



Design and Optimization of a Solar-Powered IRS and Relay Assisted MEC System

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Abstract. This paper studies a mobile edge computing system where two solar-powered nodes (i.e., a relay and an intelligent reflecting surface (IRS)) assist a user node in task offloading to an access point. To save the long-term energy consumption at the user, a novel protocol is first proposed so that the system can adaptively select the operating modes. Then, based on this protocol, the optimization problem of the system is formulated to minimize the energy consumption of task offloading and computing at the user by optimizing the system operation modes and the resource allocation in each mode, subject to the battery energy states of the IRS and the relay with the energy causality constraints. The problem is solved using the Lyapunov optimization framework and an alternating optimization algorithm. Simulation results show that the proposed system optimization scheme can save 70%-95% of energy consumption as compared to the baseline schemes.

Keywords: MEC · IRS · Cooperative Computing · Energy Harvesting · Stochastic Optimization

1 Introduction

With the rapid growth of the Internet of Things (IoT), an increasing number of IoT smart sensor relays need to perform computationally intensive tasks that typically have strict latency requirements. However, it is often costly to perform these computational tasks locally on these relays due to computational resource constraints. As one of the emerging technologies in IoT, Mobile Edge Computing (MEC) provides an effective solution to the above problems. By offloading computational tasks from IoT relays to servers with sufficient computational resources for execution, MEC is expected to alleviate these challenges [1, 2].

However, considering the complexity of the propagation environment and the deterioration of the propagation link due to the high mobility of the users, Intelligent Reflecting Surface (IRS) have received much attention in wireless transmission enhancement to improve the communication quality in MEC systems [5]. IRS is a technique that has been proposed in recent years to achieve high spectral efficiency in wireless communication systems. It is clear that IRS requires power supply for its operation, and

to ensure the high efficiency of MEC systems over a long period of time, energy harvesting (EH) technologies have attracted attention [3]. Meanwhile, in 5G networks, it is expected that there will be a large number of wireless devices with certain computational and communication resources that can act as cooperative nodes by making their computational resources available to users who need to perform urgent tasks, and this paradigm is known as cooperative computing. But the assumption in [4] that borrowable computational resources can be obtained in advance is unreasonable.

There have been many existing research works on EH-MEC systems, such as [2] and [6], but the existing works, in order to simplify the analyses, adopt the harvest-then-use (HTU) strategy for energy scheduling. Due to energy unpredictability and limited battery storage capacity, efficient use of limited energy from relay and IRS as well as energy harvesting techniques in fading channels is essential. There are two dominant approaches in the existing optimization of MEC systems to deal with the dynamic computational offloading problems: one is to transform the problem into a series of individual time-slot problems using the Lyapunov optimization framework [7, 8]. The other is to use Markov Decision Processes (MDPs), but in MDPs the high-dimensional state and action space lead to prohibitive computational complexity.

Based on the above analysis, in this paper, we consider a solar-powered IRS and relay jointly assisted time-slot system for edge computing, and our goal is to achieve the minimization of the long-term average energy consumption of users in a dynamic environment. A task offloading and cooperative computing protocol that can fully utilize the computational and communication resources of the system is first designed. Specifically, the Relay-assist MEC system under the new protocol considers the assist time allocation of the IRS on each time slot, so the paper proposes four modes. They are denoted as Mode I to Mode IV, respectively. Due to the stochastic nature of the wireless channel and task arrivals, and the fact that the system operating modes and resource allocation decisions for individual time slots are interrelated, the resulting problem is difficult to solve directly. To solve this problem, we first use the Lyapunov optimization framework to transform the described problem into a series of single time-slot optimization problems. The solution of the single time slot optimization problem is then achieved by convex optimization theory and alternating optimization (AO) algorithm.

2 System Model and New Protocol

2.1 Network Model

As shown in Fig. 1, in this paper we consider a solar-powered IRS and relay jointly assisted single user task offloading MEC system, which consists of an AP (A) base station with a MEC server, a user (U), a relay (cooperative node, N) an IRS (R), and two solar-powered power supplies used to power the relay and the IRS, respectively. This work investigates the long-term time (duration of $K * T$, where the number of time slots is K and the duration of each time slot is T). At the beginning of each time slot $k \in \mathcal{K} = \{1, \dots, K\}$, there are new computational tasks $A(k)$ arriving at the user in bits with the maximum delay constraint T . At the same time, the relay itself also has $L(k)$ tasks (in bits) to perform in each time slot k in bits, and the maximum delay constraint is also T .

