Optimal Time Scheduling in Relay Assisted Batteryless IoT Networks

Bin Lyu and Dinh Thai Hoang

***Abstract*—In this paper, we propose a novel relay transmission scheme in a batteryless IoT network for practical implementation and high energy-efficiency, where communications between a hybrid access point (HAP) and multiple batteryless sensors are assisted by energy-constrained gateways. In the proposed system, while a batteryless sensor backscatters the incident signals from the HAP to transmit data to its gateway, other gateways can simultaneously harvest energy from the HAP. Then, the gateways can use their harvested energy to forward the received signals to the HAP. Under this setup, we formulate the achievable sum-rate maximization problem by optimizing the time allocation between data backscattering, energy harvesting, and data forwarding. Then, an efficient method is proposed to find the optimal solution. Simulation results show that the proposed relay transmission scheme can achieve up to 34% sum-rate gain over two benchmark schemes.**

***Index Terms*—Wireless powered communication, backscatter communication, relay transmission, time scheduling.**

I. Introduction

THE explosive growth of Internet of Things (IoT) enables the ubiquitous deployment of wireless devices. However, there is a bottleneck of practical applications of wireless devices due to their limited battery capacities. To promote the sustainable development of IoT, deploying batteryless IoT devices has been emerging as a promising way [1]. Batteryless IoT devices typically communicate with the hybrid access point (HAP) passively by modulating and reflecting the instantaneous incident signals based on the backscatter communication (BackCom) technology [2]. Note that they can harvest energy by absorbing signals during the data backscattering process and the amount of harvested energy is sufficient to maintain backscattering operations, which was demonstrated by real experiments in [2]. Hence, the batteryless IoT devices do not need to be equipped with bulky batteries to store energy, which not only can diminish implementation costs and sizes of them, but also is very environment-friendly. Recently, batteryless IoT devices have been extensively implemented in practice, e.g., smart life, medical biology, and logistics [3]. However, the main challenge of batteryless IoT devices is their limited communication ranges, i.e., they are only appropriate for short-range communications [2], [4]. Hence, extending the communication ranges for batteryless IoT devices has become an urgent need for future development of batteryless IoT networks.

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Relay transmission is a promising way to enhance the communication ranges of power-constrained devices in IoT networks. Recently, a passive relay transmission scheme has been investigated [5], [6]. In [5], a set of relays using the BackCom mode work cooperatively for data forwarding (DF). Nevertheless, the joint design of reflection coefficients at relays is intractable to obtain in practice due to global channel status requirements. Moreover, the communication ranges of the passive relays are also limited, and thus they cannot extend network converge effectively. To address this issue, multiple BackCom devices were employed to achieve multi-hop relaying between the source node and the destination node [6]. However, the energy efficiency of this scheme is obviously low due to the fact that the HAP has to transmit incident signals continuously to enable each-hop relaying. In addition, two adjacent BackCom devices should be carefully deployed to guarantee that they are within each other's communication coverage, which might be impossible. In [7] and [8], energy-constrained relays that support both BackCom and active communication were employed. However, these relays need to be equipped with complex circuits to enable switching between dual modes and their circuit power consumption is fairly high [5]. Furthermore, the communication ranges of these relays are still limited due to using the BackCom mode. In summary, to promote the practical applications of batteryless devices for future IoT networks, the challenge of extending network coverage efficiently should be addressed. Hence, a novel relay transmission scheme should be investigated.

In this paper, we propose a highly efficient relay transmission scheme in a batteryless IoT network, where wireless-powered gateways first receive the backscattered signals from the batteryless devices and then forward the decoded signals to the HAP. Under this setup, the batteryless devices only need to be equipped with BackCom circuits, and thus can avoid the complex circuit designs compared with those hybrid devices with both active transmission and passive backscattering functions. More importantly, compared with deploying the hybrid devices directly, the ceiling of which is still limited by the BackCom mode, the coverage of batteryless IoT networks can be significantly extended by using gateways as relay nodes. In addition, we consider an efficient time scheduling to maximize the utilization of energy at the HAP, i.e., when a batteryless device backscatters the incident signals from the HAP to transmit data to its gateway, in the meantime other gateways simultaneously harvest energy from the HAP, which guarantees that the batteryless devices and gateways have sufficient time for data backscattering (DB) and energy harvesting (EH), respectively. To maximize the achievable sum-rate, we first formulate an optimization problem by investigating the time allocation between EH, DB, and DF. Then, a two-stage method is proposed to find the optimal solution, from which the relevance between DB and DF is revealed. Finally, simulation results show that the proposed relay transmission scheme can achieve up to 34% gain in term of sum-rate over two benchmark schemes.

