# Energy Minimization for Wireless Powered Data Offloading in IRS-assisted MEC for Vehicular Networks

Yuanzheng Tan*, Yusi Long*, Songhan Zhao‡, Shimin Gong*†, Dinh Thai Hoang§, and Dusit Niyato¶
*School of Intelligent Systems Engineering, Sun Yat-sen University, China
†Guangdong Provincial Key Laboratory of Fire Science and Intelligent Emergency Technology, China
‡School of Electrical Engineering, Yanshan University, China
§School of Electrical and Data Engineering, University of Technology Sydney, Australia
¶School of Computer Science and Engineering, Nanyang Technological University, Singapore

***Abstract*—In this paper, we consider an IRS-assisted and wireless-powered mobile edge computing (MEC) system that allows both edge users and the IRS to harvest energy from the hybrid access point (HAP), co-located with the MEC server. Each edge user uses the harvested energy to offload its data to the MEC server. The IRS not only assists downlink energy transfer to the edge users, but also improves the users' uplink offloading rates. To minimize the overall energy consumption, we jointly optimize the users' offloading decisions, the HAP's active beamforming, as well as the IRS's energy harvesting and passive beamforming strategies. The energy minimization problem is intractable due to complicated couplings in both the objective function and constraints. We decompose this problem into the downlink energy transfer and the uplink data offloading phases. The uplink phase can be efficiently optimized by the conventional semi-definite relaxation (SDR) method, while the downlink phase depends on the alternating optimization between the users' offloading decisions and the joint active and passive beamforming strategies. Numerical results demonstrate that the proposed offloading scheme can significantly reduce the HAP's energy consumption compared with typical benchmarks.**

## I. Introduction

Recently, intelligent reflecting surface (IRS) has been proposed as a promising technology to improve the energy- and spectrum-efficiency of future wireless networks [1]. It consists of a large array of passive reflecting elements that can be flexibly deployed on the exterior walls of buildings and the surfaces of surrounding objects, e.g, vehicles, roadside advertising panels, and light poles, making it suitable for the future vehicular networks [2]. The IRS's reconfigurability has motivated the wireless research community to integrate the IRS into wireless systems and explore the potential performance gains [3]. As such, we can achieve improved channel capacity, reduced transmit power, enhanced secrecy rate, and interference suppression in different network scenarios and applications such as the IRS-aided vehicular network [4], the IRS-aided secure communications [5], [6], and the IRS-aided mobile edge computing (MEC) systems [7]–[9]. The above-mentioned works typically assumed that the IRS's energy consumption can be negligible due to the use of passive reflecting elements.

However, when controlling the phase shifts of a large number of reflecting elements, the IRS's overall energy consumption will be comparable to that of the RF transicevers [10]. The recent advances in wireless power transfer can be employed to power IRS by using the reflecting elements to harvest a part of the incident RF power instead of the perfect reflection [3]. The IRS's self-sustainability imposes additional energy budget constraints in the optimization of IRS-assisted wireless systems. In particular, the IRS's energy budget strongly relates to the IRS's deployment and the active beamforming strategy. The RF-powered IRS has been studied in some related works to examine its feasibility. The authors in [11] analyzed the performances of the time-switching (TS) and power-splitting (PS) schemes for energy transfer to the IRS. The TS scheme allows the IRS to switch between energy harvesting and reflecting modes, while the PS scheme allows a more flexible tuning of the IRS's reflection coefficients, such that a part of the incident RF power can be harvested as energy. Different from the TS and PS schemes, the authors in [10] divided the IRS's reflecting elements into two parts. One part is used to harvest RF power to sustain the other part.

In this paper, we consider an IRS-assisted and wireless-powered multi-user MEC system, where the MEC server not only provides computation resources to the edge users, but also transfers RF energy to both the IRS and edge users via signal beamforming of the co-located multi-antenna hybrid access point (HAP). Considering that the HAP may be unaware of the IRS's existence, we employ the PS scheme for the IRS controller to adaptively adjust the IRS's amplitude reflection coefficients. Thus, a portion of the incident signals can be absorbed by the IRS. The other portion of the incident signals will be reflected to enhance the channel conditions between the HAP and the edge users. Different from the IRS, each edge user relies on the TS scheme to harvest energy and use the energy to offload its computation workload to the MEC server. To minimize the overall energy consumption, we aim to jointly optimize the edge users' offloading decisions, the HAP's active beamforming, as well as the IRS's passive beamforming and the PS ratio for energy harvesting. A similar

This work of Shimin Gong was supported in part by the National Natural Science Foundation of China under Grant 61972434 and the Shenzhen Fundamental Research Program under Grant JCYJ20190807154009444. (Corresponding author: Shimin Gong)

energy minimization problem in an IRS-assisted MEC system has also been studied in [7] and [9], whereas the IRS's self-sustainability is not taken into consideration.

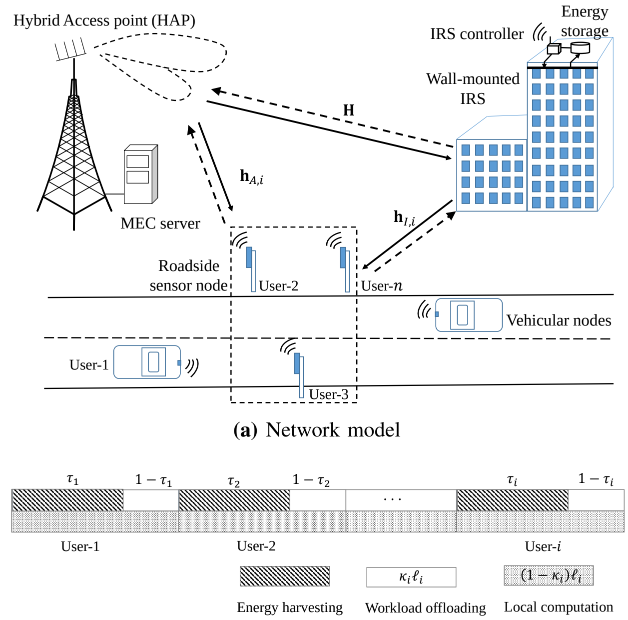
Our main difficulty lies in that the users' uplink offloading decisions are strongly coupled via the HAP's downlink energy transfer, which is controlled by the joint active and passive beamforming strategies. To bypass this difficulty, we decompose the energy minimization problem into the downlink energy transfer and the uplink offloading phases. In the uplink phase, we consider a time-slotted offloading protocol to avoid users' interference. Then we can maximize each user's channel gain by optimizing the passive beamforming strategy according to the semi-definite relaxation (SDR) method. In the downlink phase, the IRS not only harvests energy for itself but also assists the edge users' energy harvesting, whereas each user's energy budget determines its offloading decision. Hence, we further decompose the downlink phase into two sub-problems. The alternating optimization (AO) method is employed to optimize the users' offloading decisions and the joint beamforming strategy in an iterative manner. The numerical results verify that our solution can significantly reduce energy consumption compared to baseline algorithms. More interestingly, a larger-size IRS may not always achieve better performance due to its increasing energy demand, which may not be fulfilled in energy-limited wireless networks.