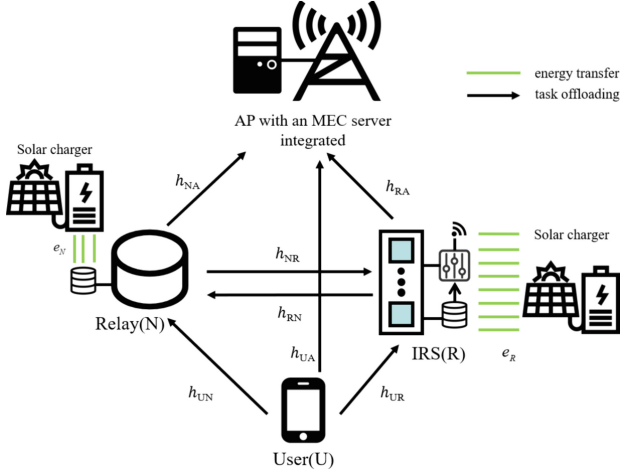


Fig. 1. Network model

2.2 New Protocol Design

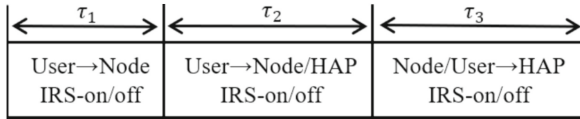


Fig. 2. The structure of one time slot in the newly designed protocol

Both the user and the relay will process their own tasks locally throughout the time slot as $\ell(k)$ and $L(k)$ respectively. In Fig. 2, a time slot is divided into three phases, $s \in \{1, 2, 3\}$. We define the IRS as assisting only the first phase, which we call mode I; assisting only the second phase, which we call mode II; assisting only the third phase, which we call mode III; and assisting the full phase, which we call mode IV. Denote the set of the above four operating modes of the MEC system as $\mathbb{M} \triangleq \{I, \dots, IV\}$. Let $\phi_m(k) \in \{0, 1\}$ be the operating mode indicator, where $m \in \mathbb{M}, k \in \mathcal{K}$. If $\phi_m(k) = 1$, the MEC system is operating in mode m in time slot k . In a time slot, the system can choose only one operating mode, so $\sum_{m \in \mathbb{M}} \phi_m(k) = 1$. The delay constraint for the user's task is:

$$\tau_1(k) + \tau_2(k) + \tau_3(k) = T \quad (1)$$

As considered in most of the MEC literatures, we also ignore the time for remote execution and result download [7].

2.3 Channel Model

In this paper it is assumed that all channels follow block fading, i.e., the channel remains constant within the current time slot but changes at the boundary of each time slot. In

each time slot k , the NLoS channel gain from the user to the AP is denoted by $h_{\text{UA}}(k)$, which is modelled as Rayleigh fading. The NLoS channel gain expression from the user to the relay and the relay to AP are both similar to $h_{\text{UA}}(k)$.

The channel gain from the user to the IRS $\mathbf{h}_{\text{UR}}(k) \in \mathbb{C}^{N \times 1}$ follows the Rician distribution. Let $\mathbf{h}_{\text{RA}}(k)$, $\mathbf{h}_{\text{RN}}(k)$, $\mathbf{h}_{\text{NR}}(k)$ denote the channels gains from the IRS to AP and the relay, and the relay to the IRS respectively, which follow Rician distribution. Their specific expressions are similar to $\mathbf{h}_{\text{UR}}(k)$.

IRS can be controlled independently in each phase s divided by time slot k . Let the diagonal matrix $\Theta_s(k) = \text{diag}(\beta_s^1(k)e^{j\theta_s^1(k)}, \beta_s^2(k)e^{j\theta_s^2(k)}, \dots, \beta_s^N(k)e^{j\theta_s^N(k)})$, where $\theta_s^n(k) \in [0, 2\pi)$, $\beta_s^n(k) \in [0, 1]$ represent the phase shift and amplitude reflection coefficients, respectively, of the n -th reflective element of the IRS during the s -th phase in the time slot k . $\forall n \in \{1, \dots, N\}$, $s \in \{1, 2, 3\}$. In each time slot k , the combined channel gain from the user to the AP is: $\left| \hat{h}_{\text{UA}}(k, s) \right|^2 = \left| \mathbf{h}_{\text{RA}}^H(k) \Theta_s(k) \mathbf{h}_{\text{UR}}(k) + h_{\text{UA}}(k) \right|^2$, $s \in \{2, 3\}$. The combined channel gains $\hat{h}_{\text{UN}}(k, s)$ and $\hat{h}_{\text{NA}}(k)$ from the user to the relay and from the relay to the AP are both similar to $\hat{h}_{\text{UA}}(k, s)$.