II. System Model

As illustrated in Fig. 1, we consider that N wireless sensor networks (WSNs) are deployed in the same area and powered by an HAP. Each WSN includes one sensor (batteryless device) and one gateway.[1] The gateway is located near its corresponding sensor, and the distance between them is much smaller than that between the sensor and the HAP. All devices are equipped with single antenna. The sensors in WSNs are typically hardware-constrained and only can operate in the BackCom mode. While the gateways adopt the harvest-then-transmit (HTT) mode [9] and can also serve as relay nodes to forward the sensors' data to the HAP because they have long transmission distances [6]. The gateways are equipped with information decoders to retrieve the received signals from the sensors because the reflected signals have different power levels [2], [5]. When the HAP transmits energy signals, the sensors utilize such signals to transmit data via BackCom. Alternatively, the gateways can harvest energy and store in their batteries.

We consider two successive working phases, i.e., EH phase and data transmission (DT) phase. In the EH phase, the sensor in WSN-i ($i = 1, \ldots, N$), denoted by U_i, backscatters signals to transmit data to its corresponding gateway (denoted by G_i) during b_i, while the gateways in other WSNs simultaneously harvest energy. Since each gateway is equipped with a single antenna, it only can either harvest energy from the HAP's signals or receive and decode backscattered signals from its sensor at a time. Hence, other users keep idle to avoid interference with WSN-i during b_i. The total EH time of G_i is thus given by $\sum_{j=0}^{N} b_j - b_i$, where b_0 is the dedicated EH time during which all gateways harvest energy.[2] In the DT phase, each gateway forwards its received signals to the HAP based on the harvested energy in a round-robin fashion, i.e., only one gateway is allowed to transmit data at a time, the duration of which is t_i. Under this setting, there will be no interferences among the gateways. For convenience, we consider a normalized transmission block, denoted by $T = 1$. Then, we have the following time constraint $\sum_{i=0}^{N} b_i + \sum_{i=1}^{N} t_i \leq 1$. The structure of time scheduling is also shown in Fig. 1. Note that the channels can be estimated at the beginning of each transmission block.

Denote the transmit signal at the HAP to be $w(t) = \sqrt{P_H}s(t)$, where P_H is the transmit power, and $s(t)$ is a known sequence with unit power. In the EH phase, the received signal at U_i

[1]This model can be straightforwardly extended to the scenario that each WSN has multiple sensors under the aftermentioned relaying and time scheduling scheme. However, it is out of the scope of this paper due to the limited space.

[2]If there is only one WSN, a dedicated EH time slot is required since the gateway forwards data based on its previous harvested energy.

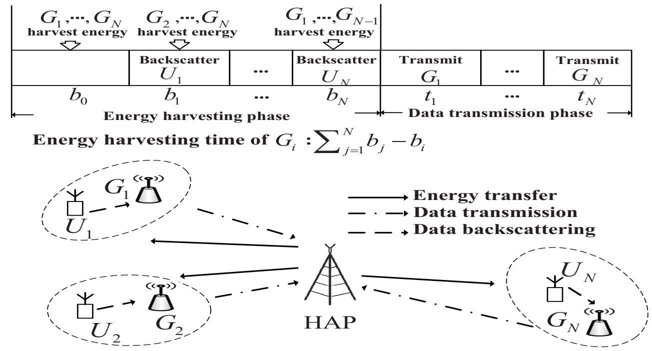


Fig. 1: System model.

is expressed by $u_i(t) = \sqrt{P_H}h_{i,u}s(t) + n_{i,a}(t)$, where $h_{i,u}$ is channel variable between the HAP and U_i, and $n_{i,a}(t)$ is the noise at the antenna. Denote the own signal and reflection coefficient of U_i as $c_i(t)$ and α_i, where $\mathbb{E}[|c_i(t)|^2] = 1$, α_i is a complex coefficient and satisfies $|\alpha_i|^2 \leq 1$. The backscattered signal at U_i, denoted by $x_i(t)$, is thus expressed by

$$x_i(t) = \sqrt{P_H}h_{i,u}s(t)\alpha_i c_i(t) + n_{i,a}(t)\alpha_i c_i(t). \tag{1}$$

