Throughput Fairness-Aware Optimization of Cognitive Backscatter Networks with Finite Alphabet Inputs

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***Abstract*—Cognitive backscatter network (CBN) is a promising paradigm for energy-constrained IoT networks, in which backscatter devices (BDs) harvest energy from the primary signals and backscatter information to a cooperative receiver. Traditional resource allocation schemes maximizing the throughput are based on the impractical Gaussian inputs and energy harvesting (EH) model, which leads to performance degradation. Taking the above factors into account, this paper focuses on the fairness-aware resource allocation scheme for multiuser CBN with finite-alphabet inputs and nonlinear EH model. We formulate a max-min throughput maximization problem to ensure the fairness among BDs, subject to the quality-of-service (QoS) of primary user and energy-causality constraints of BDs. As the formulated joint optimization problem is non-convex, we use the approximation, slack and auxiliary variables methods to transform it into a convex problem and propose an iterative algorithm to solve it. Simulation results are provided to verify the effectiveness of the proposed algorithm.**

***Index Terms*—cognitive backscatter network, resource allocation, finite-alphabet inputs, energy harvesting, fairness.**

I. Introduction

With an explosive number of Internet of Things (IoT) devices wirelessly connected to Internet, the energy-efficient communication technologies are urgently required to support the massive connectivity. Ambient backscatter communication (AmBC), which achieves ultra-low power transmission, is a promising candidate for energy-efficient IoT. The main feature of AmBCs is using the existing RF signals to harvest energy and transmit information by adjusting the load impedance of the antenna. In such way, there is no need to generate dedicated carrier signal, which removes the power-consuming RF components and greatly reduces the power consumption [1]–[3]. However, due to the inherent nature of spectrum sharing, AmBC suffers from a direct link interference (DLI), leading to performance degradation [3].

Cognitive backscatter network (CBN) has recently attracted lots of research interests. In CBN, the primary user provides vast RF signals and the backscatter device (BD) is allowed to leverage the RF signals to transmit information on the premise of ensuring primary user's communication quality. As such, the spectral efficiency is also enhanced. Compared to traditional AmBC, BD achieves reliable communications to suppress the DLI by cooperative receiver (CRx) in CBN, which is more efficient for future IoT [4].

In [5], the authors maximized the capacity of a single BD via a jointly optimizing the transmit power of the primary user and the reflection coefficient in CBN. The authors of [6] considered the full-duplex-enabled CBN with multiple BDs and maximized the sum throughput of BDs via the joint optimization of time scheduling, transmit power allocation, and reflection coefficient adjustment while guaranteeing the QoS of the primary system. In [6], a joint power allocation and reflection coefficient adjustment method was proposed to maximize the sum rate of BDs for cognitive backscatter NOMA networks. In [7], [8], and [9], the authors investigated the hybrid harvest-then-transmit and backscatter transmission strategy to improve BD's transmission rate. However, the above resource allocation schemes were designed based on the Gaussian inputs assumption. Instead, the practical communication systems employ the finite-alphabet signal sets, such as pulse amplitude modulation (PAM), quadrature amplitude modulation (QAM), and phase shift keying (PSK) modulation. Another aspect is the ideal assumption of linear energy harvesting (EH) model, which does not correspond to the practical nonlinear circuits. The considerable difference between Gaussian signals and finite-alphabet signals, and between linear and nonlinear EH model results in performance degradation when the above resource allocation schemes applied in practical systems [10], [11].

In this paper, we consider the multi-BD CBN and propose a resource allocation scheme based on max-min criterion to ensure the fairness among BDs. Specifically, we formulate a problem to maximize the max-min throughput of BDs by jointly optimizing the transmit power of primary transmitter (PT), the reflection coefficient and time scheduling for each BD. *Different from the above works, the resource allocation scheme relies on the realistic finite-alphabet inputs and practical nonlinear EH model at BD,* which increases the complexity of objective function and constraints and poses a more challenging non-convex optimization problem. To solve the non-convex problem, we approximate the subjective function and introduce the slack and auxiliary variables to transform the problem into a convex one. However, the transformed convex problem cannot be directly solved by CVX tool due to the unrecognizable fractional form in some constraints. Then we propose an iterative algorithm based on block coordinate descent to solve the problem and verify the convergence.

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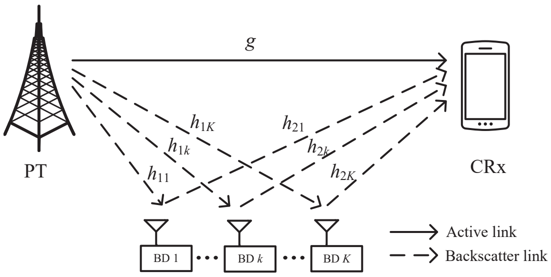

Fig. 1: System model.

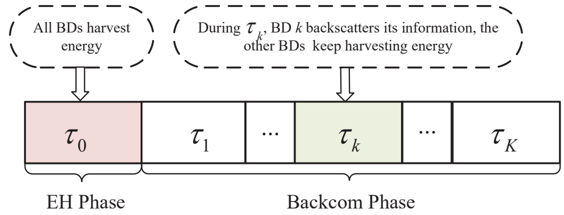

Fig. 2: Time scheduling structure.

