Backscatter-Aided Cooperative Transmission in Wireless-Powered Heterogeneous Networks

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Abstract—We propose backscatter-aided cooperative transmission for wireless-powered heterogeneous networks (WPHetNets). In WPHetNets, where various kinds of nodes such as high-power base station (e.g., TV tower and macro base station) and small-power access point (e.g., WiFi access point) coexist, we aim to increase transmission range and support fair communication through internet-of-things (IoT) device cooperation. For this, we first propose long-range bistatic backscatter (BB)-aided cooperative transmission with two-device cooperation where ambient backscatter (AB) enables short-range information exchange in sequential mode between devices nearby under energy neutral operation, termed ‘Cooperation mode’. To ensure fairness between devices, we formulate common-throughput maximization problem where an algorithm for time allocation is presented. Compared with ‘Non-cooperation mode’ (i.e., no information exchange via AB) and active RF based cooperation schemes, the proposed scheme is shown to increase both the coverage and fairness between devices for battery-less IoT networks. We then generalize the architecture of backscatter-aided cooperative transmission with multiple-device cooperation where the information exchange is performed in sequential mode and parallel (broadcasting) mode. In the sequential mode, a graph-matching based suboptimal pairing algorithm is proposed whose validity is corroborated through comparison with a heuristic search based optimal pairing, and then we compare the two modes for multiple-device cooperation.

Index Terms—Wireless-powered heterogeneous networks (WPHetNets), battery-less Internet-of-Things (IoT), bistatic backscatter (BB), ambient backscatter (AB), cooperative transmission.

I. INTRODUCTION

As Internet-of-Things (IoT) services grow, numerous low-power smart devices with small-form factor (e.g., flexible epidermal devices, radio frequency identification (RFID) tags, wearable devices) are interconnected, and the density of future IoT networks will increase rapidly. IoT services benefit various applications such as smart home/city, biomedical and logistics areas [1], which will bring more comfortable life. However, dense deployment of IoT devices will cause some critical issues, such as energy management of devices and insufficient resource for communications. To address these issues, recently many researchers have studied radio frequency (RF) energy harvesting [2] and low-power backscatter communications, which appear as promising techniques to enable self-sustainable green communications for IoT networks.

The RF energy harvesting utilizes ambient and/or dedicated RF signals as the energy sources for low-power IoT devices. In wireless-powered communications networks (WPCNs) [2], devices harvest energy from RF signals and utilize it for communications. The authors in [2] provided a comprehensive overview of RF energy harvesting and network protocols. A typical protocol for WPCNs is the well-known harvest-then-transmit (HTT), where devices first harvest energy from the hybrid-access point (H-AP) in the downlink, and then use it for sending information to H-AP in the uplink [3]. However, WPCNs may not be fully supported due to the double attenuation caused by the coupled energy/information link and the high circuit power consumption of active RF circuits. To circumvent these issues, backscatter (passive) communications are proposed recently, which consume ultra-low power (μW), and allow to decouple the energy and information links for better quality-of-service.

Backscatter communications absorb or reflect ambient (modulated) or carrier (unmodulated) signals by simply switching the load impedance, so as to realize low-power and low-cost communications for battery-less IoT networks [4]. Considering these signal sources, they can be classified as ambient backscatter (AB) and bistatic backscatter (BB) [5], whose state-of-the-art signal processing techniques were analyzed in the literature [6]. Compared to AB, BB can support large coverage thanks to the unmodulated carrier signal from carrier emitter (CE), which does not cause the direct-link interference (DLI). For flexible scalability of IoT networks, however, AB is more favorable than BB because of no infrastructure. Especially, tag-to-tag AB communication is preferred than reader-based backscatter communications [7].

As for the hardware prototypes of tag-to-tag AB, simple averaging mechanism was first adopted for decoding backscattered TV signal in [8]. Further, the authors in [9] enhanced this for increased rate and range with multi-antenna technique and novel coding scheme named μmo and μcode, respectively.
The authors in [7] presented the phase cancellation problem which largely affects the transmission range and robustness. To overcome this problem, they developed a prototype of novel multiphase signaling, and then realized multihop tag-to-tag networks, which can be applied to human activity recognition as well [10]. Various types of AB prototypes up to now are summarized in [4] and [5].

There have been many proposals to design backscatter communications for battery-less IoT networks. In [11], wireless-powered heterogeneous networks (WPHetNets) were introduced, where the hybrid access of AB and BB was proposed to ensure both uniform coverage and rate distribution. To this end, the existing works can be classified into two streams, one of which is based on backscatter-aided (or hybrid) relay cooperation to achieve cooperative diversity via decode-&-forward (DF) or passive reflection for multipath hybrid) relay cooperation. The authors in [12] considered the hybrid relay cooperation based on either HTT (active) or AB (passive) via DF relaying depending on the location of active/passive cooperation based on either HTT (active) or AB (passive) decode-&-forward (DF) or passive reflection for multipath diversity. The authors in [13] proposed the DF relaying at a hybrid radio that alternates between HTT and AB depending on the network environment.

On the other hand, [15]–[17] studied cooperative transmission to support WPCNs with increased range. In [15], the authors analyzed cooperative transmission that utilizes distributed beamforming (DTB) and space-time block code (STBC). In particular, the authors in [16] further improved the energy efficiency by adopting short-range AB for information exchange to enable two-device cooperation in [15]. Meanwhile, the authors in [17] proposed an energy-efficient cooperative communication scheme (EECCS) which performs multiple-device cooperation based on AB for information sharing and DTB for cooperative transmission. However, these works are based on active RF communications for cooperative transmission which consume high circuit power, and may not be feasible to realize battery-less IoT networks.

Unlike the previous approaches above, where active RF communications are integrated with passive AB/BB to complement each other, we have first proposed purely backscatter-aided cooperative transmission in [18], where the information exchange for two-device cooperation is performed via short-range AB and the subsequent cooperative transmission via long-range BB, subject to the energy-causality constraint for battery-less IoT networks. In this paper, we further increase the coverage of massive IoT networks through multiple-device cooperation, whose main contributions and challenges are summarized below:

• We propose a ‘Sequential Mode’ backscatter-aided cooperative transmission where the information exchange is performed over sequential multiple slots. For this, a new type of graph matching problem that considers both throughput and fairness among multiple devices while balancing between the two metrics is proposed, and the methodology to solve the proposed graph matching problem will be provided in this paper.

• In view of practical implementation, we further propose a ‘Parallel Mode’ backscatter-aided cooperative transmission, where the multiple-device cooperation is supported with integration of the μcode approach [9] for the information sharing in one-shot parallel (broadcasting) mode and the LoRa backscatter [19] for cooperative transmission. Here, the collision resolution (CR) is realized with the random delay offsets inserted intentionally at the cooperating tags, which can be designed in passive circuits, instead of the CR approach proposed in [20] with hardware offsets generated from active circuits.

• To gain useful insights into the trade-off between multiple-antenna gain and time gain, extensive numerical results are presented to show that the ‘Sequential Mode’ can achieve higher throughput performance in various scenarios, compared to the cases with no device cooperation. Based on the proposed novel graph matching optimization, we show that two-device pairing is near-optimal for the information exchange in sequential mode, due to the undue time gain loss that results from multiple-device pairing. Further, we compare both ‘Sequential and Parallel Modes’ for multiple-device cooperation, which reveals that one outperforms the other in certain environments, thus validating their advantages.

