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Posted Date: 19 September 2024

doi: 10.20944/preprints202408.1532.v2

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Article

User-Cooperative Dynamic Resource Allocation for Backscatter-Aided Wireless-Powered MEC Network

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Abstract: Backscatter communication, which transmits information by passively reflecting radio frequency (RF) signals, has become a focal point of interest due to its potential to significantly enhance the energy efficiency of Wireless Power Mobile Edge Computing (WPMEC) networks and extend the operational lifespan of terminal devices. However, there is little research on the integration of user cooperation in WPMEC scenarios within volatile network environments. In this paper, we propose a dynamic task offloading scheme for a Backscatter-assisted WPMEC system, which involves two mobile devices (MDs) and a Hybrid Access Point (HAP) with user cooperation. We formulate the energy efficiency (EE) maximization problem as a stochastic programming problem, considering the randomness of task arrivals and time-varying wireless channels. By leveraging Dinkelbach's method and stochastic network optimization technique, we transform the problem into a series of deterministic sub-problems for each time slot, and convert the non-convex sub-problem into convex ones. We propose a low-complex EE maximization algorithm to solve the convex problems efficiently. Extensive simulations are conducted to validate the performance of our algorithm under various system parameter settings. Experimental results demonstrate that our algorithm not only outperforms the benchmark algorithms by approximately 23%, but also stabilize all queues within the MEC system.

Keywords: Mobile edge computing (MEC); Wireless Power Transfer (WPT); User Cooperation (UC), backscatter communication (BackCom); Lyapunov optimization

1. Introduction

In recent years, the development of the Internet of Things (IoT), complemented by advancements in communication technologies, has enabled a vast array of mobile devices (MDs)—including cameras, sensors, and wearable devices—to collect and exchange data [1]. This proliferation has given rise to numerous application scenarios that leverage wireless devices, such as autonomous driving, face recognition, Virtual Reality (VR), and e-health [2]. However, these applications often demand substantial computational power and low latency, presenting challenges for MDs, which typically have limited computing capabilities and finite battery life. Mobile Edge Computing (MEC) has risen as a promising solution to these challenges. By offloading computationally intensive tasks to MEC servers, MDs with constrained resources can markedly enhance their computational capacity and reduce latency.

However, wireless devices often have limited battery capacity, which cannot sustain prolonged operation. Consequently, the frequent replacement of MDs' batteries presents a significant challenge. Wireless Power Transfer (WPT) has emerged as an effective solution to this challenge [3,4]. WPT utilizes a Hybrid Access Point (HAP) to broadcast Radio Frequency (RF) energy that can be harvested by wireless devices. By integrating Energy Harvesting (EH) technology, these devices can convert the captured RF signals into usable electrical energy, thereby recharging their batteries [5]. This harvested energy enables the devices to perform computational tasks either locally or by offloading them to MEC

servers. The integration of wireless power and edge computing technologies in Wireless Powered Mobile Edge Computing (WPMEC) networks significantly extends the battery lifespan of wireless devices and markedly enhances their computational capabilities.

In addition to battery limitations, the double-near-far effect can significantly impact network performance, with devices far from the HAP experiencing poor channel conditions [6]. To counteract this issue, a user cooperation (UC) mechanism has been implemented. In this mechanism, devices that are in close proximity to the HAP act as relays, forwarding signals for those located at a greater distance. This strategy not only mitigates the inefficiency of remote nodes offloading tasks directly to the Access Point (AP) but also optimizes the utilization of idle computational resources within the network, thereby enhancing the overall computational efficiency of the system. For example, the work in [7] demonstrates how user cooperation can boost the computational efficiency of a WPMEC system under dynamic channel conditions and varying task arrivals. Additionally, other studies, such as [8,9], have shown that user cooperation can effectively reduce the impact of the double-near-far effect. However, the aforementioned studies have not yet explored the potential of Backscatter technology to improve energy efficiency further.

Backscatter communication (BackCom) has garnered significant attention in recent years due to its innovative approach to wireless communication [10]. In BackCom systems, the transmitter operates in full-duplex mode, functioning in a passive mode. It modulates and reflects the incident signal to the receiver, eliminating the need to generate a carrier frequency, while simultaneously harvesting energy to support its circuitry consumption [11,12]. This approach contrasts with traditional active communication (AC), where the transmitter first harvests energy and then uses this harvested energy to transmit data, adhering to the harvest-then-transmit (HTT) protocol. Generally, AC consumes more energy than BackCom, although it can achieve a higher data transfer rate. The trade-offs between EH and data transfer are inherent in both BackCom and AC.

The motivation behind this study stems from the recognition that while integrating BackCom and AC paradigms has shown promise in enhancing the energy efficiency (EE) of WPMEC systems [8,13], current research is predominantly confined to static, single-time slot scenarios. These studies often assume constant channel conditions and user data arrivals, which contrasts sharply with the dynamic, stochastic nature of real-world MEC networks where data arrivals and channel states are subject to continuous variation. This volatility complicates the prediction and management of network operations, thereby necessitating the development of robust algorithms capable of optimizing long-term energy utilization efficiency and maintaining system queue stability. Addressing these challenges is not only of theoretical interest but also of paramount practical importance, as it directly impacts the sustainability and reliability of MEC services in fluctuating operational environments. Our study, therefore, aims to bridge this gap by proposing an algorithmic framework that can adeptly navigate the complexities of volatile network conditions, ensuring optimal energy efficiency and queue stability in WPMEC networks.

In this paper, we tackle the long-term EE maximization for a Backscatter assisted WPMEC network with user cooperation by jointly optimizing the wireless powered time fraction, BackCom offloading time fraction, AC offloading time fraction, offloading data size and transfer power of MDs. The problem presents significant challenges in two aspects: (1) The randomness of task arrivals and fluctuating wireless channel states impose challenges to achieving optimal EE while ensuring the stability of queue system; (2) The integration of BackCom and AC brings a strong coupling of energy harvest time and task offloading. To address these challenges, we formulate a stochastic optimization problem and propose an efficient, low-complexity algorithm by leveraging techniques such as the Dinkelbach method and the Lyapunov optimization framework. We first transform the sequential decision problem into a deterministic problem for each time slot by leveraging the drift-plus-penalty technique, obtaining a non-convex optimization sub-problem. Then, we convert the non-convex problem into a convex optimization problem by using variable substitution, which allows for efficient

solution. We propose a low-complexity dynamic EE maximization algorithm that operates online without requiring prior system information.

The primary contributions of this paper are listed as follows:

- We introduce an innovative dynamic task offloading model to optimize EE for a WPMEC network with integration of BackCom and AC communication under user cooperation, taking into account the randomness of task arrival and time-varying wireless channels. Our model effectively balances the trade-off between energy efficiency and system queues stability, while mitigating the double-near-far effect. Additionally, we explore the use of variable data weighting to motivate proximal users to relay data for distant users, enhancing overall network efficiency.
- We propose an online control algorithm to maximize the EE metric of WPMEC network by determining the time fraction allocation, data offloading, transmission power and the Backscatter reflection coefficients at each time slot. To address the complex coupling of user cooperation and control decisions over time, we employ Dinkelbach's method and the Lyapunov optimization theory to decouple the stochastic fractional optimization problem into deterministic sub-problems for each time slot, and transforms it into a convex problem, ensuring an efficient and optimal solution.
- We present a rigorous mathematical analysis to demonstrate the performance of our proposed algorithm, that achieves a balanced trade-off between energy efficiency and queue stability within the bounds of $[O(1/V), O(V)]$. Extensive simulation experiments are conducted to verify the algorithm's effectiveness and practical applicability. We have systematically evaluated the impact of key control parameters, including variable V , bandwidth, communication gap, and task arrival rates, on the algorithm's performance.

The remainder of this paper is organized as follows: Section II presents the details of model for Backscatter-assisted WPMEC system. In Section III, we formulate a stochastic programming optimization problem aiming to maximize energy efficiency. Section IV details the application of the Dinkelbach's method and Lyapunov optimization techniques to simplify the problem, including the algorithm design and theoretical performance analysis. Section V presents an extensive simulation-based evaluation of the proposed algorithm's performance. Finally, we conclude the paper and suggest directions for future research in Section VI.

1.1. Related Work

The combination of WPT with MEC networks, as an efficient solution for wireless devices to augment their energy and computational capacities, has been extensively studied by recent researches [14–17]. Ernest and Madhukumar [18] proposed an energy efficiency maximization algorithm based on multi-agent deep reinforcement learning for a MEC-supported vehicular network, with jointly considering transmission and computation latencies outperforming existing strategies. Zhang *et al.* [19] proposed an algorithm optimizing charging time and data offloading rates for WPT-MEC IoT sensor networks to improve computational rates in different scenarios. Li *et al.* [5] studied the system latency minimization problem for an Intelligent Reflecting Surfaces (IRS)-assisted multi-ID MEC system, and presented a hybrid multiple access scheme and optimization framework combined with Frequency Division Multiple Access (FDMA) and Non-Orthogonal Multiple Access (NOMA) technologies. Additionally, in [20], the authors introduced a deep reinforcement learning-based approach for WPT-aided mobile edge computing to dynamically adapt to real-time changes, make swift decisions, and optimize both task offloading and energy resource allocation. Our previous research [7] introduced an online control algorithm for dynamic task offloading in WPMEC networks under dynamic network conditions, designed to maximize long-term system energy efficiency. However, the aforementioned studies did not take into account the use of Backscatter technique to further enhance the energy utilization efficiency of wireless power transfer.