Denote the received signal at G_i during b_i as $y_{i,G}(t)$, which is given by

$$\begin{aligned} y_{i,G}(t) = &\sqrt{P_H}g_{i,u}h_{i,u}s(t)\alpha_i c_i(t) + g_{i,u}n_{i,a}(t)\alpha_i c_i(t) \\ &+ \sqrt{P_H}h_{i,g}s(t) + n_{i,g}(t), \end{aligned} \tag{2}$$

where $g_{i,u}$ is the channel variable between U_i and G_i, $h_{i,g}$ is the channel variable between the HAP and G_i, and $n_{i,g}(t) \sim \mathcal{CN}(0, \sigma_{i,g}^2)$ is the noise at G_i. Note that the power of $g_{i,u}n_{i,a}(t)\alpha_i c_i(t)$ is much smaller than that of $n_{i,g}(t)$ and can be negligible [5]. Hence, we omit $g_{i,u}n_{i,a}(t)\alpha_i c_i(t)$ in the following derivation. $\sqrt{P_H}h_{i,g}s(t)$ is the interference signal from the HAP. Since $s(t)$ can be prior known by the gateways [5], the self-interference cancellation technique is used to cancel the interference from $y_{i,G}(t)$ [10]. After that, the signal-noise-ratio (SNR) at G_i, denoted by $\gamma_{i,g}$, is thus given by $\gamma_{i,g} = P_H|g_{i,u}|^2|h_{i,u}|^2|\alpha_i|^2/\sigma_{i,g}^2$. According to [6], the achievable rate of the first hop of U_i, denoted by $R_{i,1}$, is then expressed as

$$R_{i,1} = b_i \log_2(1 + \gamma_{i,g}). \tag{3}$$

Due to the limited transmission ranges of the sensors, the backscattered signal from other sensors during b_j ($j \neq i$) may be unavailable at G_i. Even if the backscattered signal during b_j can be received by G_i, its power is nearly zero due to doubly path-loss and can be thus negligible. Hence, the received signal at G_i during b_j is given by

$$\bar{y}_{i,G}(t) = \sqrt{P_H}h_{i,g}s(t) + n_{i,g}(t). \tag{4}$$

The energy harvested from the noise is typically negligible. In other words, all gateways only harvest energy from the HAP. We employ a practical non-linear EH model from [11], following which the unit harvested energy at G_i, Φ_i, is formulated as $\Phi_i = \frac{\Psi_i - M_i\Omega_i}{1-\Omega_i}$, where $\Psi_i = \frac{M_i}{1+\exp(-a_i(P_H|h_{i,g}|^2 - m_i))}$ and $\Omega_i = \frac{1}{1+\exp(a_i m_i)}$. Note that Ψ_i denotes the conventional logistic function with respect to $P_H|h_{i,g}|^2$, Ω_i is a constant to capture the characteristic of EH, M_i denotes the maximum harvested energy by G_i, a_i and m_i are constants accounting for circuit specifications. Then, the total harvested energy at G_i, E_i, is given by $E_i = \Phi_i(\sum_{j=0}^{N} b_j - b_i)$. We consider that if G_i succeeds in decoding its received signal, it would forward its decoded outcome $c_i(t)$ to the HAP during t_i. Denote the transmit power of DF at G_i as $P_{G,i}$. Thus, the energy consumption constraint at G_i can be modeled as $P_{G,i}t_i + P_{C,i}t_i \le E_i$, where $P_{C,i}$ is the circuit power of G_i. The received signal from G_i at the HAP, denoted by $y_{i,H}(t)$, is given by

$$y_{i,H}(t) = \sqrt{P_{G,i}} g_{i,g} c_i(t) + n_h(t), \tag{5}$$

where $g_{i,g}$ is the channel variable between G_i and the HAP, and $n_h(t) \sim \mathcal{CN}(0, \sigma_h^2)$ is the noise at the HAP. Denote the SNR at the HAP during t_i as $\gamma_{i,h}$, which is then given by $\gamma_{i,h} = P_{G_i}|g_{i,g}|^2/\sigma_h^2$. The achievable rate of the second hop of U_i is given by

$$R_{i,2} = t_i \log_2(1 + \gamma_{i,h}). \tag{6}$$

Denote the achievable rate of U_i as R_i and it is expressed as

$$R_i = \min\{R_{i,1}, R_{i,2}\}, \tag{7}$$

which indicates that the achievable rate of U_i is determined by the hop with smaller transmission rate.