The rest of this paper is organized as follows. In Section II, we give the system model for backscatter-aided cooperative transmission. Section III presents an optimization framework for the scenario of two IoT devices to maximize the common-throughput performance. In Section IV, we generalize the optimization framework for the scenario of multiple IoT devices. For this, we introduce a two-stage approach to handle mixed-integer nonlinear programming (MINLP) where a suboptimal pairing algorithm is proposed. Section V presents numerical results to show the advantages of the proposed schemes. Finally, concluding remarks are given in Section VI.

II. SYSTEM MODEL

We consider a WPHetNet described in Fig. 1 where there exist a high-power node (i.e., H-AP), a small-power node (i.e., CE), and N IoT devices with no additional battery. H-AP
communicates with legacy primary users (PUs) while CE is assumed to transmit unmodulated carrier signal continuously for supporting BB communications. To avoid interference to PUs, we assume the frequency band of H-AP is different from that of CE. Then, the secondary IoT devices receive both signals from the H-AP (modulated) and CE (unmodulated), and they can perform self-powering for communications (i.e., RF energy harvesting) and hybrid backscattering, namely short-range AB/long-range BB.\textsuperscript{1} Then, the received signal strength at IoT device $i$ from H-AP (H) or CE (C) can be expressed as

$$P_{Ni} = \left| g_{Ni} \right|^2 \delta_{Ni}, \quad N \in \{H, C\}, \quad i \in \{1, 2, \cdots, N\}, \quad (1)$$

where $P_{Ni}$ is the transmit power of $N$, and $g_{Ni}$ is the downlink channel gain between $N$ and IoT device $i$, which is defined as

$$g_{Ni} = \left| \bar{g}_{Ni} \right|^2 = L_w \left( \frac{\sqrt{G_N G_i \lambda_{Ni}}}{4\pi} \right)^2 d_{Ni}^{-\alpha}, \quad i \in \{1, 2, \cdots, N\}. \quad (2)$$

Here, $\bar{g}_{Ni}$, $L_w$, $G_N$, $G_i$, $\lambda_{Ni}$, $d_{Ni}$, and $\alpha$ denote the complex channel gain between $N$ and IoT device $i$, blocking loss associated with partitions (i.e., wall), antenna gain of $N$, antenna gain of IoT device $i$, wavelength of modulated (H) signal or unmodulated (C) signal, distance between $N$ and IoT device $i$, and path-loss exponent, respectively.

Considering this network model, the cooperation among IoT devices can be arranged according to the flow diagram in Fig. 2. Here, the first stage is for channel estimation, where the complex channel gains between the H-AP/CE and IoT devices $i$ ($i = 1, 2, \cdots, N$) are estimated by processing the pilot signal of IoT devices for a given frame time. In the second stage, IoT devices decide the operation mode between ‘Cooperation mode’ and ‘Non-cooperation mode’, where the former requires the aid of neighboring IoT devices to exchange information through short-range AB communication.

To check the possibility of information exchange via AB, we refer to both the incident signal strength from H-AP at IoT device $i$ (i.e., AB transmitter) $P_{Hi}$ and the distance $d_{ij}$ between two IoT devices (i.e., AB transmitter and receiver). These parameters are utilized to check the reliability of AB link in many proposals as thresholds (i.e., [7] - [10]). Table I summarizes the features and parameters of tag-to-tag AB prototypes. In addition, the authors in these proposals have shown that $10^{-2}$ BER can be guaranteed if the thresholds are satisfied.\textsuperscript{2} Hence, the decoding status for AB mode can be determined based on the following feasibility conditions:

$$P_{Hi} \geq P_{th}, d_{ij} \leq d_{max}, \quad i, j \in \{1, 2, \cdots, N\}, \quad i \neq j, \quad (3)$$

where $P_{th}$ and $d_{max}$ represent the threshold power for decoding at IoT devices and the maximum distance between them to establish AB. If the above conditions are satisfied at IoT devices, they can exchange their information via AB, which then turns into ‘Cooperation mode’. Otherwise, it simply switches to ‘Non-cooperation mode’.

III. COMMON-THROUGHPUT MAXIMIZATION: TWO IoT DEVICES

In this section, we first consider the scenario of two IoT devices (i.e., $N = 2$) to show the validity of the proposed backscatter-aided cooperative transmission via simple analysis. For this, we formulate the time allocation optimization problem which maximizes the common-throughput of two IoT devices. In this network setting, it is enough to consider the two cases: the IoT devices are in either ‘Cooperation mode’ or ‘Non-cooperation mode’ below.

A. Cooperation Mode

When devices can decode their exchanged information, ‘Cooperation mode’ is activated. The timing diagram of the ‘Cooperation mode’ is described in Fig. 3, where the frame time is normalized to one. Here, we assume H-AP notifies the frame time structure to IoT devices after channel estimation, and time synchronization is maintained over the frame time. To ensure fairness between devices, we attempt to maximize the common-throughput of IoT devices by optimizing the time

\textsuperscript{1}It is possible to utilize both signals from the H-AP and CE operating in different frequency bands (i.e., AB+BB), so as to increase the limited range of device-to-device (D2D) communication via AB only. But it requires high complexity and power consumption for information decoding which would not be feasible at battery-less IoT devices.

\textsuperscript{2}In these prototypes, DLL, which largely affects the performance of AB, is eliminated via low-power envelope detector. This acts as a low-pass filter, which can smooth/average out the high-rate ambient signal but preserve the low-rate backscattered signal [8]. Thus, it is possible to distinguish ambient and backscattered signals through the rate difference.
allocation vector for ‘Cooperation mode’, denoted as $\tilde{\Gamma}_C = [t_{E}, t_{12}, t_{21}, t_{1H}, t_{2H}]$. For this, we first define the following time constraints as

$$T_{C1} : \ t_{E} + t_{12} + t_{21} + t_{1H} + t_{2H} \leq 1 - t_0, \quad (4)$$
$$T_{C2} : \ t_{E}, \ t_{12}, \ t_{21}, \ t_{1H}, \ t_{2H} \geq 0, \quad (5)$$

where $t_0$ is set aside for channel estimation.

In ‘Cooperation mode’, once channel estimation is done, devices start self-powering for supporting ‘Cooperation mode’ with time duration $t_E$, which is called energy harvesting stage. After this stage, information exchange via AB and then cooperative transmission via BB are performed sequentially.

1) Energy Harvesting Stage: To enhance the amount of harvested energy, the dual-band energy harvesting is applied to exploit both RF signals from H-AP and CE. The amount of harvested energy at IoT device $i$ can be expressed as

$$E_i(\tilde{\Gamma}_C) = \eta(P_{Ri})P_{Ri}t_E, \quad i \in \{1, 2\}, \quad (6)$$

where $P_{Ri} = P_{Hi} + P_{Ci}$ is the received signal power at IoT device $i$ from both H-AP and CE, $\eta(x)$ is the harvesting efficiency function of input power $x$. We here adopt the nonlinear far-field harvesting model as given in [23], which can be expressed as

$$\eta(x) = \sum_{i=0}^{\infty} w_i (10 \log_{10}(x))^i, \quad (7)$$

where $W$ is the degree of the polynomial, $x$ is the received signal strength at IoT device in mW scale, and $\{w_i\}$ are the coefficients obtained from the rectenna’s measured harvesting efficiency data [23], which can be found in [24].