To mitigate the double-near-far effect and fully utilize available resources, many researchers employ a user cooperation mechanism [7,9,21–23]. He *et al.* [22] presented a user cooperation scheme,

aiming to maximize the network's total throughput by jointly optimizing the local computing frequency, transmit power, task distribution, and time allocation. Wang *et al.* [21] introduced a user cooperation mechanism for a NOMA assisted WPT-MEC network, designed a iterative-based optimal algorithm to minimize overall system energy consumption by leveraging Lagrangian method. Zhang *et al.* [24] presents a hierarchical reinforcement learning-based approach for joint caching and resource allocation in a cooperative mobile-edge computing system, aiming to optimize resource utilization and balance server loads through service caching and workload offloading decisions. Sun *et al.* [25] proposed an iterative optimization algorithm for minimizing end-to-end latency in an MEC network supporting IoT applications, by jointly optimizing user association and resource allocation in a three-phase operation protocol. Su *et al.* [9] explored optimizing the energy beamforming and resource allocation to enhance computation efficiency for WPMEC system with the integration of user cooperation and NOMA, taking into account non-linear energy harvesting model.

In recent years, the integration of BackCom and active communication(AC) has emerged as an effective approach to enhance network energy efficiency, leveraging the unique characteristics of Backscatter technology to balance transmission rates and energy consumption, thereby significantly improving the system's overall performance [8,26–29]. Lyu *et al.* [30] introduces a hybrid HTT and BackCom framework for cognitive wireless powered IoT networks, optimizing time allocation and mode combination to maximize system throughput. Ye *et al.* [27] introduced a bisection-based iterative algorithm for minimizing data offloading and computing delays in a WPMEC network with hybrid BackCom and AC for IoT networks. Shi *et al.* [31] proposed a scheme for maximizing the weighted sum of computation bits in a Backscatter-assisted WPMEC network, considering a practical non-linear EH model with hybrid HTT and Backscatter communications. Wu and He [26] proposed an efficient iterative algorithm for EE maximization in a multi-access WPMEC system with the help of a relay. Lin *et al.* [32] presents an optimization framework for a BackCom NOMA system, aiming to maximize the sum uplink rate by optimizing reflection coefficients and establishing association policies between base stations and backscatter devices. Fu *et al.* [33] addressed the energy efficiency fairness among IoT nodes in a UAV-enabled WPMEC network with integrated BackCom and AC, proposed an optimization framework that maximizes the worst-case IoT node's energy efficiency by jointly optimizing UAV transmit power and trajectory, IoT nodes' BackCom and AC parameters, and local computing configurations. However, the aforementioned studies primarily focus on optimizing a single time slot and do not account for the dynamic fluctuations inherent in MEC network environments.

Different from the above research, this paper addresses the problem of hybrid communication modes (e.g., BackCom and AC) and user cooperation for EE maximization in the volatile WPMEC network, without any information about the future. Compared to [8], our approach considers both nodes capable of processing their own incoming data simultaneously, and we introduce weighted incentives to motivate proximal nodes to assist distant nodes in offloading computational tasks. We account for dynamic factors, including random task arrivals and fluctuating wireless channel states, the prior knowledge of which is difficult to pinpoint accurately, making task offloading and resource allocation significantly challenging. Moreover, the coupling between dynamic battery levels and wireless charging time further complicates the problem.

2. System Model

We consider a typical WPTMEC network that comprises two MDs and a HAP, depicted as Figure 1. The HAP directly connects with an MEC server to provide computation task offloading services and equipped with an RF energy transmitter to support wireless power to MDs. MD₁, one of the MDs, is located at a significant distance from the HAP. In contrast, MD₂, the second MD, is in a more advantageous position due to its proximity to the HAP and acts as an intermediary. Both MD₁ and MD₂ are equipped with both a BackCom circuit and an AC circuit, enabling them to select between backscatter and active communication modes.

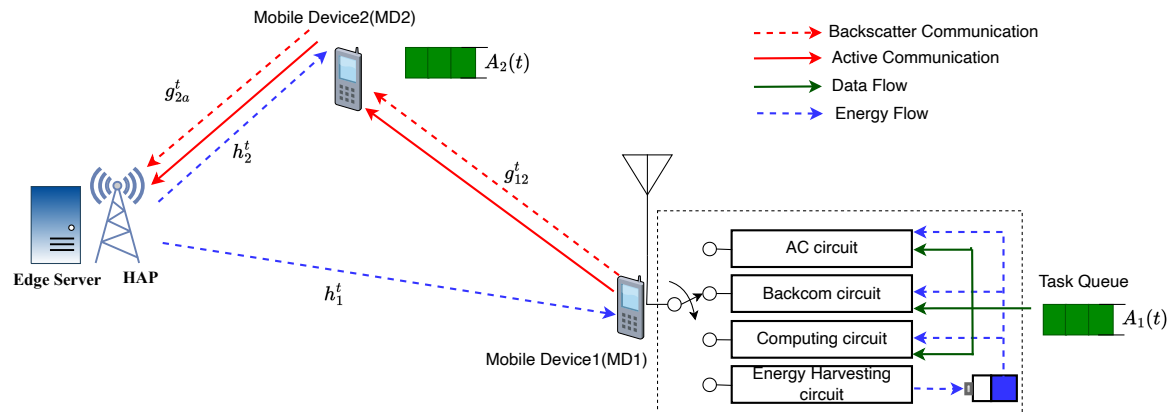


Figure 1. System model of WPMEC network with user-assisted

The WPMEC system employs a Time Division Duplex (TDD) method to alternate between communication and energy harvesting phases. Time Division Multiple Access (TDMA) technique is utilized to avoid signal interference [34]. The WPMEC system operates in a discrete time-slot mode over a time horizon period, with each time slot set to last T seconds. As depicted in Figure 2, each time slot is further divided into five time fractions dedicated to energy harvesting and task processing for the different MDs. At the start of each time slot, both MDs initiate the capture of RF signals transmitted by the HAP for the purpose of energy harvesting. A partial offloading strategy is adopted, which permits the flexible offloading of a portion or the complete set of computational data to a remote device. Owing to the terrible channel conditions between the MD₁ and the HAP, along with the compounded near-far effect, directly offloading tasks to HAP is infeasible for the MD₁, such that the MD₁ offloads tasks to the MD₂, and the MD₂ then forwards them to HAP.

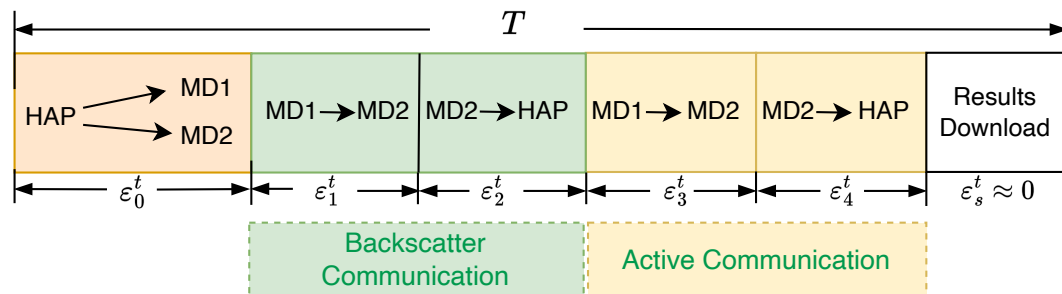


Figure 2. Time division structure

Both MDs are equipped with BackCom and AC circuits for task offloading during the communication process. At each time slot, the BackCom mode firstly is used for tasks offloading. During intervals ε_1^t and ε_2^t , computation tasks data from the remote device MD₁ are offloaded to MD₂, which then offloads these task data to the HAP. Similarly, during intervals ε_3^t and ε_4^t , the offloading process is carried out using the AC mode. In the final time allocation ε_s^t , because the computation result data is typically small, this time slot can be considered negligible and ignored.

The primary symbols and definitions used are listed in Table 1.

Table 1. Summary of Key Notations.

Notation	Definition
T	The time block
ε_0^t	The time for WPT at slot t
$\varepsilon_1^t, \varepsilon_2^t$	The time for offloading by BackCom of MD ₁ and MD ₂ at slot t
$\varepsilon_3^t, \varepsilon_4^t$	The time for offloading by AC of MD ₁ and ND ₂ at slot t
E_i^t	The energy harvested by MD _{i} at slot t
h_i^t	The WPT channel gain between MD _{i} and HAP at slot t
g_{12}^t, g_{2a}^t	The offloading channel gain between MD ₁ and MD ₂ , MD ₂ and HAP at slot t
P_0^t, P_1^t, P_2^t	The transmit power by AC at HAP, MD ₁ , MD ₂ at slot t
p_i^{ba}, p_i^{ac}	The circuit power by BackCom and AC at MD _{i}
$d_{i,loc}^t$	The amount of tasks processed locally at MD _{i} at slot t
$d_{i,ba}^t$	The amount of tasks offloaded by BackCom at MD _{i} at slot t
$d_{i,ac}^t$	The amount of tasks offloaded by AC at MD _{i} at slot t
$H_i^{loc,t}$	The energy consumed by processing tasks locally at MD _{i} at slot t
$H_{i,ba}^t$	The energy consumed by offloading tasks by BackCom at MD _{i} at slot t
$H_{i,ac}^t$	The energy consumed by processing tasks at helper at slot t
$E_{i,wp}^t$	The energy harvested by WPT at MD _{i} at slot t
$E_{i,ba}^t$	The energy harvested by Bakcom at MD _{i} at slot t
$d_{i,off}^t$	The amount of tasks of MD _{i} processed by offloading at slot t
f_i	The local CPU frequency at MD _{i}
ϕ_i	The CPU cycles required to compute one bit task at MD _{i}
β_i^t	The reflection coefficient of MD _{i} at slot t
μ	The energy conversion efficiency
κ	The computing energy efficiency
W	The channel bandwidth
σ^2	The additive white Gaussian noise

2.1. Energy Harvesting Model

The HAP, equipped with a reliable power source, is responsible for the transmission of RF energy to the MDs dispersed within its service area. In the initial phase, the HAP broadcasts RF signals to all MDs for a duration of ε_0^t . Subsequently, MD₁ offloads tasks to MD₂ during the time fraction ε_1^t using BackCom, while MD₂ can simultaneously harvest energy. In a similar fashion, MD₂ offloads tasks to the HAP during the time fraction ε_2^t using BackCom, and MD₁ harvests energy. Let $E_{1,wp}^t$ and $E_{2,wp}^t$ denote the harvested energy of MD₁ and MD₂ in the first phase, respectively. Thus, we have [8]

$$E_{1,wp}^t = \mu h_1^t P_0 (\varepsilon_0^t + \varepsilon_2^t)$$

(1)

and

$$E_{2,wp}^t = \mu h_2^t P_0 (\varepsilon_0^t + \varepsilon_1^t)$$

(2)

where $0 < \mu < 1$ represents the energy conversion efficiency, P_0 denotes the RF transmission power of the HAP. h_1^t and h_2^t represent the channel gains from the HAP to MD₁ and MD₂ respectively, which remain constant within the same time slot and vary across different time slots.