III. Sum-Rate Maximization

In this work, we aim to optimize the sum-rate by investigating the time scheduling and power allocation. The sum-rate optimization problem is usually a max-min problem. To simplify it, we first set the constraints of achievable rate as follows C1: $R_i \le b_i \log_2(1+\gamma_{i,g})$ and C2: $R_i \le t_i \log_2(1+\gamma_{i,h})$. Under the two constraints, the optimization problem can be simplified as a maximization problem, the objective function of which is $\sum_{i=1}^{N} R_i$, where R_i is also an optimization variable. Then, the time and power constraints for network are given as follows C3: $\sum_{i=0}^{N} b_i + \sum_{i=1}^{N} t_i \le 1$, C4: $0 \le b_i \le 1$, $i = 0, 1, \ldots, N$, C5: $0 \le t_i \le 1$, $i = 1, \ldots, N$, and C6: $P_{G,i}t_i + P_{C,i}t_i \le \Phi_i(\sum_{j=0}^{N} b_j - b_i)$, $i = 1, \ldots, N$. The maximization problem is thus formulated as

$$\max_{\boldsymbol{b},\boldsymbol{t},\boldsymbol{P_G},\boldsymbol{R}} \sum_{i=1}^{N} R_i, \quad \text{s.t. C1, C2, C3, C4, C5, and C6,} \tag{P1}$$

where $\boldsymbol{b} = [b_0, b_1, \ldots, b_N]$, $\boldsymbol{t} = [t_1, \ldots, t_N]$, $\boldsymbol{P_G} = [P_{G,1}, \ldots, P_{G,N}]$, and $\boldsymbol{R} = [R_1, \ldots, R_N]$. **P1** is a non-convex optimization problem due to the couple of t_i and $P_{G,i}$. To address this issue, we express $P_{G,i}$ from the constraint C6 as follows C7: $P_{G,i} = \max\{0, \Phi_i(\sum_{j=0}^{N} b_j - b_i)/t_i - P_{C,i}\}$. Note that the constraint C7 holds due to that $t_i \log_2(1 + \gamma_{i,h})$ is an increasing function with respect to $P_{G,i}$ and $P_{G,i}$ is a nonnegative variable. To solve **P1** under the constraint C7, we first give the following assumption.

Assumption 1. *The optimal solution of **P1** can be achieved under the condition that the constraint C7 is strictly positive, i.e.,* $P_{G,i} = \Phi_i(\sum_{j=0}^{N} b_j - b_i)/t_i - P_{C,i} > 0$, $\forall i$.

We will show that Assumption 1 holds in Appendix B. Moreover, we introduce $\beta = \sum_{i=0}^{N} b_i$ for substitution, which can make **P1** easier to be solved, e.g., the optimization of $[b_1, \ldots, b_N]$ will be independent. Clearly, the constraints C3-C5 are rewritten as C8: $\sum_{i=0}^{N} b_i = \beta$, C9: $\sum_{i=1}^{N} t_i \le 1 - \beta$, C10: $0 \le b_i \le \beta, \forall i$, C11: $0 \le t_i \le 1 - \beta, \forall i$, and C12: $0 \le \beta \le 1$. In addition, from Assumption 1, the constraint C2 is recast as C13: $R_i \le t_i \log_2(1 + A_i(\beta - b_i)/t_i - B_i)$, where $A_i = |g_{i,g}|^2\Phi_i/\sigma_h^2$, and $B_i = |g_{i,g}|^2 P_{C,i}/\sigma_h^2$. Then, **P1** is equivalent to the following problem

$$\max_{\boldsymbol{b},\boldsymbol{t},\boldsymbol{R},\beta} \sum_{i=1}^{N} R_i, \quad \text{s.t. C1, C8, C9, C10, C11, C12, and C13.} \tag{P2}$$

Lemma 1. ***P2** is a convex optimization problem.*

Proof. Please refer to Appendix A. □

To exploit the structure of **P2** and reveal physical insights, a two-stage method is proposed to solve **P2**. We first obtain the optimal DB time and DF time with a given β. Then, we update β with one-dimensional search methods. **P2** with a given β is recast as

$$R_{\text{sum}}(\beta) = \max_{\boldsymbol{b},\boldsymbol{t},\boldsymbol{R}} \sum_{i=1}^{N} R_i, \quad \text{s.t. C1, C8, C9, C10, C11, and C13.} \tag{P3}$$