2.4 Task Offloading and Energy Consumption Model

Let $\{p_{\text{U},1}(k), p_{\text{U},2}(k), p_{\text{U},3}(k), p_{\text{N}}(k)\}$ denotes the transmit power of the user and the relay at different phases of each mode in the time slot k . At time slot k , in the first phase of each operating mode, the maximum achievable transmission rate from the user to

the relay can be expressed as: $R_{\text{UN-irs on}}(p_{\text{U},1}(k), 1) = B \log_2 \left(1 + \frac{p_{\text{U},1}(k) |\hat{h}_{\text{UN}}(k, 1)|^2}{\sigma^2} \right)$

and $R_{\text{UN-irs off}}(p_{\text{U},1}(k)) = B \log_2 \left(1 + \frac{p_{\text{U},1}(k) |h_{\text{UN}}(k)|^2}{\sigma^2} \right)$ correspond to the two cases of whether or not the IRS is involved in the assistance, where B is the system bandwidth and σ^2 is the additive white Gaussian noise power in the system.

Similarly, in the second phase, the maximum achievable transmission rate from the user to the relay are $R_{\text{UN-irs on}}(p_{\text{U},2}(k), 2)$ and $R_{\text{UN-irs off}}(p_{\text{U},2}(k))$. The maximum achievable transmission rate from the user to AP are $R_{\text{UA-irs on}}(p_{\text{U},2}(k))$ and $R_{\text{UA-irs off}}(p_{\text{U},2}(k))$.

Note that in the third phase, the user and the relay send the task data information to the AP simultaneously using the rateless code (RC) technique, where the maximum achievable transmission rate at the AP are: $R_{\text{UNA-irs on}}(p_{\text{N}}(k), p_{\text{U},3}(k))$ and $R_{\text{UNA-irs off}}(p_{\text{N}}(k), p_{\text{U},3}(k))$.

1) Task Offloading to Relay: The amount of data and energy consumed by the user offloaded to the relay to assist in the computation in the first phase of each operating mode in time slot k are expressed as follows:

$$d_{\text{N}}(k) \leq \tau_1(k) \left(\sum_{m \in \{\text{I,IV}\}} \phi_m(k) R_{\text{UN-irs on}}(p_{\text{U},1}(k), 1) \right)$$

$$+ \sum_{m \in \{\text{II,III}\}} \phi_m(k) R_{\text{UN-irs off}}(p_{\text{U},1}(k)) \Big) \quad (2)$$

$$E_{\text{off}}^{(m-1)}(k) = \tau_1(k) p_{\text{U},1}(k), \quad \forall m \in \{\text{I}, \dots, \text{IV}\} \quad (3)$$

In the second phase, the amount of data and energy consumed by the user offloaded to the relay for assistance forwarding has the following expression:

$$d_{\text{A},1}(k) = \tau_2(k) \left(\sum_{m \in \{\text{II,IV}\}} \phi_m(k) R_{\text{UN-irs on}}(p_{\text{U},2}(k), 2) + \sum_{m \in \{\text{I,III}\}} \phi_m(k) R_{\text{UN-irs off}}(p_{\text{U},2}(k)) \right) \quad (4)$$

$$E_{\text{off}}^{(m-2)}(k) = \tau_2(k) p_{\text{U},2}(k), \quad \forall m \in \{\text{I}, \dots, \text{IV}\} \quad (5)$$

2) Task Offloading to AP: In the second phase, at time slot k , when the user offloads the assist forwarded data to the relay, the AP also receives part of this data and hence the following expression:

$$d_{\text{A},2}(k) = \tau_2(k) \left(\sum_{m \in \{\text{II,IV}\}} \phi_m(k) R_{\text{UA-irs on}}(p_{\text{U},2}(k), 2) + \sum_{m \in \{\text{I,III}\}} \phi_m(k) R_{\text{UA-irs off}}(p_{\text{U},2}(k)) \right) \quad (6)$$

In the third phase, the user and the relay send the task data information to the AP at the same time using the RC technique, at which time the received task data at the AP is :

$$d_{\text{A},3}(k) = \tau_3(k) \left(\sum_{m \in \{\text{III,VI}\}} \phi_m(k) R_{\text{UNA-irs on}}(p_{\text{N}}(k), p_{\text{U},3}(k)) + \sum_{m \in \{\text{I,II}\}} \phi_m(k) R_{\text{UNA-irs off}}(p_{\text{N}}(k), p_{\text{U},3}(k)) \right) \quad (7)$$