2.2. Dynamic Queues Model

To simulate the dynamic changes in user task data arrival and node battery levels, we have introduced the dynamic queuing model. Both MD₁ and MD₂ maintain a buffer queue for caching incoming task data, which is processed on a first-in, first-out (FIFO) principle. Let $Q_i(t), i \in \{1, 2\}$ denote the queue lengths of MD₁ and MD₂ at time slot t , respectively, which can be observed at the beginning of the time slot. The backlog of task queue $Q_i(t)$ updates as follows:

$$Q_i(t+1) = \max \left[Q_i(t) - \left(d_{i,loc}^t + d_{i,off}^t \right), 0 \right] + A_i(t), i \in \{1, 2\} \quad (3)$$

where $A_i(t)$ represents the raw task data arriving at the MD_i data queues during time slot t . We assume that the task arrival is an arbitrary process over time, there is an upper-bound by A_{max} . $d_{i,loc}^t$, $d_{i,off}^t$ represent the offloading task data and the local processing data at MD_i, respectively.

Similarly, we assume that MD nodes are equipped with batteries and maintain a battery energy level queue. The energy captured through wireless charging is first stored in the batteries, and the battery power is consumed for local computing and task offloading. Concurrently, the battery energy level has an upper limit B_{max} and a lower limit B_{min} . The B_{min} level is essential to sustain the basic operations of the MD IoT system [34]. Therefore, the battery energy of the MD nodes dynamically changes according to the following equation

$$B_i(t+1) = \min \left\{ \max \left[B_i(t) - H_{i,loc}^t - H_{i,off}^t, B_{min} \right] + E_i^t, B_{max} \right\} \quad (4)$$

where $H_{i,loc}^t$ and $H_{i,off}^t$ represent the energy consumption for local computing and task offloading, respectively. The total energy harvested by MD_i at slot t is given by $E_i^t = E_{i,wp}^t + E_{i,ba}^t$, where $E_{i,wp}^t$ is as previously defined, and $E_{i,ba}^t$ denotes the energy harvested during BackCom data transmission.

2.3. Local Computing Model

Upon task arrival at a node, local processing is prioritized; task offloading is considered only when local processing is not feasible. Since each MD is equipped with a battery, the maximum duration for local computation is denoted by T . Let f_1 and f_2 denote the local CPU frequencies of MD₁ and MD₂, ϕ_1 and ϕ_2 denote the CPU cycles required to process one bit of task at the MD₁ and MD₂, respectively. Furthermore, the maximum amount of local computation data at MD_i cannot exceed the current backlog of $Q_i(t)$. Thus, the amount of locally computed task data can be expressed as

$$d_{i,loc}^t = \min \left\{ Q_i(t), \frac{f_i T}{\phi_i} \right\}, i \in \{1, 2\} \quad (5)$$

and the corresponding energy consumption is [8]

$$H_{i,loc}^t = \min \left\{ \kappa_i(f_i)^2 Q_i(t) \phi_i, \kappa_i(f_i)^3 T \right\}, i \in \{1, 2\} \quad (6)$$

where κ_i denotes the computing energy efficiency parameter of MD_i [8]. The expression $\kappa_i(f_i)^2 Q_i(t) \phi_i$ represents the power consumption used for processing all current task data in queue $Q_i(t)$. Note that if the local processing capacity of MD_i exceeds the current backlog of $Q_i(t)$, then the amount of task for local computing is $Q_i(t)$ and the processing time is $\frac{Q_i(t) \phi_i}{f_i}$, so we can derive the energy consumption for local computing as $\kappa_i(f_i)^3 \frac{Q_i(t) \phi_i}{f_i} = \kappa_i(f_i)^2 Q_i(t) \phi_i$; otherwise, the amount of task is $f_i T / \phi_i$, with the corresponding energy consumption being $\kappa_i(f_i)^3 T$ as in [14].

2.4. Task Offloading Model

2.4.1. BackCom Data Transmission

During ε_1^t , MD₁ offloads tasks to MD₂ by BackCom. Let $0 \leq \beta_1 \leq 1$ denote the reflection coefficient of MD₁, where β_1 represents the fraction of the received signal that is utilized as a carrier for data transfer, and the remaining fraction $(1 - \beta_1)$ is allocated for energy harvesting [35]. Let g_{12}^t represent the channel gain between MD₁ and MD₂. According to Shannon's theorem [36], the amount of tasks offloaded from MD₁ to MD₂ satisfies [8]

$$d_{1,ba}^t \leq \varepsilon_1^t W \log_2 \left(1 + \frac{\zeta \beta_1^t P_0 h_{12}^t g_{12}^t}{\sigma^2} \right) \quad (7)$$

where ζ represents the performance gap reflecting real modulation [11], σ^2 is the noise power. The corresponding energy consumption by circuit is

$$H_{1,ba}^t = P_1^{ba} \varepsilon_1^t \quad (8)$$

where P_1^{ba} is the circuit power consumption of MD₁ by BackCom, which is a constant value depending on the circuit structure. Due to utilizing BackCom technology, data transmission and energy harvesting can be performed simultaneously. Thus, the energy harvested for MD₁ during ε_1^t is as [8]

$$E_{1,ba}^t = \mu h_1^t P_0 \varepsilon_1^t (1 - \beta_1^t) \quad (9)$$

After receiving the tasks offloaded from MD₁, MD₂ will relay a portion of these tasks to the HAP as a relay. Note that MD₂ will also offload its own tasks to the HAP. At time ε_2^t , the task data transmitted by MD₂ through BackCom is constrained as follows

$$d_{2,ba}^t \leq \varepsilon_2^t W \log_2 \left(1 + \frac{\zeta \beta_2^t P_0 h_2^t g_{2a}^t}{\sigma^2} \right) \quad (10)$$

where β_2^t is the reflection coefficient of the BackCom at MD₂. h_2^t represents the channel gain from the HAP to the MD₂ at time slot t , and g_{2a}^t denotes the channel gain from the MD₂ to the HAP at time slot t . The corresponding energy consumption is

$$H_{2,ba}^t = P_2^{ba} \varepsilon_2^t \quad (11)$$

where P_2^{ba} is the circuit power consumption of MD₂ by BackCom. The energy harvested by BackCom during ε_2^t is

$$E_{2,ba}^t = \mu h_2^t P_0 \varepsilon_2^t (1 - \beta_2^t) \quad (12)$$

2.4.2. AC Data Transmission

After the BackCom offloading is completed, the AC mode offloading is initiated, which proceeds through an offloading process similar to that of BackCom. The AC mode can achieve a higher data transmission rate, but it is incapable of energy harvesting during the offloading phase. During the time fraction ε_3^t , the upper limit of the amount of task from MD₁ offloading to MD₂ can be expressed as

$$d_{1,ac}^t \leq \varepsilon_3^t W \log_2 \left(1 + \frac{P_1^t g_{12}^t}{\sigma^2} \right) \quad (13)$$

where $0 \leq P_1^t \leq P_{\max}$ represents the transmit power allocated to AC at MD₁ [8], σ^2 is the noise power and g_{12} represents the channel gain from MD₁ and MD₂. The corresponding AC offloading energy consumption is

$$H_{1,ac}^t = (P_1^t + P_1^{ac}) \varepsilon_3^t \quad (14)$$

where P_1^{ac} denotes the circuit power of MD₁ through AC which is a constant value [8].

The upper limit of the amount task offloading from MD₂ to HAP by AC during ϵ_4^t is given by

$$d_{2,ac}^t \leq \epsilon_4^t W \log_2 \left(1 + \frac{P_{2,ac}^t}{\sigma^2} \right) \quad (15)$$

where $0 \leq P_2^t \leq P_{\max}$ denotes the transmit power of the MD₂ through AC. Let P_2^{ac} denote the circuit power of MD₂ through AC. The energy consumed for task offloading AC at MD₂ in slot t is

$$H_{2,ac}^t = (P_2^t + P_2^{ac}) \epsilon_4^t \quad (16)$$

2.5. Network Stability and Utility

For a dynamically changing WPMEC network system, maintaining system stability is crucial due to the stochastic arrival of tasks and the dynamic changes in the channel environment [37]. Therefore, we first provide the definition of system queue stability as follows.

Definition 1. (Queue Stability): A discrete task data queue $Q_i(t)$ is strong stable [37] if it satisfies

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=1}^K \mathbb{E}\{Q_i(t)\} < \infty, i \in \{1, 2\}$$

The energy efficiency of WPMEC system is defined as the ratio of the sum of weighted processed tasks to the total energy consumption. Specifically, the total accomplished tasks $D_{\text{tot}}(t)$ and the total energy consumption $E_{\text{tot}}(t)$ of WPMEC network at slot t can be represented as follows, respectively

$$D_{\text{tot}}(t) = \omega_1 (d_{1,loc}^t + d_{1,off}^t) + \omega_2 (d_{2,loc}^t + d_{2,off}^t) \quad (17)$$

and

$$H_{\text{tot}}(t) = H_{1,loc}^t + H_{1,off}^t + H_{2,loc}^t + H_{2,off}^t \quad (18)$$

where ω_1 and ω_2 represent the task weights of MD₁ and MD₂ respectively. $d_{i,off}^t = d_{i,ba}^t + d_{i,ac}^t$ represent the total offloading task data at MD_i, and $H_{i,off}^t = H_{i,ba}^t + H_{i,ac}^t$ represent the total energy consumption of offloading task at MD_i.