With the given β, **P3** is also a convex optimization problem and can be solved by Lagrangian duality. The Lagrangian of **P3** is given by $\mathcal{L}(\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{R}, \boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda) = \sum_{i=1}^{N} R_i - \sum_{i=1}^{N} \mu_i[R_i - b_i \log_2(1 + \gamma_{i,g})] - \sum_{i=1}^{N} \nu_i[R_i - t_i \log_2(1 + A_i(\beta - b_i)/t_i - B_i)] - \rho(\sum_{i=0}^{N} b_i - \beta) - \lambda(\beta + \sum_{i=1}^{N} t_i - 1)$, where $\boldsymbol{\mu} = [\mu_1, \ldots, \mu_N] \succeq 0$ ($\succeq$ denotes the component-wise inequality), $\boldsymbol{\nu} = [\nu_1, \ldots, \nu_N] \succeq 0$, ρ, and $\lambda \ge 0$ are the Lagrange multipliers associated with C1, C13, C8, and C9, respectively. The dual function is expressed as $\mathcal{G}(\boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda) = \max_{\boldsymbol{b},\boldsymbol{t} \in \mathcal{D}, \boldsymbol{R} \ge 0} \mathcal{L}(\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{R}, \boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda)$, where $\mathcal{D}$ is the feasible convex set of $(\boldsymbol{b}, \boldsymbol{t})$. To guarantee the dual function of **P3** is bounded, we have the following constraint $1 - \mu_i - \nu_i \le 0$, $\forall i$. Under this constraint, the dual problem is further given by $\min_{\boldsymbol{\mu},\boldsymbol{\nu},\rho,\lambda} \mathcal{G}(\boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda)$ s.t. $\mu_i + \nu_i \ge 1$, $\forall i$, $\mu_i, \nu_i \ge 0$, $\forall i$, $\lambda \ge 0$.

Proposition 1. *Given $\boldsymbol{\mu}$, $\boldsymbol{\nu}$, ρ, and λ, the solution for achieving $\mathcal{G}(\boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda)$, denoted by $[\hat{b}_0, \hat{b}_1, \ldots, \hat{b}_N]$ and $[\hat{t}_1, \ldots, \hat{t}_N]$, is given by*

$$\hat{b}_0 = \begin{cases} \beta, & \rho < 0, \\ 0, & \rho \ge 0, \end{cases} \tag{8}$$

$$\hat{b}_i = \min\{(\beta + \frac{\hat{t}_i}{A_i} - \frac{\nu_i \hat{t}_i}{\ln(2)[\mu_i \log_2(1 + \gamma_{i,g}) - \rho]} - \frac{B_i \hat{t}_i}{A_i})^+, \beta\}, \tag{9}$$

$$\hat{t}_i = \begin{cases} 0, & \nu_i = 0, \\ \min\{A_i(\beta - \hat{b}_i)/z_i^*, 1 - \beta\}, & \nu_i > 0, \end{cases} \tag{10}$$

where $i = 1, \ldots, N$, $(x)^+ = \max(0, x)$, $z_i^* > B_i$ is the solution of $\nu_i f(z_i) = \ln(2)\lambda$, and $f(z_i) = \ln(1 + z_i - B_i) - \frac{z_i}{1 + z_i - B_i}$.

Proof. Please refer to Appendix B. □

According to Proposition 1, $[\hat{b}_1, \ldots, \hat{b}_N]$ and $[\hat{t}_1, \ldots, \hat{t}_N]$ can be obtained by iteratively optimizing between $[b_1, \ldots, b_N]$