2) Information Exchange Stage: After energy harvesting, devices exchange their information via AB for cooperation. Specifically, device $i$ exchanges its information with device $j$ during the frame time $t_{ij}$. Since the transmission rate of tag-to-tag AB is rather limited by its specific transceiver design [11], the rate of AB at IoT device $i$ can be specified as $R_{i,AB} = \kappa B_P$, where $\kappa$ is the transmission efficiency to reflect detection performance of AB [11] and $B_P$ is the rate of the prototype that reflects real experiments. Hence, the achievable throughput of IoT device $i$ via AB for information exchange is given by

$$R_{ij}(\tilde{\Gamma}_C) = t_{ij}R_{i,AB}, \quad i, j \in \{1, 2\}, \quad i \neq j. \quad (8)$$

3) Cooperative Transmission Stage: Now, ‘Cooperation mode’ is activated, where IoT devices transmit their information to H-AP in cooperative manner through long-range BB. Here, the frame time $t_{ij}$ is allocated for transmission from IoT device $i$. For cooperative transmission, we employ BB based DTB through low-power analog beamforming [25]. Thus, IoT devices have backscatter circuits (i.e., short-range AB/long-range BB) with phase shifter for BB based DTB to align the phase at H-AP. Because $\tilde{g}_{Ci}$ and $\tilde{h}_{iH}$, defined as the complex channel gains between CE and IoT device $i$ and H-AP, are cascaded for the unmodulated carrier signal, each device uses the following beamforming vector:

$$v_i = \left(\tilde{g}_{Ci}^* \tilde{h}_{iH}\right)^*, \quad (9)$$

Then the transmission rates of IoT devices via BB based DTB can be expressed as

$$B_{1, BB} = B_{2, BB} = W_B \log_2 \left(1 + \frac{(\sqrt{P_{1H}} + \sqrt{P_{2H}})}{\zeta N_o} \right), \quad (10)$$

where $\zeta$, $N_o$, and $W_B$ denote the performance gap with real modulation, noise power spectral density (psd), and transmission bandwidth for BB, respectively. The received power $P_{1H}$ from IoT device $i$ with BFSK-modulated BB signaling, at H-AP is formulated as [11]

$$P_{1H} = P_C \cdot g_{Ci} \cdot h_{iH} \cdot s^2 \left(\frac{\Gamma_0 - \Gamma_1}{2}\right)^2 \left(\frac{4}{\pi}\right)^2, \quad i \in \{1, 2\}, \quad (11)$$

where $h_{iH} = |\tilde{h}_{iH}|^2$, $s$, and $\Gamma_m$ denote the uplink channel gain between IoT device $i$ and H-AP for the reflected carrier signal, similar to the downlink channel gain $g_{Hi}$, scattering efficiency, and reflection coefficient specified by the load impedance with (absorbing, reflecting) states $m \in \{0, 1\}$, respectively.

Therefore, the achievable throughput for cooperative transmission of IoT device $i$ via BB based DTB can be evaluated as

$$R_{iH}(\tilde{\Gamma}_C) = t_{iH} B_{i, BB}, \quad i \in \{1, 2\}. \quad (12)$$

Dual-band energy harvesting techniques can be supported for low-power IoT devices, which are implemented in [21], [22].

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**TABLE I**

<table>
<thead>
<tr>
<th>Features of Tag-to-Tag AB Prototypes</th>
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<tr>
<td>Incident signal strength at Tx tag</td>
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<td>Distance</td>
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<tr>
<td>Data rate</td>
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<td>Circuit power for decoding</td>
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*Here we assume ideal channel estimation for DTB. If this is not feasible, instead STBC can be adopted as noncoherent cooperative transmission [15] with inferior performance compared to DTB.*
4) Common-Throughput Maximization: Following the above steps, an optimization problem is formulated by considering the fairness between IoT devices. We define the throughput of IoT device $i$ at H-AP as

$$R_i(t_C) = \min \{ R_{ij}(t_C), R_{iH}(t_C) \}, \ i, j \in \{1, 2\}, \ i \neq j.$$  

(13)

Then the time allocation optimization problem for maximizing the common-throughput (i.e., $P_{C1}$) can be defined as

$$P_{C1}: \max \min (R_1(t_C), R_2(t_C)) \quad \text{s.t. } t_C \in T_C, \ t_C \in E_C.$$

As for the constraint, $t_C \in T_C$ stands for time causality which implies that $t_C$ should satisfy $T_C$ and $T_{C2}$ (i.e., (4) and (5), respectively). $t_C \in E_C$ denotes the energy constraint, which implies that $t_C$ should satisfy the following condition:

$$E_i(t_C) \geq P^{(T)}_{AB} t_{ij} + P^{(R)}_{AB} t_{ij} + P^{(T)}_{BB} (t_{iH} + t_{jH}), \quad i, j \in \{1, 2\}, \ i \neq j,$$

(14)

where $P^{(T)}_{AB}, P^{(R)}_{AB},$ and $P^{(T)}_{BB}$ denote the circuit powers to operate transmission circuit of AB, decoding circuit of AB, and transmission circuit of BB, respectively. The first term of right-hand side in (14) stands for the energy for operating short-range AB for information exchange, and the second term the energy for information decoding. The last term stands for the energy for operating long-range BB in cooperative transmission stage.

Because $R_{ij}(t_C)$ and $R_{iH}(t_C)$ do not diverge under the time constraints, $R_{ij}(t_C)$ and $R_{iH}(t_C)$ can reach a maximum value subject to the given time and energy constraints. Hence, the problem $P_{C1}$ with value $\bar{R}$ can be reformulated as

$$P_{C2}: \max \bar{R} \quad \text{s.t. } R_{12}(t_C) \geq \bar{R}, \ R_{21}(t_C) \geq \bar{R}, \ R_{iH}(t_C) \geq \bar{R}, \ t_C \in T_C, \ t_C \in E_C.$$

To solve the optimization problem $P_{C2}$, it is necessary to check feasibility iteratively with given $\bar{R}$. For this, the following feasibility problem with given $\bar{R}$ is formulated as

$$P_{CF}: \ \text{Find } t_C \quad \text{s.t. } R_{12}(t_C) \geq \bar{R}, \ R_{21}(t_C) \geq \bar{R}, \ R_{iH}(t_C) \geq \bar{R}, \ t_C \in T_C, \ t_C \in E_C.$$

A typical way to check the feasibility is to assume the first 4 constraints regarding the achievable rate and that $T_C$ are active. Then the optimal time allocation is set by

$$t_{12}^* = \frac{\bar{R}}{B_{1,AB}}, \ t_{21}^* = \frac{\bar{R}}{B_{2,AB}}.$$

$$t_{iH}^* = \frac{\bar{R}}{B_{i,BB}}, \ t_{2H}^* = \frac{\bar{R}}{B_{2,BB}}.$$

$$t_E^* = 1 - t_0 - (t_{12} + t_{21}^* + t_{iH}^* + t_{2H}^*).$$

Finally, the feasibility problem can be solved by utilizing the above optimal solution $t_C^*$ to check if $t_C^*$ satisfies all constraints. If so, the given $\bar{R}$ is feasible, so we can increase $\bar{R}$. Otherwise, $\bar{R}$ will decrease due to the infeasibility of $t_C^*$. Here, the detailed algorithm for ‘Cooperation mode’ is described in Algorithm 1 with given error tolerance $\epsilon$ below. Convergence of the algorithm is guaranteed because the searching range $[R_{min}, R_{max}]$ can be reduced for each iteration [26].