## II. System Model

We consider an IRS-assisted and wireless-powered MEC system consisting of one HAP and $N$ edge users, e.g., roadside meters and traffic lights, as illustrated in Fig. 1(a). The set of edge users is defined by $\mathcal{N} = \{1, 2, \ldots, N\}$. The multi-antenna HAP can firstly supply energy to users and then receive and process the data offloaded by them. Each user $i \in \mathcal{N}$ has a fixed amount of workload $\ell_i$ that needs to be processed by the HAP or itself. The overall workload can be divided into two parts by a factor $\kappa_i \in (0,1)$. A part $\kappa_i \ell_i$ of the workload will be offloaded to the HAP for edge computing, while the other part $(1-\kappa_i)\ell_i$ of the workload will be processed locally. We consider a time-slotted frame structure to coordinate the multi-user data offloading and local processing, as illustrated in Fig. 1(b). Each user-$i$ is allocated a time slot and its workload $\ell_i$ has to be successfully processed within the allocated slot. Without loss of generality, each time slot is normalized to unit one. Each user can harvest RF energy from the HAP's beamforming signals. The harvested energy is then used for both data offloading and local computation.

### A. IRS-assisted Channel Model

The wireless channels between the HAP and edge users are assisted by an IRS with $K$ reflecting elements, as shown in Fig. 1. We assume that the IRS also harvests energy from HAP's RF signals, similar to that in [11]. Let $\mathcal{K} = \{1, 2, \ldots, K\}$ denote a set of $K$ reflecting elements. Typically, the size of the IRS's reflecting elements is much larger than that of the HAP's antennas, i.e., $K \gg M$. For each single-antenna user $i \in \mathcal{N}$, the complex HAP-User and IRS-User channels are denoted by $\mathbf{h}_{A,i} \in \mathbb{C}^{M\times 1}$ and




**(a)** Network model

**(b)** Time-slotted multi-user offloading frame structure

**Fig. 1:** IRS-assisted MEC for vehicular networks.

$\mathbf{h}_{I,i} \in \mathbb{C}^{K\times 1}$, respectively. The HAP-IRS channel matrix is denoted by $\mathbf{H} \in \mathbb{C}^{M\times K}$. By channel reciprocity, we assume that the uplink channels for data offloading are the same as the downlink channels for the HAP's energy transfer. In each user's time slot $i \in \mathcal{N}$, the IRS controller can adjust the phase shift $\theta_{i,k} \in [0, 2\pi]$ of each reflecting element $k \in \mathcal{K}$ to construct desirable channel conditions. The amplitude reflection coefficient $\rho_{i,k} \in (0,1)$ can also be tuned to control the strength of signal reflection and the IRS's energy harvesting. As such, the parameter $\rho_{i,k}$ is also called the PS ratio. For simplicity, we assume that all reflecting elements have the same reflection coefficient $\rho$ [12]. Let $\boldsymbol{\theta}_i = [e^{j\theta_{i,1}}, \ldots, e^{j\theta_{i,K}}]^H$ denote the IRS's passive beamforming vector in the $i$-th time slot. Hence, the IRS-assisted channel from the HAP to the user-$i$ in the $j$-th time slot can be represented as $\hat{\mathbf{h}}_{A,i,j} = \mathbf{h}_{A,i} + \rho \mathbf{H}\text{diag}(\boldsymbol{\theta}_j)\mathbf{h}_{I,i} = \mathbf{h}_{A,i} + \rho \mathbf{H}_{\mathbf{f},i}\boldsymbol{\theta}_j$, where $\mathbf{H}_{\mathbf{f},i} \triangleq \mathbf{H}\text{diag}(\mathbf{h}_{I,i})$ and $\text{diag}(\boldsymbol{\theta}_i)$ is a diagonal matrix with the diagonal vector $\boldsymbol{\theta}_i$.

### B. Time and Workload Allocation

Each user $i \in \mathcal{N}$ can further divide its time slot into two sub-slots by the time division factor $\tau_i \in [0,1]$. The first sub-slot $\tau_i$ is used for downlink energy transfer from the HAP to the IRS and the users, while the second sub-slot $1-\tau_i$ is used for uplink data offloading from the user to the HAP assisted by the IRS. Hence, the choice of $\tau_i$ has to ensure that there is sufficient energy to offload a part of the workload $\kappa_i \ell_i$ and process the other part $(1-\kappa_i)\ell_i$ locally. Let $(\mathbf{w}_{e,i}, \mathbf{w}_{o,i})$ denote the HAP's active beamforming strategy in the downlink and uplink sub-slots. Similarly, let $\boldsymbol{\theta}_{e,i} = [e^{j\theta^e_{i,1}}, \ldots, e^{j\theta^e_{i,K}}]^H$ and $\boldsymbol{\theta}_{o,i} = [e^{j\theta^o_{i,1}}, \ldots, e^{j\theta^o_{i,K}}]^H$ denote the IRS's passive beamforming strategies in two sub-slots, respectively.