and $[t_1, \ldots, t_N]$ based on (9) and (10) until the convergence is achieved. We then proceed to minimize $\mathcal{G}(\boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda)$ by the sub-gradient method [12]. The sub-gradients of $\mathcal{G}(\boldsymbol{\mu}, \boldsymbol{\nu}, \rho, \lambda)$, denoted by $[\upsilon_{\mu_1}, \ldots, \upsilon_{\mu_N}, \upsilon_{\nu_1}, \ldots, \upsilon_{\nu_N}, \upsilon_\rho, \upsilon_\lambda]$, are given by $\upsilon_{\mu_i} = \hat{b}_i \log_2(1 + \gamma_{i,g}) - R_i(\hat{b}_i, \hat{t}_i)$, $i = 1, \ldots, N$, $\upsilon_{\nu_i} = \hat{t}_i \log_2(1 + A_i(\beta - \hat{b}_i)/\hat{t}_i - B_i) - R_i(\hat{b}_i, \hat{t}_i)$, $\upsilon_\rho = \beta - \sum_{i=0}^{N} \hat{b}_i$, and $\upsilon_\lambda = 1 - \beta - \sum_{i=1}^{N} \hat{t}_i$, respectively. Denote the optimal solution for **P3** as $[b_0^*, b_1^*, \ldots, b_N^*]$ and $[t_1^*, \ldots, t_N^*]$. $[b_1^*, \ldots, b_N^*]$ and $[t_1^*, \ldots, t_N^*]$ can be finally obtained when the optimal dual solution $[\mu_1^*, \ldots, \mu_N^*, \nu_1^*, \ldots, \nu_N^*, \rho^*, \lambda^*]$ is achieved. Moreover, we have $b_0^* = \beta - \sum_{i=1}^{N} b_i^*$. An algorithm for solving **P3** is summarized in Algorithm 1, the computational complexity of which is $O(N)$ [9], [12].

Intuitively, each sensor's DB time and DF time are coupled with each other. If b_i^* is selected, the achievable rate of the first hop of U_i and the amount of harvested energy of G_i is fixed such that t_i^* should be adjusted to control the achievable rate of the second hop of U_i. Moreover, from (9) and (10), it can be observed that the time scheduling of different sensors are mainly dominated by their channel power gains.

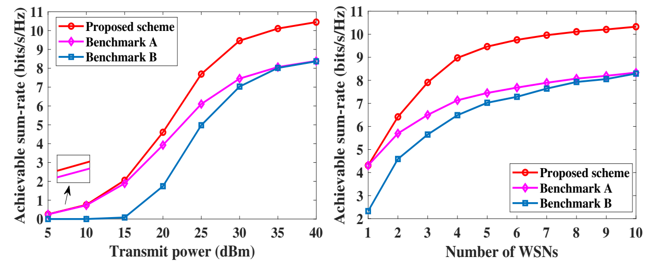
Algorithm 1 The Algorithm for Solving **P3**.

Initialize: $\mu_i \geq 0$, $\nu_i \geq 0$, $\mu_i + \nu_i \geq 1$, $\lambda \geq 0$, and ρ.
repeat
  Initialize $[\hat{t}_1, \ldots, \hat{t}_N]$.
  repeat
    Compute $[\hat{b}_1, \ldots, \hat{b}_N]$ by (9).
    Compute $[\hat{t}_1, \ldots, \hat{t}_N]$ by (10).
  until convergence is achieved.
  Compute b_0 by (8).
  Compute $R_i = \min\{\hat{b}_i \log_2(1 + \gamma_{i,g}), \hat{t}_i \log_2(1 + A_i(\beta - \hat{b}_i)/\hat{t}_i - B_i)\}$, $i = 1, \ldots, N$.
  Update $\boldsymbol{\mu}$, $\boldsymbol{\nu}$, ρ and λ.
until $\boldsymbol{\mu}$, $\boldsymbol{\nu}$, ρ and λ converge.
Set $b_i^* = \hat{b}_i$ and $t_i^* = \hat{t}_i$, $i = 1, \ldots, N$.
Set $b_0^* = \beta - \sum_{i=1}^{N} b_i^*$.

Algorithm 2 The Algorithm for Finding β^*

Initialize $m = 0$, $n = 1$, and $\psi = (\sqrt{5} - 1)/2$.
repeat
  Update $\beta_1 = n - \psi(n - m)$ and $\beta_2 = m + \psi(n - m)$.
  Obtain $R_{\text{sum}}(\beta_1)$ and $R_{\text{sum}}(\beta_2)$ via Algorithm 1.
  If $R_{\text{sum}}(\beta_1) \leq R_{\text{sum}}(\beta_2)$, set $m = \beta_1$. Else, set $n = \beta_2$.
until $|n - m| \leq \epsilon$, where ϵ is a predefined threshold.
Obtain $\beta^* = (m + n)/2$.