**Algorithm 1** Algorithm to Find an Optimal Time Allocation Vector $t_C^*$ for ‘Cooperation Mode’

1. Initialize $R_{min} = 0, R_{max} > R^*$
2. repeat
3. $\bar{R} = (R_{min} + R_{max})/2$
4. Calculate $t_C^*$ using (15)
5. if $t_{C1}^* \in T_C$ and $t_{C2}^* \in E_C$ then
6. $R_{min} \leftarrow \bar{R}$ (Feasible $R$)
7. else
8. $R_{max} \leftarrow \bar{R}$ (Infeasible $R$)
9. end if
10. until $|R_{max} - R_{min}| < \epsilon$

B. Non-Cooperation Mode

If devices cannot exchange information via AB, which implies that cooperative transmission cannot be performed, ‘Non-cooperation mode’ is activated. In the first stage, devices start self-powering for operating backscattering circuit through dual-band energy harvesting, similar to ‘Cooperation mode’. With self-powering, IoT devices can transmit their information directly to H-AP via long-range BB during the time slots $t_{iH}$ and $t_{2H}$ without cooperation, given AB cannot be performed (i.e., $t_{12} = t_{21} = 0$). Then the achievable throughput of IoT device $i$ in ‘Non-cooperation mode’ can be evaluated as

$$R_i(t_N) = t_i W_B \log \left(1 + \frac{P_H}{\zeta N_o W_B}\right), \ i \in \{1, 2\},$$

(16)

where $t_N = [t_E, t_{iH}, t_{2H}]$ is the time allocation vector for ‘Non-cooperation mode’. Then, the common-throughput maximization problem considering fairness is formulated as

$$P_N: \max \min (R_{1N}^N(t_N), R_{2N}^N(t_N)) \quad \text{s.t. } t_N \in T_N, \ t_N \in E_N.$$

Following the procedure similar to ‘Cooperation mode’, we can formulate the time and energy constraints for ‘Non-cooperation mode’ (i.e., $T_N$ and $E_N$), and then solve it by checking feasibility iteratively.

IV. COMMON-THROUGHPUT MAXIMIZATION: MULTIPLE IoT DEVICES

In this section, the previous scenario of two IoT devices is generalized to the one of multiple IoT devices, which will enable to support massive IoT networks with the proposed cooperative transmission scheme. Toward this, we consider both issues of device pairing and time allocation so that the common-throughput can be maximized for multiple IoT devices.
A. General Optimization Problem (Optimal)

In multiple IoT devices, the principle of basic operation is similar to that in case of two IoT devices. Additionally, we should consider the pairing of IoT devices to decide on the operation mode associated with their specific pairing. To proceed, we make the following assumptions:

- We count on the pairing of two IoT devices only nearby that is suitable for low-power cooperative transmission because of the low reliability of AB link.
- If IoT device $i$ is to be paired with device $j$, device $i$ is not eligible for pairing with another device except device $j$ in a given frame.

With the above assumptions, the issue of pairing IoT devices can be dealt with by invoking the graph matching theory, in which both ‘Cooperation mode’ and ‘Non-cooperation mode’ coexist in the IoT networks. Here, the timing diagram of ‘Cooperation mode’ in multiple IoT devices is described in Fig. 4, given the total frame time is normalized to one. In the timing diagram, IoT devices perform initially channel estimation for $t_0$ and harvest energy for information exchange and BB transmission (i.e., BB-based DTB or non-cooperative BB) for $t_E$ following the detailed operation as given in the previous section. Then, IoT device $i$ performs information exchange for $t_{ij}$ if paired with IoT device $j$. If not paired with IoT device $j$ or in ‘Non-cooperation mode’, $t_{ij}$ is not allocated (i.e., $t_{ij} = 0$). Finally, IoT device $i$ transmits its information to H-AP for $t_H$ via BB transmission. In ‘Cooperation mode’, BB-based DTB is performed through cooperation between paired IoT devices and otherwise, it attempts non-cooperative BB transmission.

We define $\vec{t} = [t_E, t_{12}, t_{12}, \cdots, t_{(N-1)N}, t_{N(N-1)}, t_{1H}, \cdots, t_{NH}]$ as the time allocation vector, then the throughput of IoT device $i$ to H-AP can be expressed as

$$R_i(X, \vec{t}) = \rho_i \min \left( \sum_{\forall j, j \neq i} x_{ij} B^{(AB)}_{ij} t_{ij}, \sum_{\forall j, j \neq i} x_{ij} B^{(C)}_{ij} t_{ij} \right) + (1 - \rho_i) t_{iH}^B B^{(H)}_{ij}, \quad i \in \{1, \cdots, N\}. \quad (17)$$

In the above, $\rho_i$, $B^{(AB)}_{ij}$, and $X = [x_{ij}]$ denote the operation mode, namely IoT device $i$ performs ‘Cooperation mode’ (i.e., $\rho_i = 1$) or ‘Non-cooperation mode’ (i.e., $\rho_i = 0$), transmission rate of AB at IoT device $i$, and decision matrix, respectively.

We also define the transmission rate matrix $B = [B_{ij}]$ whose entries $B_{ij}$ are defined as the transmission rate of cooperative BB-based DTB when IoT devices $i$ and $j$ are paired for $i \neq j$ (i.e., $B^{(C)}_{ij}$) and the transmission rate of non-cooperative BB transmission for $i = j$ (i.e., $B^{(H)}_{ij}$). Here, $B_{ij}$ can be evaluated as

$$B_{ij} = B^{(C)}_{ij} = W_B \log_2 \left( 1 + \frac{P_{Rj} + P_{jH}}{\xi N_0 B_W} \right) \quad \text{if} \ d_{ij} \leq d_{\text{max}},$$

$$P_{Rj}, P_{jH} \geq P_{th}, \quad \text{otherwise},$$

where $P_{th}$ was defined in (11). As for the decision matrix, $x_{ij} \in \{0, 1\}$ is binary, which takes the value of one if IoT devices $i$ and $j$ are paired and otherwise, zero. Besides, the matrix $X$ is symmetric, as IoT devices $i$ and $j$ being paired implies IoT devices $j$ and $i$ being also paired. Hence, the mode indicator $\rho_i$ can be defined with decision variables such that $\rho_i = \sum_{\forall j} x_{ij}$, which helps to reduce the number of optimization variables.

With the achievable rate given in (17), we can formulate the following common-throughput maximization problem:

$$(F_C): \max \min_{X, \vec{t}} R_i(X, \vec{t}) \quad \text{s.t.} \quad (C1) \ \vec{t} \in T, \ \vec{t} \in E,$$

$$\sum_{\forall i} x_{ij} = 1, \quad \text{for} \ \forall j,$$

$$x_{ij} = x_{ji}, \quad \text{for} \ \forall i, j,$$

$$x_{ij} \in \{0, 1\}, \quad \text{for} \ \forall i, j.$$

In addition, the detailed energy constraint $E_i(\vec{t})$ can be set to

$$E_i(\vec{t}) = \left\{ \begin{array}{ll} P^{(T)}_{(AB)} t_{ij} + P^{(R)}_{(AB)} t_{ji} + P^{(T)}_{BB} (t_{iH} + t_{jH}), & \text{if} \ \rho_i = 1, \\ P^{(T)}_{BB}, & \text{otherwise}. \end{array} \right. \quad (22)$$

The above constraints (C2)-(C4) are related to the decision matrix $X$. Specifically, (C2) indicates the maximum number of devices in the same cluster to be two. (C3) is a symmetry condition that devices $i$ and $j$ being paired implies devices $j$ and $i$ being also paired. Finally, (C4) states the boolean constraint for decision variables.

The optimization problem formulated in $F_C$ is MINLP which includes both continuous (i.e., $\vec{t}$) and discrete variables (i.e., $X$). This implies that the optimal solution cannot
easily be obtained. Therefore, we attempt to reduce computational complexity of the original optimization problem $\mathbb{P}_G$ by proposing a suboptimal solution where $\mathbb{P}_G$ turns into two-stage problem, namely pairing stage and time allocation optimization stage. The latter is made possible because $X$ is not correlated with $f$ under the constraints of $\mathbb{P}_G$.