Definition 2. (Utility-Energy Efficiency): The network utility ρ_{EE} is defined as the time-averaged amount of computation data achieved per unit of energy consumed [38]. This is expressed as the ratio of the long-term processed data to the total energy consumption, as follows:

$$\rho_{EE} = \frac{\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{D_{\text{tot}}(t)\}}{\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{E_{\text{tot}}(t)\}} = \frac{\overline{D(t)}}{\overline{E(t)}} \quad (19)$$

3. Problem Formulation

In this paper, we aim to design a dynamic offloading algorithm to maximize the ρ_{EE} subject to constraints of the system queue stability, by making decisions on time allocation $\epsilon^t = [\epsilon_0^t, \epsilon_1^t, \epsilon_2^t, \epsilon_3^t, \epsilon_4^t]$, power allocation $\mathbf{P}^t = [P_1^t, P_2^t]$, reflection coefficients $\boldsymbol{\beta}^t = [\beta_1^t, \beta_2^t]$ and the amount of offloaded tasks $\mathbf{d}^t = [d_{1,ba}^t, d_{1,ac}^t, d_{2,ba}^t, d_{2,ac}^t]$ at each time slot t . Simultaneously, our algorithm should ensure the stability of the system network when faced with randomly arriving task loads and dynamically changing wireless channel conditions. By denoting $\boldsymbol{\epsilon} = \{\epsilon^t\}_{t=1}^K$, $\mathbf{P} = \{\mathbf{P}^t\}_{t=1}^K$, $\boldsymbol{\beta} = \{\boldsymbol{\beta}^t\}_{t=1}^K$, and $\mathbf{d} = \{\mathbf{d}^t\}_{t=1}^K$ the maximization of ρ_{EE} for a Backscatter-assisted WPMEC with user cooperation can be formulated as the following problem (P0):

$$P0 : \max_{\epsilon, P, \beta, d} \rho_{EE} \quad (20a)$$

$$\text{s.t. } \epsilon_0^t + \epsilon_1^t + \epsilon_2^t + \epsilon_3^t + \epsilon_4^t \leq T \quad (20b)$$

$$B_{\min} \leq B_i(t) - H_{i,\text{loc}}^t - H_{i,\text{off}}^t + E_i^t \leq B_{\max}, i \in \{1, 2\} \quad (20c)$$

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=1}^K \mathbb{E}\{Q_i(t)\} < \infty, i \in \{1, 2\} \quad (20d)$$

$$d_{i,\text{loc}}^t + d_{i,\text{off}}^t \leq Q_i(t), i \in \{1, 2\} \quad (20e)$$

$$d_{1,\text{off}}^t \leq d_{2,\text{off}}^t \quad (20f)$$

$$(7), (10), (13), (15) \quad (20g)$$

$$\epsilon_0^t, \epsilon_1^t, \epsilon_2^t, \epsilon_3^t, \epsilon_4^t \geq 0, \quad (20h)$$

$$0 \leq P_1^t, P_2^t \leq P_{\max} \quad (20i)$$

where constraint (20b) ensures that the total offloading time in each slot does not exceed the available time. Constraint (20c) maintains the battery levels within the allowable range for both mobile devices. Constraints (20d) guarantee the stability of data queues. Constraint (20e) indicates that the amount of processed task in the current time slot must not exceed the current queue length. Constraint (20f) guarantees that tasks offloaded by MD1 to MD2 can be processed within the same slot. Constraints in (20g) denote the maximum offloading data depending on the channel condition. The problem is a fractional stochastic programming issue, which presents significant challenges due to several aspects: (1) The randomness of task arrivals, the fluctuating wireless channel state, and the dynamic battery level introduce stochastic factors to the optimization challenge; (2) The temporal coupling in the time fraction and energy consumption exhibited by BackCom and AC poses a considerable challenge in determining the allocation of offloading time.

Due to the fractional nature of the objective function of P0, traditional optimization techniques aren't directly applicable, such that we leverage Dinkelbach's method [39] to transform the problem into a more tractable one. Let ρ_{EE}^* denote the optimal value of ρ_{EE} , we derive the following Theorem 1.

Theorem 1. The optimal ρ_{EE}^* is achieved if and only if

$$\max_{\epsilon, P, \beta, d} \overline{D(t)} - \rho_{EE}^* \overline{E(t)} = 0 \quad (21)$$

Proof. For brevity, here we omit the proof details. See Theorem 1 in [38]. $\square$

Since ρ_{EE}^* is unknown during the solution process, (20) is still infeasible to tackle. In accordance with the methodology employed in [38], we introduce a new parameter $u(t)$ and define it as

$$u(t) = \frac{1}{K} \sum_{t=1}^K \frac{D_{\text{tot}}(t)}{E_{\text{tot}}(t)} \quad (22)$$

We set $u(0) = 0$ at the beginning of the problem. Replacing $\rho_{EE}(t)$ in (20), the problem P1 can be transformed into

$$P1 : \max_{\epsilon, P, \beta, d} \overline{D(t)} - u(t) \overline{E(t)} \quad (23a)$$

$$\text{s.t. } (20b) - (20i) \quad (23b)$$

where $u(t)$ is a given parameter that should be updated through the resolution process. It should be noted that $u(t)$ obtained by (22) will get closer to ρ_{EE}^* as time goes by [38]. Therefore, this transformation is reasonable and has the same optimal solution as P0. While problem P1 is more manageable than

problem P0, it still faces several challenges. The constraints (20c) and (20d), along with the equation (4), result in an interdependence of battery levels across various time slots throughout the period, which means that the current energy consumption affects future battery levels. Moreover, the unpredictability of the stochastic task arrivals and the fluctuating channel states add another complexity to the problem. The difficulty in accurately forecasting these elements leads to an inherent temporal coupling in the decision-making process.

4. Algorithm Design

First, to decouple the battery energy level across time slots and ensure the stability of the task queue, we leverage the Lyapunov network optimization technique to eliminate the long-term average constraints.

4.1. Lyapunov Optimization Formulation

To simplify the battery energy queue at MD₁ and MD₂, we introduce two virtual queues for battery level: $\hat{B}_i(t) = B_i(t) - B_{\max}, i \in \{1, 2\}$. In order to optimize the task queue and the energy queue simultaneously, we define a combined queue vector $\Theta(t) \triangleq [Q_i(t), \hat{B}_i(t)], i \in \{1, 2\}$. Following Lyapunov optimization framework, we obtain the quadratic Lyapunov function and the Lyapunov drift [37] as

$$L(\Theta(t)) \triangleq \frac{1}{2} \sum_{i \in \{1, 2\}} (Q_i^2(t) + \hat{B}_i^2(t)) \quad (24)$$

and

$$\Delta(\Theta(t)) \triangleq \mathbb{E}\{L(t+1) - L(t) \mid \Theta(t)\} \quad (25)$$

According to the Lyapunov optimization theory [37], the one slot drift-plus-penalty expression can be expressed as

$$\Delta_V(\Theta(t)) = \Delta(\Theta(t)) - V\mathbb{E}\{D_{\text{tot}}(t) - u(t)E_{\text{tot}}(t) \mid \Theta(t)\} \quad (26)$$

where control parameter V is a positive value, used to balance the trade-off between network EE and network stability. Actually, V acts as a weighting factor of the cost optimality in the drift-plus-penalty expression. Increasing the value of V causes the algorithm to focus more on network EE, which may also result in a larger backlog of the task queue. We derive an upper bound of $\Delta_V(\Theta(t))$ as Lemma 1.

Lemma 1. For any control strategy $\{\epsilon, P, \beta, d\}$ at each time slot t , the one slot Lyapunov drift-plus-penalty $\Delta_V(\Theta(t))$ is bounded by the following inequality:

$$\begin{aligned} \Delta_V(\Theta(t)) &\leq B - V\mathbb{E}\{D_{\text{tot}}(t) - u(t)E_{\text{tot}}(t) \mid \Theta(t)\} \\ &\quad + \sum_{i \in \{1, 2\}} \left\{ Q_i(t) \mathbb{E}\{A_i(t) - d_{i,\text{loc}}^t - d_{i,\text{off}}^t \mid \Theta(t)\} + \hat{B}_i(t) \mathbb{E}\{E_i^t - H_{i,\text{loc}}^t - H_{i,\text{off}}^t \mid \Theta(t)\} \right\} \end{aligned} \quad (27)$$

where B is a constant value, which satisfies $\forall t$:

$$B \geq \frac{1}{2} \sum_{i \in \{1, 2\}} \left\{ \mathbb{E}\left\{ \left(d_{i,\text{loc}}^t + d_{i,\text{off}}^t \right)^2 + A_i^2(t) \mid \Theta(t) \right\} + \mathbb{E}\left\{ E_i^2 + \left(H_{i,\text{loc}}^t + H_{i,\text{off}}^t \right)^2 \mid \Theta(t) \right\} \right\} \quad (28)$$