The offloading rate of each user depends on the channel conditions and the user's transmit power $p_{o,i}$, which can be characterized as $o_i(p_{o,i}, \mathbf{w}_{o,i}, \boldsymbol{\theta}_{o,i}) = \log_2(1 + p_{o,i}|\hat{\mathbf{h}}^H_{A,i,j}\mathbf{w}_{o,i}|^2)$. Here we assume a normalized noise power to simplify the formulation. Let $c_i$ denote the local processing capacity and we require $c_i \geq (1-\kappa_i)\ell_i$ to ensure the successful processing of the workload $(1-\kappa_i)\ell_i$ within each time slot. Therefore, we have the time and workload allocation constraints:

$$(1-\tau_i)o_i(p_{o,i}, \mathbf{w}_{o,i}, \boldsymbol{\theta}_{o,i}) \geq \kappa_i \ell_i \text{ and } c_i \geq (1-\kappa_i)\ell_i. \quad (1)$$

The first inequality of in (1) denotes that the offloading data should meet the offloading demand.

## C. Energy Budget for IRS and Receivers

Each user's energy consumption in workload offloading depends on the offloading time $1-\tau_i$ and the user's transmit power $p_{o,i}$. The energy consumption in local computation relates to the local workload $(1-k_i)\ell_i$ and the user's processing capability, i.e., CPU frequencies. Let $f_u$ denote the user's CPU frequency, i.e., the number of CPU cycles per second, and $\phi_u$ be the number of CPU cycles required to process each unit workload. Thus, each user's local processing capacity can be characterized by $c_i \triangleq f_u/\phi_u$. Give the size of local workload $(1-k_i)\ell_i$, the CPU time required for local computation is evaluated by $t_{c,i} = (1-k_i)\ell_i/c_i$. Besides, the energy consumption per CPU cycle can be characterized by $k_u f_u^2$, where the constant $k_u$ denotes the energy efficiency of the local processor [13]. Hence, the energy consumption in local computation is $e_{u,i} = t_{u,i} k_u f_u^3 = \phi_u k_u f_u^2 (1-\kappa_i)\ell_i$. Combining energy consumption in two parts, each user's overall energy consumption is given by $e_{c,i} = p_{o,i}(1-\tau_i) + \hat{\phi}_u(1-k_i)\ell_i$, where $\hat{\phi}_u \triangleq \phi_u k_u f_u^2$ can be viewed as the energy consumption per unit workload in local computing.

Let $p_0$ denote the HAP's transmit power and $\mathbf{w}_{e,i} \in \mathbb{C}^{M\times 1}$ denote the normalized energy beamforming vector of the HAP in the downlink sub-slot $\tau_i$. By adopting the linear energy harvesting model, the energy harvested by the user-$i$ in the $j$-th time slot is given by $\eta p_0 |\hat{\mathbf{h}}_{A,i,j}^H \mathbf{w}_{e,j}|^2 \tau_j$, where $\eta$ represents the energy harvesting efficiency. To sustain the users' local computation and offloading, we have the following energy budget constraint for each user $i \in \mathcal{N}$:

$$p_{o,i}(1-\tau_i) + \hat{\phi}_u(1-\kappa_i)\ell_i \leq \sum_{j\in\mathcal{N}} \eta p_0 |\hat{\mathbf{h}}_{A,i,j}^H \mathbf{w}_{e,j}|^2 \tau_j. \quad (2)$$

By tuning the IRS's PS ratio $\rho$, the IRS can sustain itself by harvesting RF power from the HAP's energy beamforming signals. The energy harvested by the IRS is given as $e_I = \eta(1-\rho^2)\sum_{i\in\mathcal{N}} \|\mathbf{H}^H \mathbf{w}_{e,i}\|^2 p_0 \tau_i$. We assume that the IRS only harvests energy in the downlink energy transfer phase. The PS ratio is set as $\rho = 1$ in the uplink offloading phase to maximize the data offloading rate. Hence, the IRS's self-sustainability implies the following energy budget constraint:

$$NK\mu \leq \eta(1-\rho^2)\sum_{i\in\mathcal{N}} \|\mathbf{H}^H \mathbf{w}_{e,i}\|^2 p_0 \tau_i, \quad (3)$$

where $\mu$ is the energy consumption of a single reflecting element. We assume that the IRS's overall energy consumption is linearly proportional to the number of reflecting elements [14].

# III. Joint Workload Allocation and Beamforming Optimization for IRS-assisted Offloading

We aim to minimize the HAP's overall energy consumption by jointly optimizing the HAP's active beamforming strategy $\mathbf{w}_i \triangleq (\mathbf{w}_{e,i}, \mathbf{w}_{o,i})$, the IRS's PS ratio $\rho$ and the passive beamforming strategy $\boldsymbol{\theta}_i \triangleq (\boldsymbol{\theta}_{e,i}, \boldsymbol{\theta}_{o,i})$, as well as the user's offloading strategy $(\tau_i, \kappa_i, p_{o,i})$. In each time slot $i \in \mathcal{N}$, the HAP's overall energy consumption includes the RF beamforming energy $p_0||\mathbf{w}_{e,i}||^2\tau_i$ in downlink energy transfer and the computation energy for processing the offloaded workload $\kappa_i\ell_i$. The HAP's energy consumption in computation can be characterized by $\hat{\phi}_A \kappa_i \ell_i$, where $\hat{\phi}_A$ denotes the energy consumption to process each unit workload. Hence, we can formulate the energy minimization problem as follows:

$$\begin{aligned}
\min_{\rho, (\boldsymbol{\theta}_i, \mathbf{w}_i), (\tau_i, \kappa_i, p_{o,i})} \quad & \sum_{i\in\mathcal{N}} (p_0||\mathbf{w}_{e,i}||^2 \tau_i + \hat{\phi}_A \kappa_i \ell_i) && \text{(4a)}\\
\text{s.t.} \quad & (1), (2), \text{ and } (3), && \text{(4b)}\\
& \boldsymbol{\theta}_{e,i}, \boldsymbol{\theta}_{o,i} \in (0, 2\pi)^K, \ \forall i \in \mathcal{N}, && \text{(4c)}\\
& ||\mathbf{w}_{e,i}|| \leq 1, ||\mathbf{w}_{o,i}|| \leq 1, \ \forall i \in \mathcal{N}, && \text{(4d)}\\
& \rho, \kappa_i, \tau_i \in (0,1), p_{o,i} \geq 0, \ \forall i \in \mathcal{N}. && \text{(4e)}
\end{aligned}$$