In this phase, the offloading energy consumption of the user and the relay are respectively:

$$E_{\text{off}}^{(m-3)}(k) = \tau_3(k) p_{\text{U},3}(k), \quad \forall m \in \{\text{I}, \dots, \text{IV}\} \quad (8)$$

$$E_{\text{off}}^{\text{N}}(k) = \tau_3(k) p_{\text{N}}(k) \quad (9)$$

To summarize, in the first seven modes, the data received at the AP for the computation task in time slot k is as follows:

$$d_{\text{A}}(k) \leq \min(d_{\text{A},1}(k), d_{\text{A},2}(k) + d_{\text{A},3}(k)) \quad (10)$$

2.5 Task Computing and Energy Consumption Model

1) Local Computing at User: Definition $C_U \geq 0$ denotes the number of CPU cycles required by the user to perform one-bit computation task. The DVFS technique [7] is applied, where the user performs local computation in each time slot using a constant CPU frequency $f_U(k)$, and $f_{U,\max}$ is the maximum CPU frequency of the user, and in this case the energy consumption of the user for local computation at time slot $k \in \mathcal{K}$ is denoted as:

$$E_{com}^U(k) = C_U \ell(k) \zeta_U (f_U(k))^2 = \zeta_U C_U^3 \ell^3(k) / T^2 \quad (11)$$

where $\zeta_U > 0$ denotes the effective capacitance coefficient of the user.

2) Cooperative Computing at Relay: We assume that the relay has two independent processors for processing its own task $L(k)$ and the user's offloaded task $d_N(k)$. $f_{N,\max}$ is the maximum CPU frequency of the two independent processors of the relay. C_N denotes the number of CPU cycles required by the relay to perform one-bit computation task. Similarly, the task execution energy consumption of relay is:

$$E_{com}^N(k) = \zeta_N C_N^3 L^3(k) / T^2 + \zeta_N C_N^3 d_N^3(k) / (T - \tau_1(k))^2 \quad (12)$$

where $\zeta_N > 0$ denotes the effective capacitance coefficient of the relay.

Based on the above analysis, the total energy consumption of the user in time slot k can be expressed as:

$$E_{total}^U(k) = E_{com}^U(k) + E_{off}^{(m-1)}(k) + E_{off}^{(m-2)}(k) + E_{off}^{(m-3)}(k) \quad (13)$$

Similarly, the total energy consumption of the relay in time slot k can be expressed as:

$$E_{total}^N(k) = E_{com}^N(k) + E_{off}^N(k) \quad (14)$$

2.6 Energy Harvesting Model

$e_N(k)$ and $e_R(k)$ denotes the energy obtained by the relay and IRS by harvesting solar energy in time slot k , where $e_N(k) = TP_H^N(k)$, $e_R(k) = TP_H^R(k)$, $P_H^N(k)$ and $P_H^R(k)$ denote the energy harvesting power of the relay and the IRS, respectively, in time slot k . $P_{H\max}^N$ and $P_{H\max}^R$ are the maximum energy harvesting power of the relay and the IRS, respectively. We denote the relay's battery energy state as $B_N(k) \geq 0$ at the beginning of time slot k , so the energy state in each battery $B_N(k)$ evolves over time as follows:

$$B_N(k+1) = \min \left\{ B_N(k) - E_{total}^N(k) + e_N(k), B_N^{\max} \right\} \quad (15)$$

where B_N^{\max} indicates the maximum energy can be stored in the relay's battery. It also follows from the causality of energy:

$$E_{total}^N(k) \leq B_N(k) \quad (16)$$

Also denote by $t_R(k)$ the assistance duration of the IRS in time slot k . The energy consumption of the IRS in time slot k is as follows:

$$E_R(k) = \mu N t_R(k) \quad (17)$$

where μ denote the power consumption of a single reflective element.

Similarly to the relay case, for the IRS we have:

$$B_R(k+1) = \min\{B_R(k) - E_R(k) + e_R(k), B_R^{\max}\} \quad (18)$$

where B_R^{\max} indicates the maximum energy can be stored in the relay's battery.