Proof. By using the inequality $(\max[a - b, 0] + c)^2 \leq a^2 + b^2 + c^2 + 2a(c - b)$, $\forall a, b, c \geq 0$ and combining the definition of task queues and battery energy queues Eq. (3)-(4), we have

$$\begin{aligned}\Delta Q_i(t) &= \frac{1}{2} \left(Q_i(t+1)^2 - Q_i(t)^2 \right) \\ &\leq \frac{\left(d_{i,\text{loc}}^t + d_{i,\text{off}}^t \right)^2 + A_i^2(t)}{2} + Q_i(t) \left(A_i(t) - d_{i,\text{loc}}^t - d_{i,\text{off}}^t \right), i \in \{1, 2\}\end{aligned}\quad (29)$$

$$\begin{aligned}\Delta \widehat{B}_i(t) &= \frac{1}{2} \left(\widehat{B}_i(t+1)^2 - \widehat{B}_i(t)^2 \right) \\ &\leq \frac{1}{2} \left[E_i^2 + \left(H_{i,\text{loc}}^t + H_{i,\text{off}}^t \right)^2 \right] + \widehat{B}_i(t) \left(E_i^t - H_{i,\text{loc}}^t - H_{i,\text{off}}^t \right), i \in \{1, 2\}\end{aligned}\quad (30)$$

Combining the above inequalities (29) and (30), we obtain the upper bound of the Lyapunov drift-plus-penalty. $\square$

According to the drift-plus-penalty technique in Lyapunov optimization theory, we seek to greedily minimize the upper bound of $\Delta_V(\Theta(t))$ at each time slot t . Notably the value of $A(t)$, $Q_i(t)$ and $\widehat{B}_i(t)$ can be observed at the beginning of each time slot t . By eliminating the constant term in the RHS (right hand side) of (27), the problem P1 can be transformed into a one-time slot problem as

$$\begin{aligned}\text{P2.1 : } \min_{\varepsilon, P, \beta, d} \quad & - (Q_1(t) + \omega_1 V) \left(d_{1,\text{loc}}^t + d_{1,\text{off}}^t \right) - (Q_2(t) + \omega_2 V) \left(d_{2,\text{loc}}^t + d_{2,\text{off}}^t \right) \\ & + \left(Vu(t) - \widehat{B}_1(t) \right) \left(H_{1,\text{loc}}^t + H_{1,\text{off}}^t \right) + \left(Vu(t) - \widehat{B}_2(t) \right) \left(H_{2,\text{loc}}^t + H_{2,\text{off}}^t \right) \\ & + \widehat{B}_1(t) E_1^t + \widehat{B}_2(t) E_2^t\end{aligned}\quad (31a)$$

$$\text{s.t.} \quad (20b) - (20c), (20e) - (20i) \quad (31b)$$

Due to the coupling between the parameters ε , P and β , the proposed problem P2.1 is still a non-convex problem. To decouple these parameters, we introduce auxiliary variables $\varphi_1^t = P_1^t \varepsilon_3^t$, $\varphi_2^t = P_2^t \varepsilon_4^t$, $\varphi_3^t = \varepsilon_1^t \beta_1$, $\varphi_4^t = \varepsilon_2^t \beta_2$. Then the problem P2.1 can be simplified as:

$$\begin{aligned}\text{P2.2 : } \min_{\varepsilon, \varphi, d} \quad & - \sum_{i \in \{1, 2\}} C_i \left(d_{i,\text{loc}}^t + d_{i,\text{off}}^t \right) \\ & + C_3 P_1^{\text{ba}} + (C_3 P_1^{\text{ba}} + C_5 + C_6) \varepsilon_1^t + C_3 \varphi_1^t \\ & + C_4 H_{2,\text{loc}}^t + (C_4 P_2^{\text{ba}} + C_5 + C_6) \varepsilon_2^t + C_4 \varphi_2^t \\ & + (C_5 + C_6) \varepsilon_0^t - C_5 \varphi_3^t - C_6 \varphi_4^t + C_7 \varepsilon_3^t + C_8 \varepsilon_4^t\end{aligned}\quad (32a)$$

$$\text{s.t.} \quad \varepsilon_0^t + \varepsilon_1^t + \varepsilon_2^t + \varepsilon_3^t + \varepsilon_4^t \leq T \quad (32b)$$

$$B_{\min} \leq B_i(t) - H_{i,\text{loc}}^t - H_{i,\text{off}}^t + E_i^t \leq B_{\max}, i \in \{1, 2\} \quad (32c)$$

$$d_{i,\text{loc}}^t + d_{i,\text{off}}^t \leq Q_i(t), i \in \{1, 2\} \quad (32d)$$

$$d_{1,\text{ba}}^t + d_{1,\text{ac}}^t \leq d_{2,\text{ba}}^t + d_{2,\text{ac}}^t \quad (32e)$$

$$d_{1,\text{ba}}^t \leq \varepsilon_1^t W \log_2 \left(1 + \frac{\zeta P_0 h_1^t g_{12}^t \varphi_3^t}{\varepsilon_1^t \sigma^2} \right) \quad (32f)$$

$$d_{2,\text{ba}}^t \leq \varepsilon_2^t W \log_2 \left(1 + \frac{\zeta P_0 h_2^t g_{2a}^t \varphi_4^t}{\varepsilon_2^t \sigma^2} \right) \quad (32g)$$

$$d_{1,\text{ac}}^t \leq \varepsilon_3^t W \log_2 \left(1 + \frac{g_{12}^t \varphi_1^t}{\varepsilon_3^t \sigma^2} \right) \quad (32h)$$

$$d_{2,\text{ac}}^t \leq \varepsilon_4^t W \log_2 \left(1 + \frac{g_{2a}^t \varphi_2^t}{\varepsilon_4^t \sigma^2} \right) \quad (32i)$$

$$\varepsilon_0^t, \varepsilon_1^t, \varepsilon_2^t, \varepsilon_3^t, \varepsilon_4^t \geq 0, \quad (32j)$$

$$0 \leq \varphi_1^t, \varphi_2^t \leq P_{\max} T \quad (32k)$$

where $C_1 = Q_1(t) + \omega_1 V$, $C_2 = Q_2(t) + \omega_2 V$, $C_3 = Vu(t) - \widehat{B}_1(t)$, $C_4 = Vu(t) - \widehat{B}_2(t)$, $C_5 = \mu h_1^t P_0 \widehat{B}_1(t)$, $C_6 = \mu h_2^t P_0 \widehat{B}_2(t)$, $C_7 = C_3 P_1^{\text{ac}}$, $C_8 = C_4 P_2^{\text{ac}}$.

Lemma 2. *P2.2 is a convex optimization problem, which can be efficiently solved by convex optimization tools, such as CVX [40].*

Proof. In problem (P2.2), the objective function (32a) is linear with respect to all variables. Constraints (32b)-(32e) are all linear inequality constraints. What's more, for constraint (32f), $\log_2 \left(1 + \frac{\zeta P_0 h_1^t g_{12}^t \varphi_4^t}{\varepsilon_1^t \sigma^2} \right)$ is the perspective of $\log_2 \left(1 + \frac{\zeta P_0 h_1^t g_{12}^t \beta_1}{\sigma^2} \right)$ which is concave with respect to φ_4 . Since the perspective operation preserves convexity [41], $\varepsilon_1^t \log_2 \left(1 + \frac{\zeta P_0 h_1^t g_{12}^t \varphi_4^t}{\varepsilon_1^t \sigma^2} \right)$ is concave with φ_4 and ε_1^t and (32f) is a convex constraint. For the same reason, (32g)-(32i) are all convex constraints. Thus, P2.2 is a convex problem. $\square$

According to Lemma 2, at each time slot, we only need to solve a convex problem P2.2, which contains a small number of variables. By doing so, we can achieve optimal long-term average EE, even without knowledge of future system information. Our proposed algorithm, the Dynamic Offloading for Backscatter-Assisted WPMEC Algorithm (DOBAM), is summarized as Algorithm 1.

Algorithm 1: Dynamic Offloading for Backscatter-Assisted WPMEC Algorithm (DOBAM)

Input: the task arrival queue $A_i(t)$; the channel gain $\{h_i^t, g_{12}^t, g_{2a}^t\}$.

- 1 Initialize $t \leftarrow 0, Q_i(0), \hat{B}_i(0), u(0), \forall i \in \{1, 2\}$.
- 2 **for** $t = 1 : K$ **do**
- 3 Observe the current time slot system state: $A_i(t), h_i^t, g_{12}^t, g_{2a}^t$.
- 4 Determine $d_{i,loc}^t, e_{i,loc}^t$ based on the current queue length $Q_i(t)$ according to (5) and (6).
- 5 Calculate the coefficients $C_1 \sim C_8$ based on P2.2.
- 6 cvx_begin
- 7 Minimize P2.2
- 8 Subject to (32b)-(32k)
- 9 cvx_end
- 10 Calculate $\mathbf{P}^t$ and β^t by $\frac{\varphi^t}{\varepsilon^t}$.
- 11 Update the task queue $Q_i(t), \forall i \in \{1, 2\}$.
- 12 Update the battery queue $\hat{B}_i(t), \forall i \in \{1, 2\}$.
- 13 Update the energy efficiency $u(t)$.

Output: $\varepsilon^t, \mathbf{P}^t$ and β^t

4.2. Algorithm Performance Analysis

At each time slot, our algorithm engages in the resolution of a straightforward convex optimization problem, denoted as P2.2, encompassing a manageable set of 13 decision variables. This problem is adeptly addressed through the application of well-established optimization techniques, such as the interior point method. Characterized by a computational complexity of approximately $O(n^{3.5} \log(1/\epsilon))$, where n is the number of decision variables, this approach ensures efficiency even for problems of considerable size.

In the following part, we analyze that the proposed scheme can achieve the optimal long-term time-average solution. First, we give some assumptions as follows:

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} D_{\text{tot}}(t) = d^{\text{ave}} \quad (33)$$

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} E_{\text{tot}}(t) = e^{\text{ave}} \quad (34)$$

$$\lim_{K \rightarrow \infty} u(t) = \frac{\frac{1}{K} \sum_{t=0}^{K-1} D_{\text{tot}}(t)}{\frac{1}{K} \sum_{t=0}^{K-1} E_{\text{tot}}(t)} = u^{\text{ave}} \quad (35)$$

then, we can obtain that the expectation can also converge the same solutions

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}[D_{\text{tot}}(t)] = d^{\text{ave}} \quad (36)$$

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}[E_{\text{tot}}(t)] = e^{\text{ave}} \quad (37)$$

$$\lim_{K \rightarrow \infty} \mathbb{E}[u(t)] = u^{\text{ave}} \quad (38)$$

Lemma 3. Based on (36)-(38), we have

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}[u(t)E_{\text{tot}}(t)] = \overline{D(t)} \quad (39)$$

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}[u(t)] \leq u \quad (40)$$

To start with, we give the existence of the optimal solution based on the current queue status.