### B. Two-Stage Problem (Suboptimal)

1) Device Pairing Stage:

Since the general optimization problem $\mathbb{P}_G$ is common-throughput maximization problem, we should look into both the performance and fairness among IoT devices in the pairing stage. Under the two assumptions made in the previous subsection, we employ maximal matching for the suboptimal pairing. For this, we define the undirected graph $G = (V, E)$ where $V$ is the set of vertices (i.e., IoT devices) and $(i, j) \in E$ is the set of edges between two vertices to represent the reliability of AB link between IoT devices $i$ and $j$. In our proposed scheme, the weight assigned to each edge $(i, j)$ is defined as the data rate for cooperative transmission when devices $i$ and $j$ are paired (i.e., $B_{ij} = B^C_{ij}$), or the data rate for non-cooperative transmission (i.e., $B_{ii} = B^H_i$).

Using the weights defined above, we can formulate a maximal matching problem which balances the performance and fairness. Specifically, with a balancing parameter $\delta \geq 0$, the matching problem aims to maximize the sum transmission rate (i.e., performance) while minimizing its variance among IoT devices (i.e., fairness). This problem is formulated in $\mathbb{P}_{GP}$, shown at the bottom of the next page, where $M_0 \odot M_1$ and $(M_2)_{ij}$ indicate entry-wise multiplication of two matrices $M_0$ and $M_1$, and element of row $i$ and column $j$ of matrix $M_2$, respectively.

Lemma 1: The objective function of $\mathbb{P}_{GP}$ is convex of $X$.

Proof: Please refer to Appendix A.

Lemma 1 states that the optimization problem $\mathbb{P}_{GP}$ is a convex maximization problem, which implies that it cannot be solved by the well-known convex optimization technique in [26]. The latter is usually adopted for convex minimization or concave maximization problem. Instead, we adopt nonlinear parametric optimization technique, called C-programming [27], [28]. This provides an indirect way to tackle the convex maximization problem, such as variance minimization problem, which relaxes the square term in the objective function to a linear term by introducing the parameter $\lambda$. Then, $\mathbb{P}_{GP}$ can be reformulated in $\mathbb{P}_{PR}$, shown at the bottom of the next page.

Next, we discuss about $\lambda$ which establishes a link between the original pairing problem $\mathbb{P}_{GP}$ and $\mathbb{P}_{PR}$. It allows to circumvent directly solving the original problem $\mathbb{P}_{GP}$ [27]. For some $\lambda$, the optimal solution of $\mathbb{P}_{PR}$ is the same as $\mathbb{P}_{GP}$, which is defined as $\lambda^*$ (i.e., optimal $\lambda$). Therefore, finding $\lambda^*$ is important to find the suboptimal pairing. To show the existence of $\lambda^*$, we first define the following functions:

$$\phi(z) = \delta z^2$$

and

$$u(X) = \frac{1}{N} \sum_{i} \sum_{j} B_{ij} x_{ij},$$

where $\phi(u(X))$ denotes a convex term of $\mathbb{P}_{GP}$. Then, the existence of $\lambda^*$ is guaranteed by the following proposition [27]:

**Proposition 1:** Because $\phi(u(X))$ is convex with respect to $u(X)$, there exists $\lambda^*$ that can be expressed as

$$\lambda^* = \nabla \phi(u(X^*)) = \frac{2\delta}{N} \sum_{i} \sum_{j} B_{ij} x_{ij},$$

where $X^* = [x_{ij}^*]$ is the optimal solution of the problem $\mathbb{P}_{GP}$ and $\nabla \phi(u(z))$ is the derivative of $\phi(u(z))$ with respect to $z$.

Then, $\lambda^*$ satisfies the following condition:

$$X^*(\lambda^*) = X^*$$

where $X^*(\lambda) = [x_{ij}^*(\lambda)]$ is the optimal solution of the problem $\mathbb{P}_{PR}$ with given $\lambda$.

Consequently, by solving the optimization problem $\mathbb{P}_{PR}$ which is an integer linear programming (ILP) instead of the convex maximization problem (i.e., $\mathbb{P}_{GP}$), we can obtain the results (i.e., $X^*$) for the suboptimal IoT device pairing. To solve the ILP problem, we adopt CVXPY [29] to obtain an optimal solution of $\mathbb{P}_{PR}$ (i.e., $X^*(\lambda)$) with given $\lambda$. Next, we look into how to find $\lambda^*$, for which the following proposition suggests an exclusionary rule to reduce the searching range of $\lambda$. The latter will provide an effective way to reach the optimal $\lambda^*$ [27]:

**Proposition 2:** Let $\psi(X(\lambda))$ and $X^*(\lambda) = [x_{ij}^*(\lambda)]$ denote the objective function and the optimal solution of the problem $\mathbb{P}_{PR}$ with given $\lambda$ respectively. Then, the following condition is satisfied:

$$\psi(X^*(\lambda)) \geq \psi(X^*(\lambda'))$$

where $\lambda' \in E(\lambda, X^*(\lambda))$, which is defined as

$$E(\lambda, X^*(\lambda)) = \left\{ \theta \lambda + \frac{2(1 - \theta)\delta}{N} \sum_{i} \sum_{j} B_{ij} x_{ij}^*(\lambda), \quad \theta \leq 1 \right\}.$$  

From Proposition 2, we can derive the following theorem in searching $\lambda^*$ and $X^*(\lambda^*)$:

**Theorem 1:** Let $V$ denote a set satisfying $\nabla \phi(u(X)) \in V$ and $\lambda(m), 1 \leq m \leq M$ denote any finite sequence such that

$$V \subset \bigcup_{\forall m} E(\lambda(m), X^*(\lambda(m))).$$

Then, $X^* = X^*(\lambda^*)$ where $m^*$ satisfies

$$m^* = \arg \max_{\forall m} \psi(X^*(\lambda(m))).$$

By Theorem 1, we can finally construct the C-programming algorithm [27] to obtain the suboptimal pairing $X^* = X^*(\lambda^*)$, which is described in Algorithm 2. Because of (24), it is required to find the range of $\nabla \phi(u(X))$ to define the set $V$ in line 1 of Algorithm 2. For this, the following optimization problem is formulated to find $v_{min}$:

$$v_{min} = \min_X \frac{2\delta}{N} \sum_{i} \sum_{j} (B \circ X)_{ij} \quad \text{s.t.} \quad \sum_{i} x_{ij} \leq 2, \quad x_{ij} = x_{ji}, \quad x_{ii} = 1, \quad x_{ij} \in \{0, 1\}.$$
Algorithm 2: C-Programming Based Suboptimal Pairing Algorithm

1: Find a set \( V = [v_{\text{min}}, v_{\text{max}}] \).
2: Select an element \( \lambda^{(1)} \) from \( V \).
3: Solve the problem \( \mathcal{P}_{PR} \) with given \( \lambda^{(1)} \), and calculate \( X^*(\lambda^{(1)}) \).
4: Set \( V^{(1)} = E(\lambda^{(1)}, X^*(\lambda^{(1))) \), \( X^* = X^*(\lambda^{(1)}) \), and \( m = 1 \).
5: if \( V \subset V^{(m)} \) then
6: Stop.
7: else
8: repeat
9: Select an element \( \lambda^{(m+1)} \) from \( V \).
10: Solve the problem \( \mathcal{P}_{PR} \) with given \( \lambda^{(m+1)} \), and calculate \( X^*(\lambda^{(m+1)}) \).
11: if \( \psi(X^*(\lambda^{(m+1)})) \geq \psi(X^*(\lambda^{(m)})) \) then
12: Set \( X^* = X^*(\lambda^{(m+1)}) \).
13: end if
14: Set \( V^{(m+1)} = V^{(m)} \cup E(\lambda^{(m+1)}, X^*(\lambda^{(m+1)}) \).
15: Set \( m = m + 1 \).
16: until \( V \subset V^{(m)} \)
17: end if

Here, \( v_{\text{max}} \) can be found similarly by the above optimization framework, but the objective is maximization instead of minimization. Because both problems to calculate \( v_{\text{min}} \) and \( v_{\text{max}} \) are ILP, we adopt CVXPY [29] to solve them.