$$E_R(k) \leq B_R(k) \quad (19)$$

3 Solution to the Proposed Problem

3.1 Problem Statement

In this paper, we focus on a MEC system in which solar-powered IRS and relay jointly assist a single user in task offloading by jointly optimizing the mode selection $\phi(k)$, task allocation $\mathbf{D}(k)$, time allocation $\mathbf{t}(k)$, IRS reflection coefficient matrix $\Theta(k)$, and user and relay transmit power allocations $\mathbf{p}(k)$ at each time slot, where $\Psi(k) = \{\phi(k), \mathbf{D}(k), \mathbf{t}(k), \Theta(k), \mathbf{p}(k)\}$, $\phi(k) = \{\phi_I(k), \phi_{II}(k), \phi_{III}(k), \phi_{IV}(k)\}$, $\mathbf{D}(k) = \{\ell(k), d_N(k), d_A(k)\}$, $\mathbf{t}(k) = \{\tau_1(k), \tau_2(k), \tau_3(k)\}$, $\Theta(k) = \{\Theta_1(k), \Theta_2(k), \Theta_3(k), \Theta_R(k)\}$, $\mathbf{p}(k) = \{p_{U,1}(k), p_{U,2}(k), p_{U,3}(k), p_N(k)\}$ to achieve the minimization of the user's long-term average energy consumption E_{avg} . Thus, the optimization problem of the MEC system studied in this paper can be expressed as follows:

$$(P1) \quad \min_{\Psi(k)} \mathbb{E}_{\text{avg}} = \lim_{K \rightarrow \infty} \frac{1}{K} E \left\{ \sum_{k=0}^{K-1} \left(E_{\text{total}}^U(k) \right) \right\} \quad (20a)$$

s.t. (1), (2), (10), (16), (19) and

$$\phi_m(k) \in \{0, 1\}, \quad \sum_{m \in \mathbb{M}} \phi_m(k) = 1 \quad (20b)$$

$$|\Theta_s^{n,n}(k)| \leq 1, \quad \forall n, \forall s \in \{1, 2, 3\} \quad (20c)$$

$$0 \leq \tau_i(k) \leq T, \quad \forall i = \{1, 2, 3\} \quad (20d)$$

$$\ell(k) + d_A(k) + d_N(k) = A(k) \quad (20e)$$

$$d_A(k) \geq 0, \ell(k) \geq 0, d_N(k) \geq 0 \quad (20f)$$

$$\frac{C_U \ell(k)}{T} \leq f_{U, \text{MAX}}, \quad \frac{C_N d_N(k)}{T - \tau_1(k)} \leq f_{N, \text{MAX}} \quad (20g)$$

$$0 \leq p_{U,1}(k) \leq p_{U,max}, \forall i = \{1, 2, 3\}, 0 \leq p_N(k) \leq p_{N,max} \quad (20h)$$

where $p_{U,max}$ and $p_{N,max}$ denote the maximum transmit power of the user and the relay, respectively. In problem (P1), (20b) and (20c) are the mode selection constraints and the IRS reflection coefficient constraints, (16) and (19) are the energy causality constraints for the relay and the IRS, respectively, (1) and (20d) are the time allocation constraints, (20e), (20f), (20g), (2) and (10) are the task allocation constraints, (20h), (2), (10) are the user and relay transmission power constraints.

Problem (P1) is a classical dynamic optimization problem that is difficult to solve directly, and the Lyapunov optimization framework is considered as an effective solution. Therefore, in this paper, the original problem is first simplified based on the Lyapunov optimization method, and then the simplified problem is solved by convex optimization theory and AO algorithm, so as to propose an efficient algorithm with low complexity.

3.2 Problem Transformation

To solve the problem (P1) using the Lyapunov optimization method, first, define two virtual queues for the energy states $B_N(k)$ and $B_R(k)$, respectively, as $X(k) = B_N(k) - G_1$, $Y(k) = B_R(k) - G_2$, where G_1 and G_2 are time independent constants, in this paper $G_1 = B_N^{max}$, $G_2 = B_R^{max}$. The problem (P1) can then be rewritten as:

$$(P2) \quad \min_{\Psi(k)} VE_{total}^U(k) + X(k) \left(e_N(k) - E_{total}^N(k) \right) + vY(k) \left(e_R(k) - E_R(k) \right) \quad (21)$$

s.t. (1), (2), (10), (16), (19) and (20b–h)

where v is a non-negative constant, and V is a non-negative weighting factor.

Unlike problem (P1), problem (P2) only requires solving the optimization variables for one time slot, making it a relatively simple problem to solve.

3.3 Solving Single Time-Slot Optimization Problem

To solve problem (P2), note that the system operation mode indicator $\phi(k)$ is a binary optimization variable, but since there are only four system operation modes, the optimal solution to problem (P2) can be obtained by solving the corresponding optimization problems under each of the four system operation modes separately, and then determining the optimal system operation mode.