Lemma 4. If the problem (P1) is feasible, there exists a policy $\{\epsilon, \mathbf{P}, \boldsymbol{\beta}, \mathbf{d}\}^*$ that satisfies the following conditions $\forall t, \epsilon > 0$:

$$\mathbb{E}[D_{\text{tot}}^*] \leq (u^* - \epsilon) \mathbb{E}[E_{\text{tot}}^*] \quad (41)$$

$$\mathbb{E}[H_{i,\text{loc}}^{t*} + H_{i,\text{off}}^{t*} - E_i^{t*}] \leq \epsilon, i \in \{1, 2\} \quad (42)$$

$$\mathbb{E}[A_i(t) - d_{i,\text{loc}}^{t*} - d_{i,\text{off}}^{t*}] \leq \epsilon, i \in \{1, 2\} \quad (43)$$

where $*$ represents the value under optimal solution.

Proof. See the parts 4 and part 5 of [37]. $\square$

Theorem 2. The optimal long-average utility function obtained by P1 is limited by a lower bound that is independent with the time space. The following solutions can be achieved by the algorithm,

1. $u(t) \geq u^* - B/(Ve^{\text{ave}})$,
2. All queues $Q(t)$, $\hat{B}_m(t)$, $\hat{B}_h(t)$ are mean rate stable, and thus the constraints are satisfied.

Proof. For any $\epsilon > 0$, let us consider the policy and queue state in (41)-(43). Since the result values are independent of queue status $\boldsymbol{\Theta}(t)$, we have

$$\mathbb{E}[D_{\text{tot}}^* | \boldsymbol{\Theta}(t)] \leq (u^* - \epsilon) \mathbb{E}[E_{\text{tot}}^* | \boldsymbol{\Theta}(t)] \quad (44)$$

$$\mathbb{E}[H_{i,\text{loc}}^{t*} + H_{i,\text{off}}^{t*} - E_i^{t*} | \boldsymbol{\Theta}(t)] \leq \epsilon, i \in \{1, 2\} \quad (45)$$

$$\mathbb{E}[A_i(t) - d_{i,\text{loc}}^{t*} - d_{i,\text{off}}^{t*} | \boldsymbol{\Theta}(t)] \leq \epsilon, i \in \{1, 2\} \quad (46)$$

By integrating these results to (27) and making $\epsilon \rightarrow 0$, we have

$$\begin{aligned}
\Delta_V(\Theta(t)) &\leq B - V\mathbb{E}\{D_{tot}^*(t) - u^*E_{tot}^*(t)\} + Q_i(t) \sum_{i=1,2} \mathbb{E}\{A_i(t) - d_{i,loc}^{t,*} - d_{i,off}^{t,*}\} \\
&\quad + \widehat{B}_i(t) \sum_{i=1,2} \mathbb{E}\{E_i^{t,*} - H_{i,loc}^{t,*} - H_{i,off}^{t,*}\} \\
&\leq B - V\mathbb{E}\{D_{tot}^*(t)\} + Vu^*\mathbb{E}\{E_{tot}^*(t)\}
\end{aligned} \tag{47}$$

Note that $u(t)$ is a constant value, which is independent of the current queue status $\Theta(t)$. Utilizing the iterated expectation and obtaining the sum of the above inequality over time $t \in \{0, 1, \dots, K-1\}$, we have

$$\begin{aligned}
\mathbb{E}\{L[\Theta(K)]\} - \mathbb{E}\{L[\Theta(0)]\} &- V \sum_{t=0}^{K-1} \mathbb{E}\{D_{tot}(t)\} + V \sum_{t=0}^{K-1} \mathbb{E}\{u(t)E_{tot}(t)\} \\
&\leq K[B - Vu^*\mathbb{E}\{E_{tot}^*(t)\}] + V \left[\sum_{t=0}^{K-1} \mathbb{E}\{u^*\}E_{tot}^*(t) \right]
\end{aligned} \tag{48}$$

Dividing both sides of (48) by VK , utilizing the Jensens inequality and the fact that

$$-\left[\frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{D_{tot}(t)\} \right] + \left[\frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{uE_{tot}(t)\} \right] \leq \frac{B}{V} - u^*\mathbb{E}\{E_{tot}^*(t)\} + \left(\frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{u(t)\} \right) E_{tot}^*(t) \tag{49}$$

Furthermore, letting $K \rightarrow \infty$, we have

$$\begin{aligned}
&-\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{D_{tot}(t)\} + \lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{u(t)E_{tot}(t)\} \\
&\leq \frac{B}{V} - u^*\mathbb{E}\{E_{tot}^*(t)\} + \left(\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{u(t)\} \right) E_{tot}^*(t)
\end{aligned} \tag{50}$$

considering $\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E}\{u(t)\} \leq u$, we have

$$0 \leq \frac{B}{V} - u^*\mathbb{E}\{E_{tot}^*(t)\} + u\mathbb{E}\{E_{tot}^*(t)\} \tag{51}$$

Furthermore we obtain

$$u \geq u^* - \frac{B}{Vd^{ave}} \tag{52}$$

□

Theorem 3. Let e_1^{upper} be the upper bound of $e_1(t)$, the time-average sum rate of queue length is bounded by

$$Q_1 + Q_2 \leq \frac{B}{\varepsilon} + \frac{ue_1^{\text{upper}}}{\varepsilon} \tag{53}$$

Proof. By taking iterated expectation and using telescoping sums over $t \in \{0, 1, \dots, K-1\}$, we have

$$\begin{aligned}
&\mathbb{E}\{L[\Theta(K)]\} - \mathbb{E}\{L[\Theta(0)]\} - V\mathbb{E}\{D_{tot}(t) - u(t)E_{tot}(t) \mid \Theta(t)\} \\
&\leq KB - \varepsilon \sum_{t=0}^{K-1} \mathbb{E}\{Q_1(t) + Q_2(t) + \widehat{B}_1(t) + \widehat{B}_2(t)\} + V\mathbb{E}\{u(t)E_{tot}(t)\}
\end{aligned} \tag{54}$$

Dividing both sides of (54) by $K\varepsilon$, taking $K \rightarrow \infty$, rearranging terms yield

$$\frac{B}{\varepsilon} - \lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E} \{ Q_1(t) + Q_2(t) + \hat{B}_1(t) + \hat{B}_2(t) \} + V u E_{tot}^{upper} \geq 0 \quad (55)$$

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \mathbb{E} \{ Q_1(t) + Q_2(t) + \hat{B}_1(t) + \hat{B}_2(t) \} \leq \frac{B}{\varepsilon} + V \frac{u E_{tot}^{upper}}{\varepsilon} \quad (56)$$

□

Theorems 2 and 3 provide a rigorous mathematical performance analysis for our proposed algorithm. They demonstrate that the time-average η_{EE} scales as $O(1/V)$, while the queue length increases at a rate of $O(V)$. The WPMEC system η_{EE} can be improved by adjusting the value of V . However, the time-average task queue Q increases as V grows. Therefore, we can tune V to achieve a $[O(1/V), O(V)]$ trade-off between η_{EE} network EE and task queue length. According to Little's Law [37], the latency is proportional to the time-average task queue length. This also implies that our proposed algorithm can achieve a trade-off between and latency. This balance is critical in many real-world applications where both efficiency and latency are critical.

5. Simulation Results

In this section, we evaluate the performance of our proposed algorithm for a Backscatter-assisted WPMEC system with user cooperation through extensive numerical simulation. The experiments are conducted on a high-performance platform equipped with a 2.10 GHz Intel(R) Xeon(R) Silver 4116 CPU and four GeForce RTX 2080 Ti GPUs, ensuring efficient simulation execution. We employed the free-space path loss model to simulate signal propagation, where the average channel gain $\bar{h}$ is calculated by the following formula [42]:

$$\bar{h} = A_d \left(\frac{3 \times 10^8}{4\pi f_c d_i} \right)^{d_e}, \quad (57)$$

where $A_d = 3$ (antenna gain), $f_c = 915$ MHz (carrier frequency), $d_e = 3$ (path loss exponent), and d_i represents the distance between nodes (in meters).

The dynamic channel gains for WPT and task offloading, following the Rayleigh fading model, are represented by the vector $\mathbf{h}^t = [a_1^t h_1^t, a_2^t h_2^t, a_3^t g_{12}^t, a_4^t g_{2a}^t]$. In the model, the channel fading factors $[a_1^t, a_2^t, a_3^t, a_4^t]$ all follow an exponential distribution with an expectation of 1, simulating the natural variability of wireless channels. For the sake of model simplification, we assume that the vector of fading factors remains constant at $[1.0, 1.0, 1.0, 1.0]$ within each time slot, thereby considering the channel gain to be static during that slot.

At each time slot t , the expected arrival rates of computational tasks $A_i(t)$ satisfy $\mathbb{E}\{A_i(t)\} = \lambda_i, i \in \{1, 2\}$. It is assumed that $A_i(t)$ follow an exponential distribution, where the rate parameters λ_1 and λ_2 correspond to 1.2 and 1.5, respectively. The main source code is available online at <https://github.com/Toxic-Gulu/bac-with-ac>. Other simulation parameters are detailed in Table 2.

To comprehensively evaluate the performance of our algorithm, we conducted comparative simulations with three representative benchmarks as follows:

(1) UC with the AC scheme (UAC) [43]: In the WPMEC system, task offloading is facilitated through user collaboration, where MD₁ and MD₂ communicate exclusively via the AC mode, without the integration of Backscatter modules. This approach only leverages the AC communication model for data transmission.