2) Time Allocation Stage: With the obtained suboptimal pairing \( X^* \), the general optimization problem can be simplified since we do not consider the pairing problem in the objective function (i.e., \( R_i(x, t) \)). Then, we redefine the achievable rate of IoT devices according to their suboptimal operation mode (i.e., \( \rho_i \)). We can evaluate the achievable rate of IoT device \( i_C \in \{i | \rho_i = 1\} \) which is in ‘Cooperation mode’ with paired device \( j_C \) (i.e., \( x_{iCJ} = 1 \) as

\[
R_{iC}(\bar{t}) = \min(B_{iCJ}A \bar{t}_{iCJ}, B_{iCJ} t_{iCJ}) \quad \text{(30)}
\]

In case of IoT device \( i_N \in \{i | \rho_i = 0\} \) which is in ‘Non-cooperation mode’, the achievable rate can be evaluated as

\[
R_{iN}(\bar{t}) = B_{iNH} t_{iNH} \quad \text{(31)}
\]

Therefore, the general optimization problem \( \mathcal{P}_G \) with given suboptimal pairing \( X^* \) can be reformulated as

\[
(\mathcal{P}_{GT}): \quad \max_{\bar{t}} \min_{\bar{t}} \left( R_{iC}(\bar{t}), R_{iN}(\bar{t}) \right)
\]

s.t. \( \bar{t} \in T, \bar{t} \in \mathcal{E} \)

\[\forall i_C \in \{i | \rho_i = 1\}, i_N \in \{i | \rho_i = 0\}.\]

Since \( R_{iC}(\bar{t}) \) and \( R_{iN}(\bar{t}) \) are linear with respect to \( \bar{t} \), their achievable rates do not diverge under the time constraints, and hence we can compute their maximum achievable rates subject to the given time and energy constraints (i.e., \( T, \mathcal{E} \)). Hence, the problem \( \mathcal{P}_G \) with given rate \( \bar{R} \) can be reformulated as

\[
(\mathcal{P}_{GT1}): \quad \max_{\bar{t}} \bar{R}
\]

s.t. \( B_{iC,AB} t_{iCJ} \geq \bar{R}, B_{iCJ} t_{iCJ} \geq \bar{R}, B_{iNH} t_{iNH} \geq \bar{R}, \bar{t} \in T, \bar{t} \in \mathcal{E}, \forall i_C \in \{i | \rho_i = 1\}, j_C \in \{j | \rho_j = 1, x_{iCJ} = 1\}, i_N \in \{i | \rho_i = 0\}.\)

To solve the optimization problem \( \mathcal{P}_{GT1} \), it is required to check feasibility iteratively with given \( \bar{R} \). For this, the following feasibility problem with given \( \bar{R} \) is formulated as

\[
(\mathcal{P}_{GT2}): \quad \max_{\bar{t}'} \bar{R}
\]

s.t. \( B_{iC,AB} t_{iCJ} \geq \bar{R}, B_{iCJ} t_{iCJ} \geq \bar{R}, B_{iNH} t_{iNH} \geq \bar{R}, \bar{t} \in T, \bar{t} \in \mathcal{E}, \forall i_C \in \{i | \rho_i = 1\}, j_C \in \{j | \rho_j = 1, x_{iCJ} = 1\}, i_N \in \{i | \rho_i = 0\}.\)

Following the approach in the previous section, the optimal time allocation can be set to

\[
t^{*}_{iCJ} = \frac{\bar{R}}{B_{iC,AB}}, \quad t^{*}_{iCJ} = \frac{\bar{R}}{B_{iCJ}}, \quad t^{*}_{iNH} = \frac{\bar{R}}{B_{iNH}}
\]

\[
t^{*}_{E} = 1 - t_0 - \left( \sum_{iC} t^{*}_{iCJ} + \sum_{iC} t^{*}_{iCJ} + \sum_{iN} t^{*}_{iNH} \right).
\]

Finally, we adopt Algorithm 1 to calculate the optimal time allocation vector \( \bar{t}^{*} \).

\(3\) In line 4 of Algorithm 1, \( \bar{t} \) is calculated using (32). Also, in line 5, \( T \) and \( \mathcal{E} \) are adopted for the time and energy constraints instead of \( T_C \) and \( \mathcal{E}_C \).
C. Practical Scenario of Multiple-Device Pairing in Parallel Mode

As one of the benchmark schemes, we propose a practical scenario termed parallel (broadcasting) mode where one device is paired with multiple devices for cooperative transmission. The timing diagram for the practical scenario is shown in Fig. 5 with frame time normalized to one. If ambient RF power threshold is satisfied at a transmit tag, device \( i \) with information first broadcasts its information via AB transmission. Neighboring devices within the tag-to-tag AB transmission range successfully receive the information, which is then considered to form a cluster that cooperatively transmits device \( i \)’s information to H-AP. This practical scenario of broadcasting and parallel transmission range successfully receive the information, which is then considered to form a cluster that cooperatively transmits device \( i \)’s information to H-AP. This practical scenario of broadcasting and parallel transmission greatly reduces the processing complexity of DTB and the time gain loss due to the information exchange in sequential mode. This scheme becomes more effective especially when H-AP power and device density are high because of the increased cluster size, leading to the enhanced signal strength at H-AP.

The transmission rates of IoT devices in parallel mode can be evaluated as

\[
B_{i,P} = W_B \log_2 \left( 1 + \frac{\sum_{j=1}^{M} P_j}{\zeta N_0 W_B} \right), \quad i \in \{1, 2, \cdots, n\},
\]

where \( M \) is the number of cooperating devices involved in a cluster for device \( i \) including itself, and \( P_j^{(i)} \) denotes the received power from device \( j \) in cluster \( i \). Here we assume a noncoherent cooperative transmission which does not require the phase alignment at H-AP for the practical scenario, unlike the case of two-device pairing with DTB over BB transmission. We define the time allocation vector \( \vec{t}_P = \{t_{E}, t_{1B}, t_{1T}, \cdots, t_{nB}, t_{nT}\} \), where \( t_{E} \) is set to the maximum harvesting time among \( n \) devices, and \( t_{1B} \) and \( t_{1T} \) indicate the broadcasting time and transmission time of device \( i \), respectively. Then, the achievable rate of device \( i \) can be evaluated as

\[
R_i(\vec{t}_P) = \min \left( t_{iB} B_{i,AB}, t_{iT} B_{i,P} \right), \quad i \in \{1, 2, \cdots, n\}.
\]

With this achievable rate, an optimization problem for the parallel mode considering fairness can be formulated as

\[
\mathcal{P}: \max \min \left( R_1(\vec{t}_P), R_2(\vec{t}_P), \cdots, R_n(\vec{t}_P) \right) \quad \text{s.t. } \vec{t}_P \in T_P, \quad \vec{t}_P \in \mathcal{E}_P.
\]

The time and energy constraints \( T_P \) and \( \mathcal{E}_P \), respectively, can be set to

\[
T_P : \quad t_E + t_{1B} + t_{1T} + \cdots + t_{nB} + t_{nT} \leq 1 - t_0,
\]

\[
t_{E}, t_{1B}, t_{1T}, \cdots, t_{nB}, t_{nT} \geq 0,
\]

\[
\mathcal{E}_P : \quad E_i(\vec{t}_P) = P_{AB}^{(T)} t_{iB} + P_{AB}^{(R)} \sum_{k \in \mathcal{I}_P} t_{kB} + P_{BB}^{(T)} t_{iT},
\]

where the three terms of the energy constraint \( E_i(\vec{t}_P) \) are related to device \( i \)’s operation for AB broadcasting and reception, and noncoherent cooperative transmission via BB to H-AP, respectively. Here, the index set \( \mathcal{I}_P = \{1, \cdots, k, \cdots, K\} \) denotes all clusters where device \( k (1 \leq k \leq K) \) broadcasts and device \( i \) participates as a receive tag.