Problem (4) is complicated due to the non-convex structure and complex coupling among different control variables. In the following part, we decompose problem (4) into two sub-problems for the downlink energy transfer and the uplink offloading phases, respectively. Each sub-problem will be individually solved by exploiting the problem structure.

## A. Uplink Offloading Beamforming Optimization

The optimization of uplink data offloading can be transformed to maximize the uplink channel gain from each user-$i$ to the HAP, which involves the HAP's receiver beamforming vector $\mathbf{w}_{o,i}$ and the IRS's passive beamforming vector $\boldsymbol{\theta}_{o,i}$ in each sub-slot $1-\tau_i$. By employing the SDR method, we can easily formulate a joint active and passive beamforming optimization problem, similar to that in [15]. In particular, given a fixed $\boldsymbol{\theta}_{o,i}$, the HAP's receiver beamforming vector can be determined by the maximum ratio combining (MRC) scheme [16], i.e., $\mathbf{w}_{o,i}^* = \hat{\mathbf{h}}_{A,i,i}/||\hat{\mathbf{h}}_{A,i,i}||$. Then, the next step is to maximize the channel gain of $\hat{\mathbf{h}}_{A,i,i}$ by optimizing the uplink passive beamforming vector $\boldsymbol{\theta}_{o,i}$:

$$\max_{\boldsymbol{\theta}_{o,i}\in[0,2\pi]^K} \ \|\mathbf{h}_{A,i} + \mathbf{H}_{\mathbf{f},i}\boldsymbol{\theta}_{o,i}\|^2. \quad (5)$$

Problem (5) can be easily transformed into a semi-definite program (SDP) and solved by the interior-point algorithm efficiently. Given the optimized solution $\boldsymbol{\theta}_{o,i}^*$ to (5) and the corresponding MRC beamformer $\mathbf{w}_{o,i}^*$, the offloading rate $o_i(p_{o,i}, \mathbf{w}_{o,i}^*, \boldsymbol{\theta}_{o,i}^*)$ only depends on the user's transmit power $p_{o,i}$. Then, we can simplify the offloading rate as $o_i(p_{o,i}) = \log_2(1 + p_{o,i}||\hat{\mathbf{h}}_{A,i,i}^*||^2)$, where $\hat{\mathbf{h}}_{A,i,i}^*$ denotes the optimal channel of the user-$i$ enhanced by the IRS in the $i$-th time slot. Given $\boldsymbol{\theta}_{o,i}^*$ and $\mathbf{w}_{o,i}^*$, we can also simplify the constraint in (1) as $(1-\tau_i)o_i(p_{o,i}) \geq \kappa_i\ell_i \geq \ell_i - c_i$.

## B. Downlink Energy Beamforming Optimization

The downlink energy beamforming controls the wireless energy transfer to all users and the IRS. Meanwhile, the IRS's PS ratio $\rho$, the user's time allocation $\tau_i$, and the HAP's energy beamforming $\mathbf{w}_{e,i}$ are also coupled, as shown in (3). Thus, it is difficult to directly solve the joint optimization problem (4).

In the following, the above bottleneck will be addressed by using the AO method that optimizes the control variables of different entities in an iterative manner.

*1) Optimizing users' offloading decisions:* In the first sub-problem, we optimize the users' offloading decisions including the transmit power, time and workload allocation strategies, given the HAP's active beamforming $\mathbf{w}_{e,i}$ and the IRS's passive beamforming strategy $(\rho, \boldsymbol{\theta}_{e,i})$. In this case, the quadratic terms $|\hat{\mathbf{h}}_{A,i,j}^H \mathbf{w}_{e,i}|^2$ and $\|\mathbf{H}^H \mathbf{w}_{e,i}\|^2$ become constants in (2) and (3). Let $c_{e,i,j} \triangleq |\hat{\mathbf{h}}_{A,i,j}^H \mathbf{w}_{e,i}|^2$ and $c_{s,i} \triangleq \|\mathbf{H}^H \mathbf{w}_{e,i}\|^2$ for simplicity. We can transform problem (4) as follows:

$$\min_{\tau_i,\kappa_i,p_{o,i}} \sum_{i\in\mathcal{N}} (p_0 ||\mathbf{w}_{e,i}||^2 \tau_i + \hat{\phi}_A \kappa_i \ell_i) \tag{6a}$$

$$\text{s.t. } (1-\tau_i) o_i(p_{o,i}) \geq \kappa_i \ell_i \geq \ell_i - c_i, \tag{6b}$$

$$\sum_{j\in\mathcal{N}} \eta p_0 c_{e,i,j} \tau_j \geq p_{o,i}(1-\tau_i) + \hat{\phi}_u (1-\kappa_i)\ell_i, \tag{6c}$$

$$\sum_{i\in\mathcal{N}} \eta p_0 c_{s,i} \tau_i \geq \frac{NK\mu}{(1-\rho^2)}, \tag{6d}$$

$$\kappa_i \in [0,1], \tau_i \in [0,1], p_{o,i} \geq 0, \text{ and } i \in \mathcal{N}. \tag{6e}$$

Problem (6) can be easily transformed into a convex form by introducing $\tau_i' = 1 - \tau_i$ and $e_{o,i} = p_{o,i}(1-\tau_i)$, where $e_{o,i}$ denotes the user's energy consumption in data offloading. As such, the first inequality in (6b) becomes joint convex in $(\tau_i', e_{o,i})$. All other constraints and the objective function are linear with respect to $(\tau_i, \kappa_i, e_{o,i})$. Therefore, we can find the optimal $(\tau_i^*, \kappa_i^*, e_{o,i}^*)$ and $p_{o,i}^* = e_{o,i}^*/(1-\tau_i^*)$ to problem (6) efficiently by the off-the-shelf optimization toolbox.