(2) UC with the BackCom scheme (UBC) [8]: The WPMEC network employs a collaborative approach among users, with inter-user communication solely relying on the Backscatter technique. Specifically, the HAP continuously broadcasts RF energy to the users throughout each time slot, resulting in the highest energy expenditure for the HAP due to its non-stop energy emission.

(3) Without UC With Integrated BackCom and AC scheme (BC+AC) [44]: The WPMEC network forgoes user collaboration, with MD₁ and MD₂ establishing direct communication links with the HAP. In this configuration, MD₁ and MD₂ are autonomous, eschewing collaborative interactions.

Furthermore, each device is integrated with a Backscatter module, enabling the utilization of both BackCom and AC for their communication needs.

(4) Random Offloading Scheme (ROS) : The WPMEC network employs a typical task offloading approach where MD₁ and MD₂ independently offload a random subset of their tasks to the HAP. There is no collaboration between the two nodes in terms of communication. Importantly, both nodes are not integrated with Backscatter modules, and they exclusively utilize AC communication.

To ensure a fair comparison, all baseline algorithms are implemented utilizing the Lyapunov optimization framework, which is designed to maintain system stability.

Table 2. SIMULATION PARAMETERS.

Symbol	Value
Time slot length	1 s
Maximum battery capacity $B_{\max}$	50 J
Minimum battery capacity $B_{\min}$	0 J
Transmit power of the AP P_0	5 W
Noise power σ^2	10^{-3} W
The circuit consumption of the BackCom p_1^{ba} and p_2^{ba}	0.1 W
The circuit consumption of the AC p_1^{ac} and p_2^{ac}	0.7 W
CPU frequency of MD ₁ f_1	500 MHz
CPU cycles to compute 1 bit task of MD ₁ ϕ_1	490 cycles/bit
CPU frequency of MD ₂ f_2	480 MHz
CPU cycles to compute 1 bit task of MD ₂ ϕ_2	470 cycles/bit
Equal computing efficiency parameter of MD ₁ κ_1	10^{-8}
Equal computing efficiency parameter of MD ₂ κ_2	10^{-8}

Figure 3 demonstrates the performance comparison of EE under different schemes, with parameters set as $V = 40$, $\zeta = -16$ dB, and $W = 1.2$ MHz. It can be observed that our proposed algorithm performs the best in terms of EE, followed by the UBC, then the UAC, the BC+AC ranking fourth, and the ROS method performing the worst. Compared to the other four schemes, our proposed algorithm has improved the EE by 23%, 38%, 48% and 64%, respectively. This superior performance highlights the advantage of integrating both BackCom and AC. The scheme of UBC, suffers from limited transmission capability when ζ is small, leading to poor performance. Although the UAC can transmit sufficient data, its high circuit power consumption results in it ranking third. Due to the poor channel conditions of remote users, the BC+AC, as well as the ROS method, also have lower energy efficiency. This indicates that even with the integration of BackCom and AC, poor channel conditions between MD₁ and HAP may still limit energy harvesting and task offloading. This further emphasizes the importance of user cooperation in enhancing the performance of remote users.

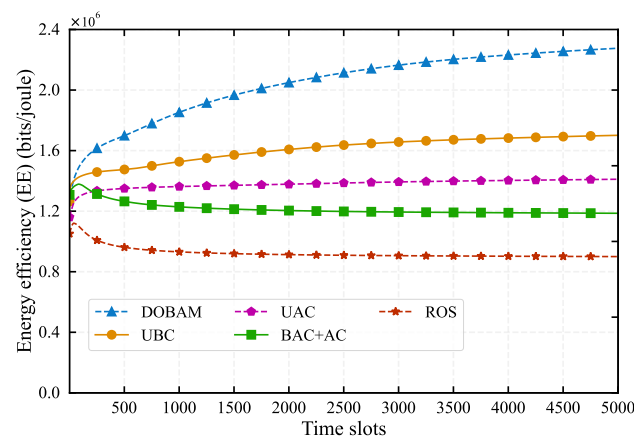


Figure 3. Energy efficiency EE in different schemes over time slots.

Figure 4 illustrates the impact of controlling the performance gap ζ on EE. The EE for the other four schemes improve with an increase in ζ , contrasting with the UAC and ROS scheme's stable EE. Our proposed scheme consistently delivers the best system performance and the ROS method performing the worst. With $\zeta > -17$ dB, the UBC scheme outperforms the UAC scheme in EE, prompting the system to favor the BackCom mode. Upon reaching a higher threshold, the UAC scheme's EE matches that of our proposed scheme, leading to its predominance use by users. Conversely, when $\zeta < -21$ dB, our scheme defaults to the AC mode. The BC+AC and the ROS scheme experience the least performance gains due to suboptimal channel conditions. Overall, the proposed scheme outshines others in flexibility and adaptability, adeptly tuning to varying ζ levels for optimal EE.

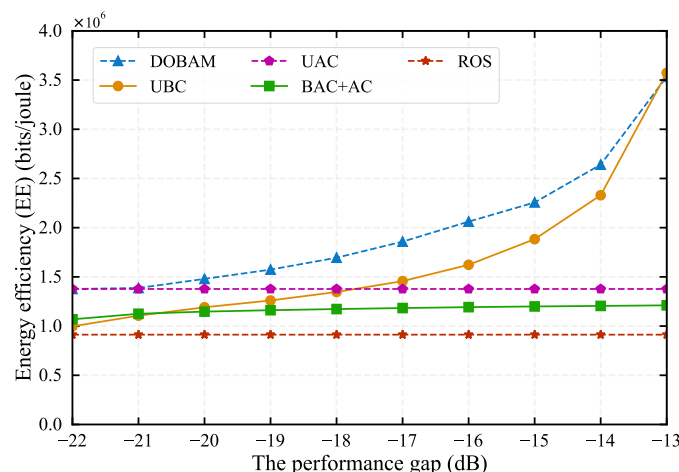


Figure 4. Energy efficiency EE in different schemes versus the performance gap.

Figure 5 demonstrates the impact of network bandwidth on the performance under different schemes, with the time slot set to 2000. As shown in Figure 5, within the bandwidth range of $[1.00, 1.45] \times 10^6$ Hz, the EE of all schemes increases with the expansion of bandwidth. This is attributed to the increased bandwidth allows more tasks to be transmitted to the edge server for processing using edge computing resources. Our proposed scheme consistently outperforms other schemes across the different bandwidth scenarios, especially as the bandwidth approaches 1.45MHz. At this point, the advantage in energy efficiency becomes markedly evident, substantially outperforming other baseline algorithms. This not only showcases the high adaptability of our scheme in managing bandwidth but also underscores its effectiveness in utilizing network resources in high-bandwidth scenarios, thereby maximizing energy efficiency.

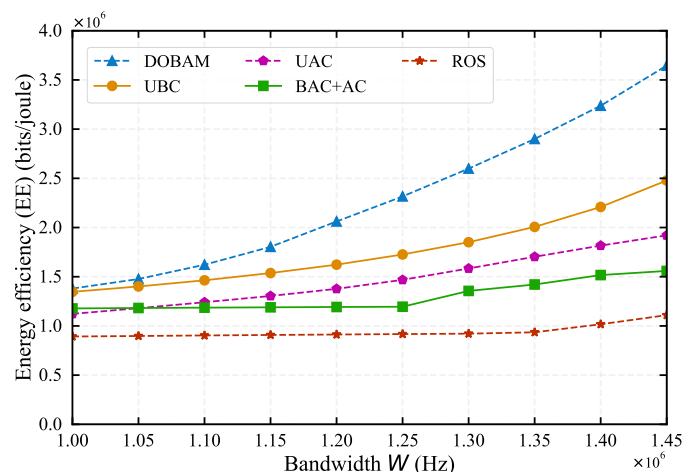


Figure 5. Energy efficiency EE in different schemes versus bandwidth W.

In Figure 6, we evaluate the system performance of various algorithms under different weight configurations, where the weight ω varies in the range $[0, 3]$, with $\omega_1 = \omega/(\omega + 1)$ and $\omega_2 = 1/(\omega + 1)$. As ω increases, the EE of all schemes generally declines because a higher ω implies that tasks offloading from MD₁ receive more resources at the expense of overall EE. Our algorithm consistently performs the best across all weight settings and the ROS algorithm exhibits the poorest performance among the evaluated approaches. Specifically, at $\omega = 3$, our algorithm achieves an EE improvement of 23%, 38%, 46% and 55% over other algorithms. This demonstrates that our algorithm can more effectively leverage the advantages of the UC scheme, combined with BackCom and AC. Additionally, Figure 6 indicates that excessively high weights for edge devices can rapidly degrade network performance, underscoring the importance of proper weight distribution. In Figure 6, we observe an inversion of the purple curve, which occurs due to the system's inclination to allocate more resources to support the task offloading of MD₁ as the weight system increases. Schemes without user cooperation, constrained by the absence of collaborative efforts and poor channel conditions, experience a sharp decline. Consequently, at a weight coefficient of 0.6, a crossover of the curves is observed, where the EE represented by the purple curve falls below that of any other scheme with user cooperation.

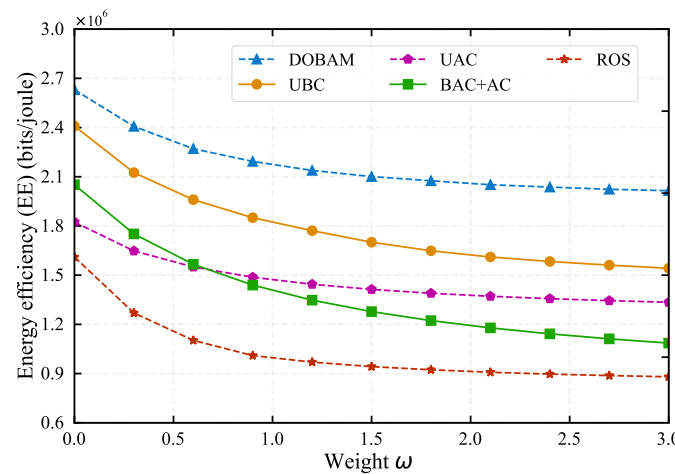


Figure 6. Energy efficiency EE in different schemes versus weight ω .