Combined with the protocol design in the previous section, an in-depth analysis of problem (P2) shows that for the four modes of the system, there is no difference in the structure of the optimization problems corresponding to them. Therefore, in the following section, only the steps for solving the optimization problem when the system is in the first mode are given. The details are as follows:

when $\phi_1(k) = 1$, the system works in the first mode, let $\Psi^I(k) = \{\phi(k), \mathbf{D}(k), \mathbf{t}(k), \mathbf{p}(k)\}$ and the problem (P2) can be shorten as follows:

$$(P2.1) \quad Y_I(k) = \min_{\Psi^I(k)} VE_{total}^U(k) + X(k) \left(e_N(k) - E_{total}^N(k) \right)$$

$$+ vY(k)(e_R(k) - \mu N \tau_1(k)) \text{ s.t. } (1), (16), (20c - h) \text{ and} \quad (22a)$$

$$|\Theta_s^{n,n}| \leq 1, \forall n, \forall s \in \{1\} \quad (22b)$$

$$\mu N \tau_1(k) \leq B_R(k) \quad (22c)$$

$$d_N(k) \leq \tau_1(k) R_{\text{UN-irs on}}(p_{U,1}(k), 1) \quad (22d)$$

$$d_A(k) \leq \tau_2(k) R_{\text{UN-irs off}}(p_{U,2}(k)) \quad (22e)$$

$$d_A(k) \leq \tau_2(k) R_{\text{UA-irs off}}(p_{U,2}(k)) + \tau_3(k) R_{\text{UNA-irs off}}(p_N(k), p_{U,3}(k)) \quad (22f)$$

To solve the problem (P2.1), we introduce an auxiliary variable vector $\mathbf{E}(k) = \{E_{U,1}(k), E_{U,2}(k), E_{U,3}(k), E_N(k)\}$ with $E_{U,i}(k) = \tau_i(k)p_{U,i}(k), \forall i \in \{1, 2, 3\}, E_N(k) = \tau_3(k)p_N(k)$. The same applies to $E_N(k)$. So the problem (P2.1) can be rewritten as:

$$(P3.1) \min_{\mathbf{D}(k), \mathbf{t}(k), \Theta(k), \mathbf{E}(k)} V \left(E_{\text{com}}^U(k) + \sum_{i=1}^3 E_{U,i}(k) \right) + X(k) \cdot \\ \left(e_N(k) - E_{\text{com}}^N(k) - E_N(k) \right) + vY(k)(e_R(k) - \mu N \tau_1(k)) \quad (23a)$$

subject to (1),(16),(20d-20g), (22b-22c) and

$$0 \leq E_{U,i}(k) \leq \tau_i(k)p_{U,max}, \forall i = \{1, 2, 3\} \quad (23b)$$

$$0 \leq E_N(k) \leq \tau_3(k)p_{N,max} \quad (23c)$$

$$d_N(k) \leq \tau_1(k) R_{\text{UN-irs on}} \left(\frac{E_{U,1}(k)}{\tau_1(k)}, 1 \right) \quad (23d)$$

$$d_A(k) \leq \tau_2(k) R_{\text{UN-irs off}} \left(\frac{E_{U,2}(k)}{\tau_2(k)} \right) \quad (23e)$$

$$d_A(k) \leq \tau_2(k) R_{\text{UA-irs off}} \left(\frac{E_{U,2}(k)}{\tau_2(k)} \right) + \tau_3(k) R_{\text{UNA-irs off}} \left(\frac{E_N(k)}{\tau_3(k)}, \frac{E_{U,3}(k)}{\tau_3(k)} \right) \quad (23f)$$

The problem (P3.1) remains intractable because the optimization variables are coupled. To make it manageable, the AO technique [6] is proposed to solve the problem, where the problem (P3.1) is divided into two phases to be solved.

1.1) Phase 1: Jointly Optimizing $\{\mathbf{D}(k), \mathbf{t}(k), \mathbf{E}(k)\}$.

When $\Theta(k)$ is fixed, the (P3.1) can be rewritten as:

$$\begin{aligned}
\text{(P3.1.1)} \quad & \min_{\mathbf{D}(k), \mathbf{t}(k), \mathbf{E}(k)} V \left(\frac{\zeta_U C_U^3 \ell^3(k)}{T^2} + \sum_{i=1}^3 E_{U,i}(k) \right) \\
& + X(k) \left(e_N(k) - \frac{\zeta_N C_N^3 L(k)^3}{T^2} - \frac{\zeta_N C_N^3 d_N(k)^3}{(T - \tau_1)^2} - E_N(k) \right) \\
& + vY(k)(e_R(k) - \mu N \tau_1(k)) \\
& \text{s.t. (1), (16), (20d) - (20g), (22c) and (23b) - f}
\end{aligned} \tag{24a}$$

It can be shown that problem (P3.1.1) is a convex optimization problem, and the optimal solution can be obtained efficiently using convex optimization solvers such as CVX.