*2) Joint active and passive beamforming:* In the second sub-problem, we aim to minimize the HAP's energy consumption by optimizing the joint beamforming strategy $(\rho, \boldsymbol{\theta}_{e,i}, \mathbf{w}_{e,i})$. Given the users' offloading decisions $(\tau_i, \kappa_i, p_{o,i})$, problem (4) can be simplified as follows:

$$\min_{\rho,\boldsymbol{\theta}_{e,i},\mathbf{w}_{e,i}} \sum_{i\in\mathcal{N}} (p_0 ||\mathbf{w}_{e,i}||^2 \tau_i + \hat{\phi}_A \kappa_i \ell_i) \tag{7a}$$

$$\text{s.t. } \sum_{j\in\mathcal{N}} |\hat{\mathbf{h}}_{A,i,j}^H \mathbf{w}_{e,j}|^2 \tau_j \geq \frac{E_i}{\eta p_0}, \tag{7b}$$

$$\sum_{i\in\mathcal{N}} (1-\rho^2) \|\mathbf{H}^H \mathbf{w}_{e,i}\|^2 \tau_i \geq \frac{NK\mu}{\eta p_0}, \tag{7c}$$

$$\rho \in (0,1), \boldsymbol{\theta}_{e,i} \in (0, 2\pi)^K, ||\mathbf{w}_{e,i}|| \leq 1, \tag{7d}$$

where the constant $E_i = p_{o,i}(1-\tau_i) + \hat{\phi}_u(1-\kappa_i)\ell_i$ denotes the user-$i$'s overall energy consumption in both data offloading and local computation. The inequality in (7b) implies that the active beamforming vector $\mathbf{w}_{e,i}$ should be jointly optimized with the passive beamforming strategy $(\rho, \boldsymbol{\theta}_{e,i})$ to ensure sufficient energy supply to all users. The PS ratio $\rho$ also relates to the IRS's energy budget constraint in (7c). Given a feasible $(\mathbf{w}_{e,i}, \boldsymbol{\theta}_{e,i})$ to (7), it is easy to verify that constraints (7b) and (7c) define the lower and upper bounds for the PS ratio $\rho$, similar to the observations in [17]. This implies that we can solve problem (7) by an iterative two-step method.

In the first step, given the PS ratio $\rho$, the beamforming vectors $(\mathbf{w}_{e,i}, \boldsymbol{\theta}_{e,i})$ can be optimized by the AO method. With the fixed $\boldsymbol{\theta}_{e,i}$, we replace the quadratic terms in (7b) and (7c) by the following linear matrix inequalities:

$$\sum_{j\in\mathcal{N}} \mathbf{Tr}(\hat{\mathbf{G}}_{i,j} \mathbf{W}_{e,j}) \tau_j \geq \frac{E_i}{\eta p_0}, \quad \forall i \in \mathcal{N}, \tag{8}$$

$$\sum_{i\in\mathcal{N}} \mathbf{Tr}(\mathbf{H}\mathbf{H}^H \mathbf{W}_{e,i}) \tau_i \geq \frac{NK\mu}{\eta p_0 (1-\rho^2)}, \tag{9}$$

where $\hat{\mathbf{G}}_{i,j} = \hat{\mathbf{h}}_{A,i,j} \hat{\mathbf{h}}_{A,i,j}^H$ denotes the channel matrix from the HAP to the $i$-th user in the $j$-th time slot. The matrix variable $\mathbf{W}_{e,i} \succeq 0$ is the rank-one relaxation of the quadratic term $\mathbf{w}_{e,i}\mathbf{w}_{e,i}^H$. Given $\rho$ and $\boldsymbol{\theta}_{e,i}$, we can assume that the channel matrix $\hat{\mathbf{G}}_{i,j}$ can be estimated by the HAP, and then we can optimize $\mathbf{W}_{e,i}$ by solving the following problem:

$$\max_{\mathbf{W}_{e,i}\succeq 0, \mathbf{Tr}(\mathbf{W}_{e,i})\leq 1} \sum_{i\in\mathcal{N}} \mathbf{Tr}(\mathbf{W}_{e,i}) p_0 \tau_i, \text{ s.t. } (8)-(9). \tag{10}$$

Now problem (10) becomes a standard SDP and efficiently tractable. As the matrix solution $\mathbf{W}_{e,i}$ may not lead to a rank-one solution, the Gaussian randomization method can be further applied to extract its rank-one approximation [15].

The optimization of $\boldsymbol{\theta}_{e,i}$ becomes a feasibility check with the fixed $\mathbf{w}_{e,i}$. In this case, we can introduce a set of auxiliary variables $\{\alpha_i\}_{i\in\mathcal{N}}$ to reformulate problem (7) as follows:

$$\max_{\boldsymbol{\theta}_{e,j},\alpha_i} \sum_{i\in\mathcal{N}} \alpha_i \tag{11a}$$

$$\text{s.t. } \sum_{j\in\mathcal{N}} |\hat{\mathbf{h}}_{A,i,j}^H \mathbf{w}_{e,j}|^2 \tau_j \geq \alpha_i + \frac{E_i}{\eta p_0}, \ \forall i \in \mathcal{N} \tag{11b}$$

Note that the IRS-assisted channel $\hat{\mathbf{h}}_{A,i,j}$ depends on the IRS's passive beamforming vector, i.e., $\hat{\mathbf{h}}_{A,i,j} = \mathbf{h}_{A,i} + \rho \mathbf{H}_{\mathbf{f},i} \boldsymbol{\theta}_{e,j}$. Problem (11) can be converted into an efficiently tractable SDP by the SDR method similarly applied to problem (5).

