4W$  and the maximum offloading power for each WD is  $P_i^{max} = 0.3W$ . The maximum CPU frequency and battery capacity of each WD are  $f_i^{max} = 1GHz$  and  $B_i^{max} = 10J$ , respectively. As in [12], all the channels follow Rayleigh fading and the mean values of  $h_{ij}^U$  and  $h_{ij}^D$  are 0.1 and 0.2, respectively. The other parameters used in our simulations are  $B = 0.1MHz$ ,  $\mu_i = 0.51$ ,  $\kappa_i = 10^{-27}$ ,  $v_i = 1.1$ ,  $\phi_i = 1000 \text{ cycles/bit}$ , and  $\sigma_j^2 = 10^{-9}W$ .

The impact of control parameter  $V$  on the system energy consumption and average delay are demonstrated in Fig. 2 and Fig. 3, respectively. In all algorithms, the energy consumption decreases with  $V$  and the average delay grows with  $V$ , which is in accordance with the energy-delay tradeoff of Lyapunov

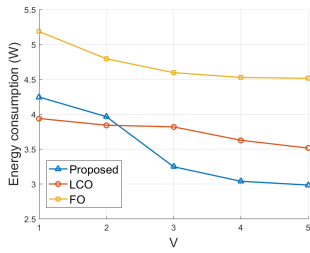


Fig. 2. System energy consumption vs. parameter  $V$ .

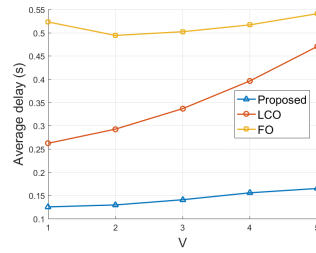


Fig. 3. Average delay vs. parameter  $V$ .

optimization. As shown in Fig. 2, the energy consumption of the proposed algorithm is slightly higher than LCO when  $V$  is small, but is significantly better than the other two when  $V$  is large. Meanwhile, the average delay induced by our algorithm outperforms the two benchmarks in all cases. This is because our algorithm performs local computation and computation offloading simultaneously, thus resulting in higher process rate and better energy efficiency.

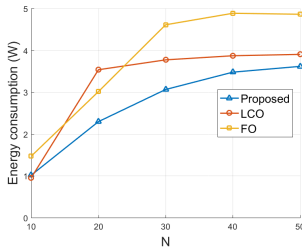


Fig. 4. System energy consumption vs. number of WDs.

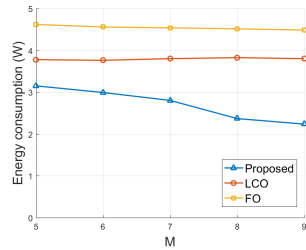


Fig. 5. System energy consumption vs. number of APs.

In addition to the varying parameter  $V$ , we also conducted simulations under distinct network scales. The system energy consumption under different number of WDs and different number of APs are presented in Fig. 4 and Fig. 5. The default value of  $V$  is set to 3 in all simulations. The growth of  $N$  means there are more data to be processed in the system, thus results in higher energy consumption. When  $N = 40$ , APs already operate at the peak WPT power in FO but we still observed an extremely large average delay. We analyzed the run-time data and found that the generated workload exceeds the system capacity. This also explains why the energy consumption of FO does not increase when  $N$  grows from 40 to 50. In Fig. 5, the energy consumption of FO decreases with respect to  $M$  because WDs can choose closer APs to offload their computation tasks. However, the improvement on LCO is very limited. In both situations, our algorithm can utilize the advantages of both local computation and computation offloading, thus achieves the minimal energy consumption and average delay.

## V. CONCLUSIONS

In this paper, we investigate the computation scheduling problem in WP-MEC networks with multiple APs. To minimize energy consumption, we propose an online algorithm that jointly optimizes the resource allocation in WPT and

computation scheduling. The time complexity of our algorithm is significantly reduced via the relax-then-adjust technique and the Alternating Minimization method. Simulations are conducted to validate the performance of our algorithm.

## VI. ACKNOWLEDGEMENT

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