Figure 7 illustrates the impact of the control parameter V on EE and the average stable queue length, with parameter settings of $\zeta = -18$ dB, $W = 1.2$ MHz, a distance of 120 meters between nodes MD₁ and MD₂, and a task arrival rate at MD₂ of $\lambda_2 = 1.5$ Mbps. As V increases, EE is enhanced, and the stable queue threshold also increases. This indicates that with the increase of V , EE becomes the primary concern, while the current queue length plays a relatively minor role in the objective function. However, when V reaches a certain threshold, the gain in energy efficiency becomes saturated, and further increasing V will no longer have a significant impact on system performance and queue length. This trend can be interpreted as follows: a larger V allows the system to buffer more data, which is consistent with the previous theoretical analysis. Thus, the problem is transformed into seeking to maximize EE while to some extent disregarding the current queue length.

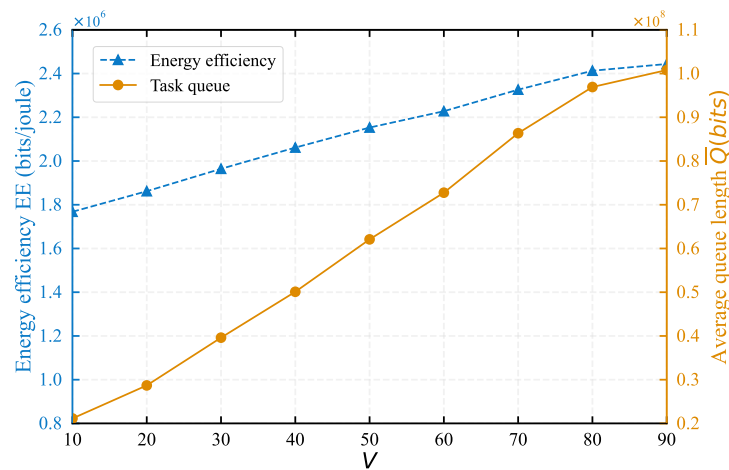


Figure 7. Convergence performance of energy efficiency EE versus parameter V .

Figure 8 illustrates the optimal time allocation of ε versus the performance gap ζ . Initially, when ζ is low, despite the lower energy consumption of the BackCom mode, achieving a larger number of computational bits at the same energy consumption is challenging. Consequently, MDs prefer the AC mode and allocate more time ε_0^* for energy collection to meet data processing needs. As ζ increases, ε_0^* gradually decreases, and when ζ exceeds -20 dB, $\varepsilon_0^* \approx 0$. This is because, as ζ increases, the BackCom mode can not only achieve more computational bits at the same energy consumption but also collect sufficient energy to support the circuit consumption under the AC mode, significantly improving energy efficiency. Therefore, as ζ increases, users are more inclined to choose the BackCom mode, using its reflection capability to perform task transmission and energy collection to meet the circuit consumption [45]. This scheme ensures that under different ζ conditions, the system can operate at the highest efficiency, optimizing energy usage.

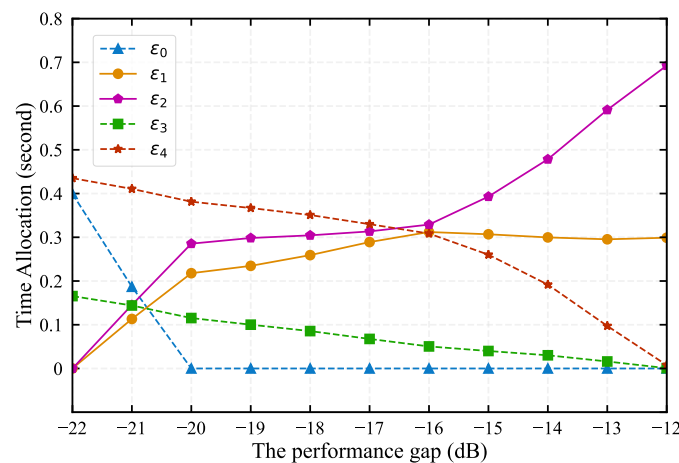


Figure 8. The optimal time allocation versus the performance gap.

Figure 9 illustrates that the EE under varying distances between MD₁ and MD₂, with $V = 40$. The distance between the remote MD and the helper device ranges from 80 to 180 meters. It is observed that EE decreases as the distance increases. This is because an increase in distance leads to a reduction in channel gain, necessitating more time and higher power to transmit data to maintain a shorter data queue, thereby increasing energy consumption. This indicates that in practical deployment, the distance between edge node devices and helper devices should be kept within a reasonable range to

avoid a rapid decline in network performance. This assessment not only quantifies the specific impact of distance on energy efficiency but also emphasizes the importance of considering the distance factor in the design of efficient networks.

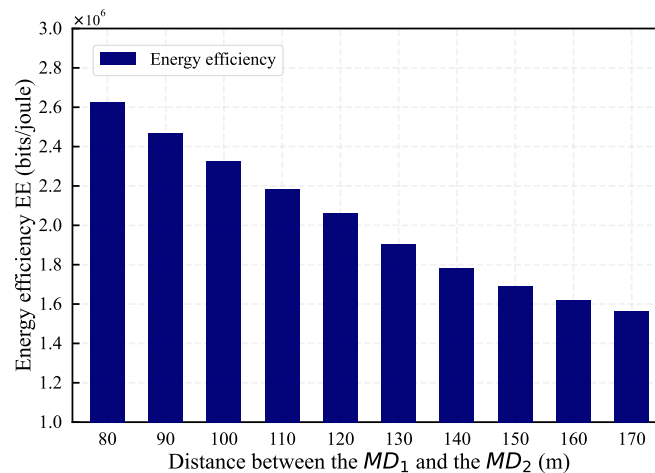


Figure 9. Energy efficiency EE versus different distances between MD_1 and MD_2 .

In Figure 10, we evaluate the EE and the average task queue length as the task arrival rate at MD_2 varies. The distance between MD_1 and MD_2 is set to 120 meters, and control parameter V is set to 40. As the computation task data arrival rate at MD_2 increases, the EE decreases. The rise in data rate causes the local data queue to expand, necessitating a higher data transmission rate from the system. This not only entails processing a larger volume of data but also results in greater energy expenditure to maintain shorter data queues, thereby increasing overall energy consumption. Despite this trade-off in energy efficiency, our algorithm optimizes energy usage, ensuring that the system maintains efficient data processing and rapid response capabilities even as data rates increase.

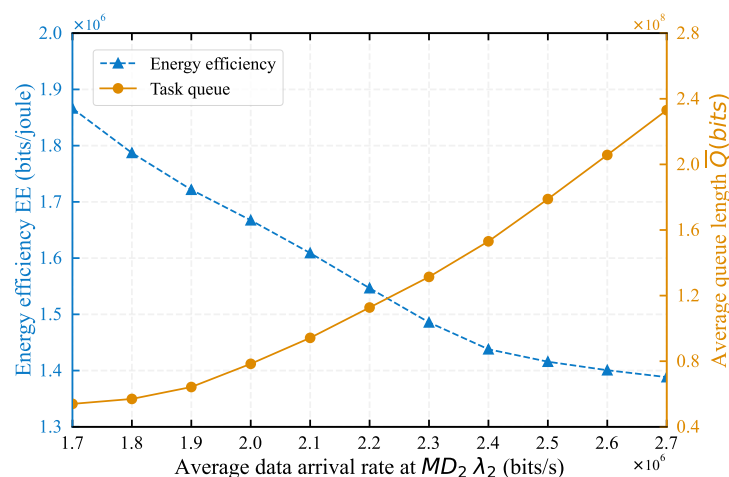


Figure 10. Energy efficiency versus different task arrival rate MD_2

6. Conclusions

In WPMEC systems, the volatility of the network environment and the time coupling of battery charging and discharging present significant challenges for the joint optimization of computation offloading and resource allocation. The integration of BackCom and AC is crucial for enhancing the performance of WPMEC systems across various user scenarios, especially with user collaboration, as

it can significantly improve the performance of edge node devices with poor channel conditions. In this study, we design a user collaboration-assisted WPMEC system that integrates BackCom and AC, aiming to maximize EE by jointly optimizing the backscatter reflection coefficient, AC transmission power, time, and task allocation under dynamic loads and time-varying channel conditions. To address the complexity brought about by the coupling of multiple parameters, we propose a dynamic control algorithm, which employs variable substitution, fractional programming, Lyapunov optimization, and convex optimization techniques to simplify the problem into a convex optimization form and decouple the sequential decision-making problem into independent optimization tasks for each time slot. Simulation results show that our scheme effectively enhances EE while ensuring system stability, surpassing existing technologies. Furthermore, future research directions include exploring scenarios with multiple edge nodes and a few helper nodes, which is expected to further improve the system's practicality and adaptability in real-world applications.

Author Contributions: Methodology, H.H.; Validation, Z.C. and Y.Y.; Formal analysis, H.H.; Investigation, H.H. and H.F.; Resources, H.H.; Data curation, H.H. and S.H.; Writing—original draft, H.H. and H.F.; Writing—review and editing, H.H.; Supervision, L.S. and S.H.; All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Science and Technology Planning Project of Guangdong Province, China (No.2021A0101180005), Science and Technology Development Fund of Macao (FDCT), Macao, China (#0033/2023/RIA1).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Acknowledgments: We thank all of the reviewers for their valuable comments.

Conflicts of Interest: The authors declare no conflicts of interest.

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