In the second step, we update the IRS's PS ratio $\rho$ to further decrease the HAP's energy consumption given the joint beamforming strategy $(\mathbf{w}_{e,i}, \boldsymbol{\theta}_{e,i})$. By using the following proposition, we can obtain lower and upper bounds of the PS ratio, denoted as $\rho_{\min}$ and $\rho_{\max}$, respectively. This implies that we can update the PS ratio by the bisection method.

**Proposition 1:** *Given the joint beamforming strategy* $(\mathbf{w}_{e,i}, \boldsymbol{\theta}_{e,i})$*, the upper bound* $\rho_{\max}$ *of the PS ratio in problem* (7) *is determined by* (7c) *and given as follows:*

$$\rho_{\max} = \left(1 - \frac{NK\mu}{\eta p_0 \sum_{i\in\mathcal{N}} ||\mathbf{H}^H \mathbf{w}_{e,i}|| \tau_i}\right)^{\frac{1}{2}}. \tag{12}$$

*For each user* $i \in \mathcal{N}$*, let* $\rho_{i,\min}$ *denote the solution to the quadratic equation* $a_i\rho^2 + b_i\rho + c_i = 0$*, where the constant parameters are given in* (13)*. Then, the lower bound of the PS ratio is given by* $\rho_{\min} = \max_i\{\rho_{i,\min}, i \in \mathcal{N}\}$.

$$a_i = \sum_{j\in\mathcal{N}} \tau_j |(\mathbf{H}_{\mathbf{f},i}\boldsymbol{\theta}_{e,j})^H \mathbf{w}_{e,j}|^2, \tag{13a}$$

$$b_i = \sum_{j\in\mathcal{N}} 2\tau_j Re((\mathbf{H}_{\mathbf{f},i}\boldsymbol{\theta}_{e,j})^H \mathbf{W}_{e,j} \mathbf{h}_{A,i}), \tag{13b}$$

$$c_i = \sum_{j\in\mathcal{N}} \tau_j |\mathbf{h}_{A,i}^H \mathbf{w}_{e,j}|^2 - \frac{E_i}{\eta p_0}. \tag{13c}$$

**Algorithm 1** AO Algorithm for Problem (4)

1: Initialize $k = 0$, $(\tau_i^{(k)}, \kappa_i^{(k)}, p_{o,i}^{(k)})$, $(\boldsymbol{\theta}_{e,i}^{(k)}, \mathbf{w}_{e,i}^{(k)}, \rho^{(k)})$, and the HAP's energy consumption $E_o^{(k)}$ randomly;
2: Update $(\boldsymbol{\theta}_{o,i}, \mathbf{w}_{o,i})$ by solving (5) and MRC;
3: **repeat**
4: $\quad k = k + 1$;
5: $\quad$ Update $(\tau_i^{(k)}, \kappa_i^{(k)}, p_{o,i}^{(k)})$ by solving (6);
6: $\quad$ Update $(\mathbf{w}_{e,i}^{(k)}, \boldsymbol{\theta}_{e,i}^{(k)})$ by solving (10) and (11);
7: $\quad$ Update $\rho^{(k)} = (\rho_{\min}^{(k)} + \rho_{\max}^{(k)})/2$ by Proposition 1;
8: $\quad$ Compute the objective function value $E_o^{(k)}$ in (4);
9: **until** $|E_o^{(k)} - E_o^{(k-1)}| < \epsilon$

The proof of Proposition 1 follows a similar idea as that in [18]. The details are omitted here for brevity. Given $(\mathbf{w}_{e,i}, \boldsymbol{\theta}_{e,i})$ and $[\rho_{\min}, \rho_{\max}]$ in Proposition 1, we can update $\rho$ by the bisection method. Till this point, we can summarize the solution procedure in Algorithm 1. The computational complexity of the SDP in line 2 of Algorithm 1 is $\mathcal{O}(NK^{3.5})$. The computational complexity in lines 5-7 can be estimated by $\mathcal{O}(N^{2.5})$, $\mathcal{O}(I_{\max}(M^{4.5}+K^{4.5})N^{2.5})$, and $\mathcal{O}(N^2)$, respectively, where $I_{\max}$ denotes the maximum number of iterations. The overall computational complexity can be evaluated by $\mathcal{O}(NK^{3.5} + \log_2(\frac{1}{\epsilon})(N^{2.5} + I_{\max}(M^{4.5} + K^{4.5})N^{2.5}))$ [19], where $\epsilon$ denotes the error tolerance to terminate Algorithm 1.

## IV. Numerical Simulation

In this section, numerical results are presented to evaluate the proposed IRS-assisted and wireless-powered MEC system. Apart from the proposed algorithm, the other three benchmarks are considered for comparison, i.e., Random Phase, Complete Harvesting, and Without IRS. The Random Phase scheme denotes that the IRS applies random phase shifts in both uplink and downlink phases. The Complete Harvesting scheme represents that the IRS only harvests energy in the downlink phase by setting the PS ratio to 0. It is assumed that the signal propagation follows a log-distance model with the path loss $L_0 = 30$ dB at the reference distance. The path loss exponents of links HAP-IRS, IRS-User, and HAP-User are set to 2, 2.8 and 3.5, respectively. The small-scale fading follows the complex Gaussian distribution with zero mean and unit variance. To facilitate our analysis, we assume that each user has the same amount of workload $\ell$ in the simulation. The nodes' topology is set as follows. The HAP is placed at the origin of the coordinate and the IRS is located at $(5, 0)$. Three edge users are placed at $(6, 2)$, $(8, 1.5)$ and $(8, 2)$, respectively. The default parameter settings are given as follows: HAP's antenna size $M = 4$, energy harvesting efficiency $\eta = 0.8$, HAP's transmit power $p_0 = 60$ dBm, channel bandwidth $W = 1$ MHz, $\mu = 1.5\times10^{-7}$ W, $\epsilon = 10^{-3}$, $f_u = 5 \times 10^8$ cycle/s, $k_u = 10^{-28}$, $\phi_u = 700$ cycle/bit, $\hat{\phi}_A = 10^{-9}$ J/bit [13]. Fig. 2 shows the convergence of Algorithm 1 with $K = 80$ and $\ell = 1000$ bit. It is seen that the HAP's energy consumption can be significantly reduced as the number of iterations increases. This result verifies the effectiveness of the proposed algorithm for energy saving in this paper. Meanwhile, the IRS's PS ratio $\rho$ increases gradually as the algorithm converges. An increasing $\rho$ allows more signal power to be reflected to the users, which can be harvested by the users and used for both local computation and data offloading. Compared to the case with a fixed PS ratio, our method can avoid unnecessary energy consumption in the IRS. This observation also reflects that our method can improve energy efficiency effectively while satisfying the IRS's energy requirement. It is worth noting that the proposed algorithm achieves convergence within a few iterations. This implies its applicability in practical implementation.