We then proceed to find the optimal value of β, which is defined as $\beta^* = \arg\max_{0 \leq \beta \leq 1} R_{\text{sum}}(\beta)$. It is noted that $R_{\text{sum}}(\beta)$ is the maximum of the objective function in **P2** with respect to $\boldsymbol{b}$, $\boldsymbol{t}$, and $\boldsymbol{R}$. According to [12], maximizing a jointly concave function over some variables in a convex set leads to a concave function, from which we obtain that $R_{\text{sum}}(\beta)$ is a concave function with respect to β. Hence, we use the golden section search method to find β^* efficiently. The algorithm to find β^* is given in Algorithm 2, the number of iterations required for which is $\lceil \log 2(\frac{1}{\epsilon}) \rceil$ [12]. Hence, the total computational complexity of the two-stage method is $O(\lceil \log 2(\frac{1}{\epsilon}) \rceil N)$. **P2** can also be solved by the interior-point method [12], the complexity of which using the solver in CVX is $O(N^3)$. Compared with the interior-point method, our proposed scheme can significantly reduce the complexity.



(a) Sum-rate versus P_H. (b) Sum-rate versus N.

Fig. 2: Performance evaluation.

IV. Simulation Results

In this section, simulation results are provided to evaluate the performance of the proposed scheme. The simulation parameters are given as follows. Channel power gains are modeled as $|h_{i,u}|^2 = \theta_{h,i,u} d_{h,i,u}^{-\epsilon}$, $|h_{i,g}|^2 = \theta_{h,i,g} d_{h,i,g}^{-\epsilon}$, $|g_{i,u}|^2 = \theta_{g,i,u} d_{g,i,u}^{-\epsilon}$, and $|g_{i,g}|^2 = \theta_{g,i,g} d_{h,i,g}^{-\epsilon}$, respectively. $\theta_{h,i,u}$, $\theta_{h,i,g}$, $\theta_{g,i,u}$, and $\theta_{g,i,g}$ denote the short-term fading and are independent exponential random variables with unit mean. ϵ is the path-loss exponent and is set as 3. $d_{h,i,u}$, $d_{h,i,g}$, and $d_{g,i,u}$ denote the distances between the HAP and U_i, between the HAP and G_i, and between U_i and G_i, respectively. For the non-linear EH model, we set $M = 1.4$ mW, $a_i = 2000$, and $m_i = 0.0003$, which are calculated via the standard cruve fitting tool [11], [13]. In addition, we assume $|\alpha_i|^2 = 0.9$, $P_{C,i} = 1$ mW, $\sigma_{i,g}^2 = \sigma_h^2 = -80$ dBm. The scheme that all gateways only harvest energy during a dedicated time slot is used as a benchmark (benchmark A). In addition, the equal time allocation is also used as a benchmark (benchmark B). The simulation results are obtained by using CVX for fair comparisons.

We first evaluate the system performance with $d_{h,i,u} = 10$ m, $d_{h,i,g} = 9$ m, and $d_{g,i,u} = 2$ m. Fig. 2(a) investigates the sum-rate versus the transmit power with $N = 5$. As shown in Fig. 2(a), we observe that the proposed scheme always achieves the highest sum-rate. This reason is given as follows. G_i under the proposed scheme can harvest energy over the entire EH phase only except the time slot that it receives the backscattered signals from U_i. However, the gateways under the benchmark A can only harvest energy during a dedicated time slot. The EH time of the proposed scheme is thus significantly extended. Comparing with the benchmark B, more time can be allocated to the WSNs with better channel conditions. An interesting observation from the benchmark B is that when the transmit power is less than 15 dBm, the achievable sum-rate is equal to zero. The reason is that the harvested energy is not sufficient to activate the gateways to forward data. Fig. 2(b) shows the effect of number of WSNs on sum-rate with $P_H = 30$ dBm. As the number of WSNs increases, the sum-rates of all schemes increase but the increment speed gradually becomes lower. The reason is that adding more WSNs improves the total harvested energy of the gateways, but the improvement is finally limited by the transmission block duration. When the number of WSNs is equal to one, the achievable sum-rates of the proposed scheme and the benchmark A are the same because the gateway of the proposed scheme also only harvest energy from a dedicated EH time. However, when the number of WSNs exceeds 2, the sum-rate gaps between the proposed scheme and the benchmark schemes are obvious.