Similarly as before, the above optimization problem \( \mathcal{P} \) can be redefined to maximize the value of variable \( \bar{R} \) with \( t_{iB} B_{i,AB} \geq \bar{R} \) and \( t_{iT} B_{i,P} \geq \bar{R}, \forall i \). Then, a feasibility problem to find \( \vec{t}_P \) with given \( \bar{R} \) is formulated, with which the optimal time allocation can be set to

\[
t_{iB} = \frac{\bar{R}}{B_{i,AB}}, \quad t_{iT} = \frac{\bar{R}}{B_{i,P}}, \quad t_E = \max \left( \frac{E_i(\vec{t}_P^{(i,B)}), t_{iT}}{\eta(P_{RI}^{(T)}, P_{RI}^{(R)})} \right).
\]

Finally, the feasibility problem can be solved by iteratively checking and updating (37) with given \( \bar{R} \) according to Algorithm 1.

One feasible approach to implement this practical scenario is to use LoRa chirp signals for efficient collision resolution (CR), as proposed in [20]. Unlike conventional LoRa, LoRa backscatter [19] is passive communication, so there is no hardware offset as assumed in [20]. Instead we can leverage the delay diversity such that timing offsets are deliberately induced for CR by controlling the backscatter switching time of IoT devices. This assures the noncoherent cooperative transmission, yielding the transmission rates as given in (33).

V. NUMERICAL RESULTS

We present numerical results for backscatter-aided cooperative transmission, relative to active RF based cooperative transmission with/without AB. The path-loss exponent \( \alpha \) and channel estimation time \( t_0 \) are set to 2.5 and 0.2, respectively. The high-power H-AP transmits the PU signal at 900MHz with 100kHz bandwidth. The transmit power of the unmodulated carrier signal from CE is set to 23dBm whose bandwidth and frequency band are 100kHz and 2.4GHz, respectively. The transmit and receive antenna gains of H-AP and CE are set to 6dBi, and the antenna gain of IoT devices is set to 1.8dBi [11]. The receiver sensitivities for HTT protocol, BB and AB transmissions are set to \(-10\)dBm, \(-27\)dBm [11] and \(-36\)dBm [4], respectively. We adopt the receiver in [10] for tag-to-tag AB which consumes 3\( \mu \)W for decoding AB signal with 10kbps transmission rate, and transmission efficiency \( \kappa \) is set to 0.85. Further, scattering efficiency \( s \), performance gap \( \zeta \), and noise \( psd N_s \) (i.e., parameters for BB operation) are set to 0.5, 5dB, and \(-120\)dBm/Hz, respectively.

Fig. 6 shows the common-throughput with varying distances between H-AP and IoT devices (i.e., \( d_{H1} \) and \( d_{H2} \)). Here,
we have assumed $d_{H1} = d_{H2}, d_{12} = 1.5m,$ and $d_{C1} = d_{C2} = 3m$. We see that the proposed BB based DTB is more attractive for long-range communications compared to both active RF based cooperative DTB and non-cooperative transmissions, as active RF based ones are less likely to meet the requirement of high circuit power consumption as $d_{Hi}$ increases. Hence, the proposed scheme can effectively increase the coverage of IoT devices as well as fairness between them.

Fig. 7 shows the common-throughput with varying transmit power of H-AP. We observe the mode switching from ‘Non-cooperation mode’ to ‘Cooperation mode’ with increasing $P_H$. This is because for low $P_H$, the incident signal strength at IoT devices is too weak to operate AB, so that ‘Non-cooperation mode’ has to be operated. As $P_H$ increases, IoT devices receive a stronger incident signal that is enough to operate AB. Thus, in high-power region, IoT devices can activate ‘Cooperation mode’ (i.e., BB based DTB) which provides higher throughput. We also notice that the throughputs of two IoT devices are same (i.e., $\bar{R} = \bar{R}_1 = \bar{R}_2$), and fair communications can be supported with the proposed scheme.

For the scenario of multiple IoT devices, we validate the proposed suboptimal pairing algorithm by comparing with the optimal pairing based on heuristic search6 and the suboptimal pairing with $\delta = 0$ (sum transmission rate only). As for the deployment of IoT devices, we consider the network where $N$ IoT devices are deployed within the service area of CE in outdoor environment with no blocking loss assumed (i.e., $L_w = 0dB$). Specifically, $N_1 = \lceil \frac{2\pi}{N_1} \rceil$ IoT devices are deployed in a cluster with radius $r_i = 2m$ and angle $\chi_i = \frac{2\pi}{N_1}i$, $i \in \{1, 2, \cdots, N_1\}$. The rest $N_2 = N - N_1$ IoT devices are deployed in the cluster with radius $r_j = 1m$ and angle $\chi_j = \frac{2\pi}{N_2}j$, $j \in \{1, 2, \cdots, N_2\}$. For numerical results presented here, we assume 7 IoT devices are deployed in the network (i.e., $N = 7$), and H-AP is located at $x = 20m$ in cartesian coordinate.

Fig. 8 shows the common-throughput with varying distance between H-AP and CE. We compare between two-device pairing and three-device one for the information exchange in sequential mode. We see the throughput performance degrades as the number of IoT devices for cooperation increases. This is mainly because losing the time gain due to the information exchange is much greater than achieving the multiple-antenna gain that results from cooperation.

In addition, we see the non-cooperative transmission is optimal in near region from H-AP. This is because of the performance bottleneck and time gain loss caused by AB for information exchange. However, we can obtain the multiple-antenna gain in far region, which implies that we can increase the transmission range through cooperative transmission.

Finally, as for the pairing algorithm, the proposed suboptimal pairing with $\delta = 0.9$ is shown to match well with the optimal pairing in far region. This clearly shows that we should consider both the throughput (i.e., sum rate) and fairness

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6It searches all cases heuristically to find an optimal pairing that maximizes the common-throughput.
Figs. 9 (a) and (b) show the average and total throughput with varying number of IoT devices, respectively. We see that the total throughput increases as the number of IoT devices increases, while the average throughput decreasing. This is mainly because the total frametime is limited, so the allocated time for transmission and information exchange decreases for individual IoT devices. We also see that the throughput with optimal and proposed suboptimal pairing perfectly matches each other, which shows the validity of the proposed device pairing algorithm.

Figs. 10 (a) and (b) show the elapsed time of pairing algorithm with varying number of IoT devices, and searching range/throughput for each iteration when \( N = 5 \). The elapsed time increases as the number of IoT devices increases. Further, the computation time of the proposed suboptimal pairing algorithm is much smaller than that of the optimal pairing based on heuristic algorithm. Thus, the suboptimal pairing algorithm can reach the optimal pairing results with time gain. In addition, we observe the searching range being reduced while the throughput converging to the maximum value for each iteration. This implies the proposed exclusionary rule effectively reduces the searching range of \( \lambda \) and guarantees the convergence of the algorithm.