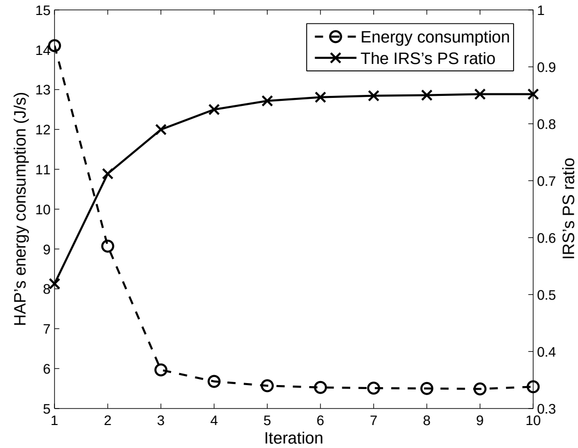
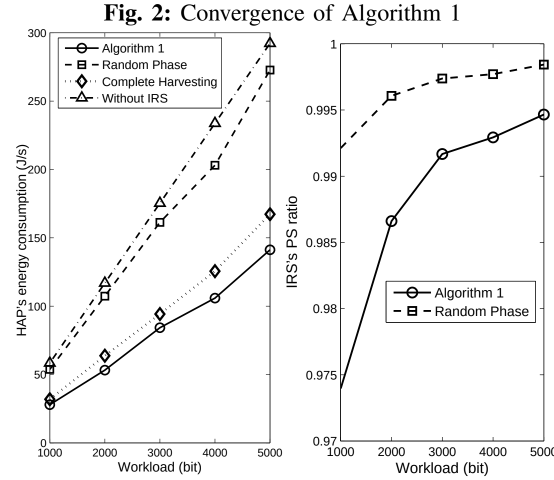


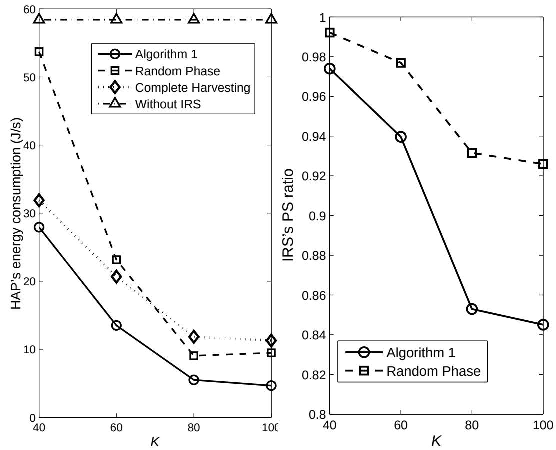

**Fig. 2:** Convergence of Algorithm 1




**(a)** Energy consumption **(b)** IRS's PS ratio $\rho$

**Fig. 3:** Energy consumption with different amount of workload.

Fig. 3 depicts the comparison results of the HAP's energy consumption in different algorithms as the amount of workload $\ell$ increases. The size of the IRS is fixed at $K = 40$. It is clear that the HAP's energy consumptions in all algorithms increase in $\ell$. The reason is straightforward as the users need more energy for both local computation and data offloading when increasing their computation workloads. We also observe that the PS ratio $\rho$ also increases in $\ell$, as shown in Fig. 3(b). This implies that $\rho$ can be jointly adapted to reduce the HAP's energy consumption as the overall workload becomes heavier. Compared to the case without IRS, the other three schemes can achieve better performance by using the IRS to create a more desirable multi-path effect, even with the




**(a)** Energy consumption **(b)** IRS's PS ratio $\rho$

**Fig. 4:** Energy consumption with different size of the IRS.

random phase configuration in Random Phase scheme and the partial reflection in the Complete Harvesting scheme, as shown in Fig. 3(a). Moreover, since we optimize the passive beamforming in both the uplink and downlink phases, the proposed Algorithm 1 always achieves the best performance compared to the other three benchmarks.

In Fig. 4, we present the comparison results of the HAP's energy consumption as the size of IRS $K$ gradually increases. Each user's workload is fixed at $\ell = 1000$ bit. With the assistance from an IRS, the HAP's energy consumption dramatically decreases as $K$ increases. This shows that the IRS can be a very effective way to reduce the HAP's energy consumption, even with the randomized passive beamforming strategy, as shown in Fig. 4(a). We also observe that the IRS working in the uplink offloading phase only can still outperform the case without IRS. As shown in Fig. 4(b), we observe that the IRS's PS ratio $\rho$ is inversely proportionally to the size $K$. That is because the IRS requires more energy supply with a larger number of reflecting elements. Hence, the IRS will tune down its PS ratio $\rho$ to harvest more energy. An interesting observation is that the energy saving by using the IRS becomes slowing down, as the size of the IRS increases. This observation implies that a larger-size IRS with a higher energy demand becomes a burden to the IRS-assisted wireless system. The overall energy saving by using the IRS can be canceled out by the extra energy consumption of the IRS.