1.2) Phase 2: Optimizing IRS Reflection Coefficients.

Based on the results of the first phase, (P3.1) turns out to be a feasibility problem with only the optimization variable $\Theta(k)$, i.e.:

$$\begin{aligned}
\text{(P3.1.2)} \quad & \text{Find } \Theta(k) \\
& \text{s.t. (22b) and (22d)}
\end{aligned} \tag{25}$$

To deal with the non-convex constraints (22d), we have: $s\Theta_1(k)\mathbf{h}_{UN}(k) + h_{UN}(k)$, $Z_{UN}^{(1)}(k) = \text{Im}(\mathbf{h}_{RN}^H(k)\Theta_1(k)\mathbf{h}_{UN}(k) + h_{UN}(k))$ are the introduced slack variables, where $\text{Re}(W)$, $\text{Im}(W)$ are the real and imaginary parts of W , respectively. We then use the successive convex approximation (SCA) technique. Specifically, at the r -th iteration, given the initial point $(\mathbf{X}_{UN}^{(1),(r)}(k), Z_{UN}^{(1),(r)}(k))$ there has:

$$\begin{aligned}
& \left(\mathbf{X}_{UN}^{(i)}(k) \right)^2 + \left(Z_{UN}^{(i)}(k) \right)^2 - 3 \left(\mathbf{X}_{UN}^{(1),(r)}(k) \right)^2 + \left(Z_{UN}^{(1),(r)}(k) \right)^2 \\
& + 2\mathbf{X}_{UN}^{(1),(r)}(k) \left(\mathbf{X}_{UN}^{(1)}(k) - \mathbf{X}_{UN}^{(1),(r)}(k) \right) \\
& + 2Z_{UN}^{(1),(r)}(k) \left(Z_{UN}^{(1)}(k) - Z_{UN}^{(1),(r)}(k) \right) = \mathbf{R}_{UN}^{(1),lb}
\end{aligned}$$

herefore, at the r -th iteration, the convex optimization problem for solving problem (P3.1.2) can be expressed as:

$$\begin{aligned}
\text{(P3.1.2.1)} \quad & \text{Find } \Theta(k) \\
& \text{s.t. (22b) and}
\end{aligned} \tag{26a}$$

$$d_N(k) \leq \tau_1(k) B \log_2 \left(1 + \frac{p_{U,1}(k) R_{UN}^{(1),lb}}{\sigma^2} \right) \tag{26b}$$

which can be solved using the interior point method.

Finally, after obtaining the optimal solutions of the corresponding optimization problems for each of the four system operation modes, the value of $Y_m(k), \forall m \in \mathbb{M}$ can be determined, and thus the optimal system operation mode for the k -th time slot can be determined by:

$$m^*(k) = \arg \min_{m \in \mathbb{M}} Y_m(k).$$

4 Simulation Results

In this section, the performance of the design scheme of the solar-powered IRS and intelligent relay joint-assisted MEC system proposed in this paper is verified by simulation. In the simulation, it is assumed that AP, IRS, relay and user are located in a two-dimensional coordinate system, and their positions are set to $(x_A, y_A) = (20, 0)$, $(x_R, y_R) = (1, -1)$, $(x_N, y_N) = (10, 2)$ and $(x_U, y_U) = (0, 10)$, respectively. The path-loss exponent for UR, UN, NR, NA and RA links are set to $\alpha_{UR} = \alpha_{UN} = \alpha_{NR} = \alpha_{NA} = \alpha_{RA} = 2$. And since the UA link is assumed to have obstacles, the path-loss exponent of the UA link is set to $\alpha_{UA} = 4$. The bandwidth of the system is $B = 1$ MHz. The variances of AWGN are set as $\sigma^2 = -80$ dBm. We set the time slot duration $T = 0.08$ s. Furthermore, we set $P_{Hmax}^N = 8$ mW, $P_{Hmax}^R = 0.2$ msW, $B_N^{max} = 20 TP_{Hmax}^N$ J, $B_R^{max} = 20 TP_{Hmax}^R$ J, $N = 20$, $\nu = 2 * 10^3$, $V = 0.5626$.

Besides, the computation parameters of the user and relay in the considered MEC system are set as $C_U = C_N = 1000$ cycle/bit, $f_{U,max} = 2$ GHz, $f_{N,max} = 3$ GHz, $\zeta_U = 10^{-27}$, $\zeta_N = 3 * 10^{-28}$. The maximum transmission power is set to $p_{U,max} = 2$ W and $p_{N,max} = 3$ W for the user and the relay respectively. All of the above parameters are used in the following simulations unless otherwise stated.