V. Conclusions

In this paper, we have proposed a relay transmission scheme for a batteryless IoT network for real implementation and high energy-efficiency, where the batteryless sensors transmit data passively to the HAP with the assistance of energy-constrained gateways adopting active communication. In this network, while a batteryless sensor backscatters the signals from the HAP to transmit data to its gateway, other gateways can simultaneously harvest energy from the HAP. The gateways then use their harvested energy to forward the received signals to the HAP. This time scheduling design can avoid interference among sensors' data transmission and significantly improve the utilization of energy at the HAP. To further maximize the achievable sum-rate, we have formulated an optimization problem and proposed an efficient method to find the optimal time scheduling. Finally, we have provided simulation results to show the superiority of the proposed relay transmission scheme.

Appendix A
Proof of Lemma 1

Define $g_i(b_i) = \log_2(1 + A_i(\beta - b_i) - B_i)$, which is a concave function with respect to b_i. It is obvious that $t_i \log_2(1+A_i(\beta - b_i)/t_i - B_i)$ is a perspective function of $g_i(b_i)$. Due to that the perspective operation keeps concavity [12], it is straightforward to obtain that $t_i \log_2(1 + A_i(\beta - b_i)/t_i - B_i)$ is a concave function with b_i and t_i. The constraint C13 is thus convex. All other constraints are all affine. Moreover, the objective function is linear. Hence, **P2** is a convex optimization problem.

Appendix B
Proof of Proposition 1

Given $\boldsymbol{\mu}$, $\boldsymbol{\nu}$, λ, and ρ, the partial derivative of $\mathcal{L}$ with respect to b_i and t_i are given by

$$\frac{\partial L}{\partial b_i} = \mu_i \log_2(1 + \gamma_{i,g}) - \nu_i \frac{A_i}{\ln(2)(1 + A_i(\beta - b_i)/t_i - B_i)} - \rho, \quad (11)$$

$$\frac{\partial L}{\partial t_i} = \nu_i \log_2(1 + A_i(\beta - b_i)/t_i - B_i) - \nu_i \frac{A_i(\beta - b_i)/t_i}{\ln(2)(1 + A_i(\beta - b_i)/t_i - B_i)} - \lambda. \quad (12)$$

By setting $\partial L/\partial b_i = 0$ and from $0 \le b_i \le \beta$, b_i is obtained as given in (9). It is easy to prove that $\beta + \sum_{i=1}^{N} \tau_i = 1$. From the slackness condition $\lambda(\beta + \sum_{i=1}^{N} t_i - 1) = 0$, we obtain $\lambda > 0$. If $\nu_i = 0$, $\partial L/\partial t_i = -\lambda < 0$ always holds. Then, we have $t_i = 0$. If $\nu_i > 0$, by setting $\frac{\partial L}{\partial t_i} = 0$, we can have

$$f(z_i) = \ln(2)\lambda/\nu_i, \quad (13)$$

where $f(z_i)$ is defined Proposition 1, and $z_i = A_i(\beta - b_i)/t_i$. It is obvious that $f(z_i)$ is an increasing function with respect to $z_i \ge 0$. Since $\ln(2)\lambda/\nu_i > 0$, there exists a unique solution $z_i^* > B_i$ satisfying (13). Moreover, considering that $0 \le t_i \le 1 - \beta$, $t_i = \min\{A_i(\beta - b_i)/z_i^*, 1 - \beta\}$. Note that $A_i(\beta - b_i)/z_i^* \ge 0$ due to $\beta \ge b_i$. It can be found that $\mathcal{L}$ is a linear function with respect to b_0 with the given $\boldsymbol{\mu}$, $\boldsymbol{\nu}$, λ, and ρ. Hence, b_0 is straightforwardly obtained as shown in (8).

We proceed to verify Assumption 1. If $\nu_i = 0$, $t_i = 0$ such that $t_i \log_2(1 + P_{G,i}|g_{i,g}|^2/\sigma_h^2) = t_i \log_2(1 + A_i(\beta - b_i)/t_i - B_i) = 0$. Hence, setting $P_{G,i} = \Phi_i(\sum_{j=0}^{N} b_j - b_i)/t_i - P_{C,i} > 0$ will not affect the result. If $\nu_i > 0$, (13) holds iff $z_i > B_i$, i.e., $P_{G,i} = \Phi_i(\beta - b_i)/t_i - P_{C,i} > 0$. Hence, Assumption 1 is verified.

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