## V. Conclusions

In this paper, we have investigated the energy minimization problem in an IRS-assisted and wireless-powered MEC system. Based on the decomposition of the original problem, we have proposed an individual solution to each sub-problem, by adaptively optimizing the joint beamforming strategy, the users' offloading decisions, and the IRS's PS ratio for energy harvesting. Numerical results have revealed some interesting observations that can be used to guide the IRS's practical deployment in wireless-powered MEC systems.

## References


[1] R. MD, M. Debbah, D. T. Phan-Huy, A. Zappone, M. S. Alouini, C. Yuen, V. Sciancalepore, G. C. Alexandropoulos, J. Hoydis, and H. Gacanin, "Smart radio environments empowered by AI reconfigurable meta-surfaces: An idea whose time has come," *EURASIP J. Wireless Commun. Netw.*, vol. 19, no. 129, pp. 1–20, Mar. 2019.

[2] Y. Zhu, B. Mao, Y. Kawamoto, and N. Kato, "Intelligent reflecting surface-aided vehicular networks toward 6G: Vision, proposal, and future directions," *IEEE Veh. Techn. Mag.*, vol. 16, no. 4, pp. 48–56, Oct. 2021.

[3] S. Gong, X. Lu, D. T. Hoang, D. Niyato, L. Shu, D. I. Kim, and Y.-C. Liang, "Toward smart wireless communications via intelligent reflecting surfaces: A contemporary survey," *IEEE Commun. Surv. Tutor*, vol. 22, no. 4, pp. 2283–2314, Jun. 2020.

[4] Y. Chen, Y. Wang, J. Zhang, and Z. Li, "Resource allocation for intelligent reflecting surface aided vehicular communications," *IEEE Trans. Veh. Techn.*, vol. 69, no. 10, pp. 12 321–12 326, Jul. 2020.

[5] C. Gong, X. Yue, X. Wang, X. Dai, R. Zou, M. Essaaidi, and J. Cui, "Intelligent reflecting surface aided secure communications for NOMA networks," *IEEE Trans. Veh. Techn.*, vol. 21, no. 99, pp. 1–1, Nov. 2021.

[6] A. U. Makarfi, K. M. Rabie, O. Kaiwartya, X. Li, and R. Kharel, "Physical layer security in vehicular networks with reconfigurable intelligent surfaces," in *Proc. IEEE VTC-Spring*, Antwerp, Belgium, May 2020, pp. 1–6.

[7] T. Bai, C. Pan, H. Ren, Y. Deng, M. Elkashlan, and A. Nallanathan, "Resource allocation for intelligent reflecting surface aided wireless powered mobile edge computing in OFDM systems," *IEEE Trans. Wireless Commun.*, vol. 20, no. 8, pp. 5389–5407, Aug. 2021.

[8] T. Bai, C. Pan, Y. Deng, M. Elkashlan, A. Nallanathan, and L. Hanzo, "Latency minimization for intelligent reflecting surface aided mobile edge computing," *IEEE J. Sel. Area. Commun.*, vol. 38, no. 11, pp. 2666–2682, Jul. 2020.

[9] C. Sun, W. Ni, Z. Bu, and X. Wang, "Energy minimization for intelligent reflecting surface-assisted mobile edge computing," *IEEE Trans. Wireless Commun.*, vol. 22, no. 10, pp. 1–1, Feb. 2022.

[10] S. Hu, Z. Wei, Y. Cai, C. Liu, D. W. K. Ng, and J. Yuan, "Robust and secure sum-rate maximization for multiuser MISO downlink systems with self-sustainable IRS," *IEEE Trans. Commun.*, vol. 69, no. 10, pp. 7032–7049, Jul. 2021.

[11] B. Lyu, P. Ramezani, H. Dinh Thai, S. Gong, Z. Yang, and A. Jamalipour, "Optimized energy and information relaying in self-sustainable IRS-empowered WPCN," *IEEE Trans. Commun.*, vol. 69, no. 1, pp. 619–633, Oct. 2020.

[12] Y. Zou, S. Gong, J. Xu, W. Cheng, D. T. Hoang, and D. Niyato, "Joint energy beamforming and optimization for intelligent reflecting surface enhanced communications," in *Proc. IEEE WCNCW*, Seoul, Korea (South), Jun. 2020, pp. 1–6.

[13] T. Bai, C. Pan, H. Ren, Y. Deng, M. Elkashlan, and A. Nallanathan, "Resource allocation for intelligent reflecting surface aided wireless powered mobile edge computing in OFDM systems," *IEEE Trans. Wireless Commun.*, vol. 20, no. 8, pp. 5389–5407, Mar. 2021.

[14] H. Chongwen, A. Zappone, G. Alexandropoulos, m. Debbah, and C. Yuen, "Reconfigurable intelligent surfaces for energy efficiency in wireless communication," *IEEE Trans. Wireless Commun.*, vol. 18, no. 8, pp. 4157–4170, Jun. 2019.

[15] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5394–5409, Aug. 2019.

[16] G. Yu, X. Chen, C. Zhong, D. W. Kwan Ng, and Z. Zhang, "Design, analysis, and optimization of a large intelligent reflecting surface-aided B5G cellular internet of things," *IEEE Internet Things J.*, vol. 7, no. 9, pp. 8902–8916, May 2020.

[17] Y. Deng, Y. Zou, S. Gong, B. Lyu, D. T. Hoang, and D. Niyato, "Robust beamforming for IRS-assisted wireless communications under channel uncertainty," in *Proc. IEEE WCNC*, Nanjing, China, May 2021, pp. 1–6.

[18] Y. Zou, Y. Long, S. Gong, H. Dinh Thai, W. Liu, W. Cheng, and D. Niyato, "Robust beamforming optimization for self-sustainable intelligent reflecting surface assisted wireless networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 21, no. 9, pp. 1–1, Dec. 2021.

[19] Z.-Q. Luo, W.-K. Ma, A. M.-C. So, Y. Ye, and S. Zhang, "Semidefinite relaxation of quadratic optimization problems," *IEEE Signal Process. Mag.*, vol. 27, no. 3, pp. 20–34, May 2010.