In the simulation, the design scheme of this paper will be compared with the following two other baseline schemes: 1) Unactive optimization of IRS energy consumption scheme: The optimization problem corresponding to this scheme differs from problem (P2) in that its objective function does not include the IRS term and the IRS tends to assist the three phases. 2) Unactive optimization of the relay energy consumption scheme: The optimization problem corresponding to this scheme differs from problem (P2) in that it excludes the IRS term and the relay term from its objective function and assumes that each time slot the IRS tends to assist the three phases.

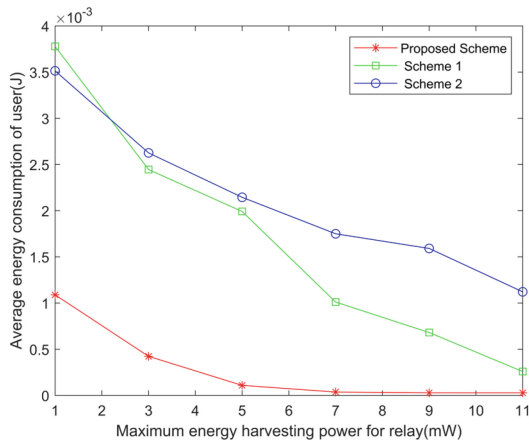


Fig. 3. User's average energy consumption versus the maximum energy harvesting power for relay

Figure 3 plots the variation of the user's average energy performance of the proposed scheme in this paper and the two baseline schemes when the maximum energy harvesting power (i.e., P_{Hmax}^N) varies in the relay. Here, the system operates with a number of time slots of 600, i.e., $K = 600$. As can be seen from Fig. 3, the average energy consumption of the proposed scheme in this paper is the lowest compared to the two baseline schemes. Specifically, the average energy consumption of the system of the proposed scheme in this paper is only 5–30% of the average energy consumption compared to scheme 1, and the savings are more compared to scheme 2. Therefore, by using the new protocol and the system optimization algorithm proposed in this paper, the energy consumption at the user side can be saved significantly. In addition, it can be seen that when P_{Hmax}^N is large (e.g., $P_{Hmax}^N = 11$ mW), the average energy consumption of scheme 1 and scheme 2 is also significantly reduced, and the gap between their energy performance and that of the scheme proposed in this paper is further narrowed, which is due to the fact that in this case, the energy collected by the relay at each time slot k is already more sufficient, and the long-term benefits of the system's active optimization of its energy consumption are reduced. However, when $P_{Hmax}^N = 7$ mW, the average energy consumption of the proposed scheme in this paper is much lower than that of schemes 1 and 2, thus illustrating the need for the system to proactively optimize the energy consumption of the relay.

Figure 4 plots the effect of changing the relay location on the average energy performance of the different schemes. From Fig. 4, it can be seen that for the scheme proposed in this paper, scheme 1 and scheme 2, the average energy performance of the scheme proposed in this paper is significantly better than the performance of the two baseline schemes, regardless of the changes in relay location. Our proposed scheme exploits energy conservation based on the relay and IRS battery energy states and opportunistic transmission based on channel conditions to minimize the user's long-term average energy consumption. Unlike our scheme, the alternative schemes do not jointly dynamically optimize the user, relay and IRS as a whole, and/or focus only on minimizing user energy consumption in the current time slot.

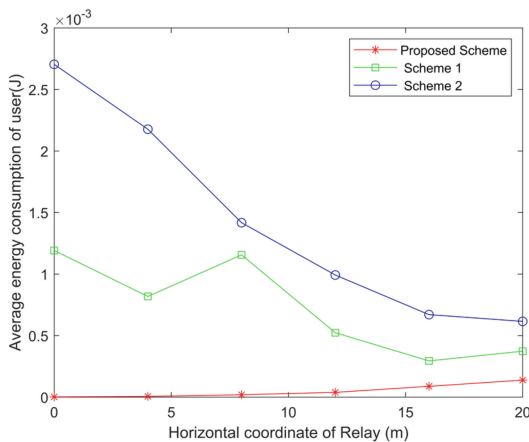


Fig. 4. Performance comparisons under varying relay horizontal coordinates

5 Conclusion

This paper investigated the design and optimization of a solar-powered IRS and relay (cooperative node), jointly assisted MEC system. Minimizing user's long-term average energy consumption by jointly optimizing mode selection, task allocation, time allocation, IRS reflection coefficient matrix, user and relay transmit power allocation for each time slot, an efficient algorithm was developed to achieve superior performance in the system. Simulation results showed that the energy performance of this algorithm in MEC systems is significantly better than the baseline schemes studied.

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