Next, we look into the impact of wireless environment on the performance, and then discuss how to adjust the balancing parameter \( \delta \). Fig. 11 (a) and (b) show the common-throughput with varying blocking loss (i.e., \( L_w \)) in indoor environment for the network scenarios assumed in Fig. 12 (a) and (b). Note that the network turns into outdoor environment when \( L_w = 0 \) dB. In Fig. 11 (a), we assume one partition at \( x = 2 \) m in cartesian coordinate, as shown in Fig. 12 (a), where IoT devices are deployed in one region. In Fig. 11 (b), we assume additional partition at \( y = 0 \), as shown in Fig. 12 (b), which divides the service area of CE into two regions: the upper and lower regions. Then, IoT devices are deployed in two regions. For those IoT devices deployed along with the second partition at
Fig. 11. Common-throughput with varying $|L_w|$.

Fig. 12. Placement of partitions: (a) and (b) show the network scenarios of Fig. 11 (a) and (b), respectively.

$y = 0$, we assume IoT devices are located in the lower region for $\chi_i = 0$, while for $\chi_i = \pi$ in the upper region. CE is assumed to be located in the lower region. Then, we assume AB cannot be operated through the second partition, and hence an IoT device in one region cannot perform BB-based DTB with another IoT device in the other region.

As the blocking loss increases, the common-throughput decreases since the amount of received power and harvested energy at H-AP decreases. Further, the existence of second partition affects the pairing as blocking due to the partition prohibits cooperation with IoT devices in another region. In Fig. 11 (a) with one partition, we see the suboptimal pairing with $\delta = 0.9$ finds the optimal pairing which maximizes the common-throughput of IoT devices. In Fig. 11 (b) with two partitions, however, we notice $\delta = 1$ is optimal, and the suboptimal pairing with $\delta = 0.9$ does not yield the optimal pairing any more. Hence, $\delta$ should be adjusted considering the wireless environment, especially in indoor environment.

Fig. 13 (a) and (b) show the common-throughput with varying transmit power of CE (i.e., $P_C$) for two deployment scenarios in outdoor environment. In Fig. 13 (a), deployment of IoT devices follows the scenario (i.e., Scenario 1) as shown in Fig. 12 (a) with no partition. In Fig. 13 (b), the location of $N = 7$ IoT devices follows deployment with radius $r_i = \frac{2i}{N}$ and angle $\chi_i = \pi$, $i \in \{1, 2, \cdots, N\}$ (i.e., Scenario 2). We observe throughput increasing as $P_C$ increases, since the transmission rate of BB-based cooperative transmission increases. In Scenario 1, the suboptimal pairing with $\delta = 0.9$ finds the optimal pairing. Meanwhile, the suboptimal pairing with $\delta = 0.5$ yields the same performance as non-cooperative transmission, which is not optimal in Scenario 1. On the other hand, the suboptimal pairing with $\delta = 0.5$ reaches near the optimal pairing in Scenario 2. Therefore, we can conclude that optimal $\delta$ varies with a specific deployment scenario of IoT devices as well as wireless environment, which requires further study to optimize the balancing parameter $\delta$. 
Fig. 13. Common-throughput with varying transmit power of CE.

Fig. 14. Common-throughput with varying transmit power of H-AP.

Fig. 14 shows the common-throughput of two-device pairing in sequential mode, multiple-device pairing in parallel mode, and no pairing (i.e., non-cooperative) mode for comparison, with varying transmit power of H-AP. To look into the effect of different cluster size, the coordination changes slightly such that all devices are deployed on a circle of radius 2m while placing CE at the origin and H-AP at the same position as before. For the parallel mode, the graph jumps twice around H-AP power of 35dBm and 47dBm, where the cluster size increases drastically. In the first-jump region, two-device pairing in sequential mode may not be effective compared to the parallel mode with at least 2 or 3 cluster size. Here, the gain over two-device pairing results from the slightly larger cluster size with less timing overhead. In the middle region of H-AP power 38-47dBm, the two modes are likely to have similar cluster size, but two-device pairing provides more gain because of coherent combining, namely DTB over BB transmission to H-AP. In the second-jump region above 47dBm, the cluster size of parallel mode is far larger enough to overwhelm the two-device pairing. Therefore, the validity of parallel (broadcasting) mode when H-AP power and device density are high is well demonstrated.

VI. CONCLUSION

We have proposed backscatter-aided cooperative transmission in WPHetNets to increase the transmission range and support fair communication of battery-less IoT devices. In the network with two IoT devices, either ‘Cooperation mode’ or ‘Non-cooperation mode’ could be selected depending on whether or not the condition for operating short-range AB is met for the information exchange in sequential mode. For cooperative transmission, we adopted long-range BB based DTB with two-device cooperation where the common-throughput maximization problem was formulated considering fairness. Further, we have generalized this to the network with multiple-device cooperation in both sequential and parallel modes, where the suboptimal solution based on graph matching theory was proposed in the sequential mode to reduce the computational complexity of the generalized common-throughput maximization problem. Numerical results demonstrated that the proposed schemes with multiple-device cooperation can effectively increase the transmission range of IoT devices while meeting the required fairness. We also validated the importance of considering both throughput and fairness in the device pairing stage.

For future research, we will optimize the balancing parameter $\delta$ which plays a crucial role in determining the pairing of multiple IoT devices. Especially, optimal $\delta$ depends on the wireless environments as well as specific deployment scenarios of IoT devices, and a learning algorithm can be employed to address the issue of further optimizing the balancing parameter.

APPENDIX A

PROOF OF LEMMA 1

For the proof of Lemma 1, we reformulate the matrix $X$ and $B$ using the vectors $\vec{y}$ and $\vec{b}$, respectively,

$$\vec{y} = [y_1, y_2, \ldots, y_N]^T = [x_{11}, x_{12}, \ldots, x_{1N}, x_{21}, \ldots, x_{NN}],$$

$$\vec{b} = [b_1, b_2, \ldots, b_N]^T = [B_{11}, B_{12}, \ldots, B_{1N}, B_{21}, \ldots, B_{NN}].$$

(38)
Then, the objective function of ($\mathcal{P}_{GP}$) can be reformulated as
\[
\tilde{\psi}(\overline{y}) = \sum_{i} b_i y_i - \delta \left\{ \frac{1}{N} \sum_{i} b_i^2 y_i - \left( \frac{1}{N} \sum_{i} b_i y_i \right)^2 \right\}.
\] (39)

To check the convexity of $\tilde{\psi}(\overline{y})$, we evaluate the Hessian $\nabla^2 \tilde{\psi}(\overline{y})$ which is given by
\[
\nabla^2 \tilde{\psi}(\overline{y}) = \left[ \frac{\partial^2}{\partial y_i \partial y_j} \tilde{\psi}(\overline{y}) \right] = \frac{2\delta b_i b_j}{N^2}.
\] (40)

For an arbitrary real vector $z = [z_1, z_2, \ldots, z_N]^T$, the following related expression can be derived
\[
z^T \nabla^2 \tilde{\psi}(\overline{y}) z = \frac{2\delta}{N^2} \sum_{i=1}^{N^2} b_i z_i^2.
\] (41)

Given $\delta \geq 0$, (41) becomes positive, which implies $\nabla^2 \tilde{\psi}(\overline{y})$ is positive semidefinite. Thus, we confirm that $\tilde{\psi}(\overline{y})$ is convex with respect to $\overline{y}$. This proves Lemma 1.

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