II. System Model and Working Flow

We consider the multiuser CBN that includes a PT, K BDs and a CRx, as depicted in Fig. 1. The PT transmits primary signals to CRx, and BD can harvest energy from the primary signals, and modulate its data on primary signals to convey information. The CRx jointly decode the information from PT and BD. All devices are equipped with single antenna. Assume that the channel coefficients remain constant in one transmission block, but may change from one to another, and the channel coefficients are known to the receiver. We denote g, h_{1k}, h_{2k} channel coefficients for the link from PT-CRx, PT- the k-th BD, and the k-th BD-CRx, respectively. As depicted in Fig.2, the time division multiple access protocol is performed in backscatter transmission, where each time block contains two phases, i.e., EH phase and backscatter communication (Backcom) phase. In EH phase τ_0, all BDs harvest energy from the primary signals. In Backcom phase, the time block are divided into K slots, i.e., $\{\tau_1, \tau_2, ..., \tau_K\}$, where BDs take turns to backscatter information and the non-backscattering BDs keep harvesting energy.

In τ_0, the received signal at the k-th BD the is described as

$$y = \sqrt{P} h_{1k} x_e, \tag{1}$$

where P is the transmit power of PT, x_e satisfying $\mathbb{E}\left[|x_e|^2\right] = 1$, is the transmit signal from PT. The additive noise is ignored at BD since the circuits only consists of passive components.

In τ_0, the harvested energy at the k-th BD subject to the non-linear EH model in [11], which is given by

$$E_k^{\tau_0} = \left(\frac{aP|h_{1k}|^2 + b}{P|h_{1k}|^2 + c} - \frac{b}{c} \right) \tau_0, \tag{2}$$

where a, b and c denote the related coefficients in EH model.

In τ_k, the received signal at the k-th BD is split into two parts by the reflection coefficient α_k: the α_k portion for information transmitting, the $(1-\alpha_k)$ portion for EH. Thus, in τ_k, the received signals at CRx is

$$y_{\mathrm{R}} = \underbrace{g\sqrt{P}x_e}_{\text{the first term}} + \underbrace{h_{1k}h_{2k}\sqrt{\alpha_k P}x_e c_k}_{\text{the second term}} + n, \tag{3}$$

where the first term denotes the primary signal from PT and the second term denotes the backscatter signal from the k-th BD, c_k is the transmitted signal by the k-th BD, which is selected from the equiprobable discrete constellation C denoted by $C = \{c_1, c_2, ..., c_M\}$ with cardinality M; n is the received additive Gaussian white noise at the CRx with mean zero and variance σ^2.

The achievable rate of the k-th BD from information-theoretical perspective is written as [12]

$$R_k = \frac{\log_2 M}{2} - \frac{1}{2M}\sum_{i=1}^{M} \mathbf{E}_n \left(\log_2 \left(\sum_{j}^{M} \exp\left(\frac{-d_{ij,k}}{\sigma^2} \right) \right) \right), \tag{4}$$

where $d_{ij,k} = \left| h_{1k}h_{2k}\sqrt{\alpha_k P}x_e (c_i - c_j) + n \right|^2 - |n|^2$, $\mathbf{E}_n$ denotes the expectation function about n, c_i and c_j represent the i-th and j-th possible signal taken from the constellation C. The achievable throughput is derived by

$$I_k (P, \tau_k, \alpha_k) = \tau_k R_k. \tag{5}$$

In τ_k, the harvested energy at k-th BD is modeled as

$$E_k^{\tau_k} = \left(\frac{a|h_{1k}|^2 (1-\alpha_k) P + b}{|h_{1k}|^2 (1-\alpha_k) P + c} - \frac{b}{c} \right) \tau_k. \tag{6}$$

Based on the above working flow, the total harvested energy in the transmission block at the k-th BD is expressed as

$$\begin{aligned} E_k^{total} &= \left(\tfrac{a|h_{1k}|^2 (1-\alpha_k) P + b}{|h_{1k}|^2 (1-\alpha_k) P + c} - \tfrac{b}{c} \right) \tau_k \\ &+ \left(\tfrac{aP|h_{1k}|^2 + b}{P|h_{1k}|^2 + c} - \tfrac{b}{c} \right) \sum_{i=0, i\neq k}^{K} \tau_i. \end{aligned} \tag{7}$$

III. Fairness-aware resource allocation

In this section, we propose the fairness-aware resource allocation scheme. Firstly, we formulate an joint optimization problem to maximize the throughput of BDs based on the max-min criterion, while satisfying the QoS requirement of PT and the energy-causality constraints of BDs. Then we transform the non-convex problem into a convex one and propose to solve it with an iterative algorithm.

A. Problem formulation

The max-min throughput based optimization problem is modeled as

$$\begin{aligned} \mathbf{P1}: &\max_{\tau_0, P, \alpha_k, \tau_k} \ \min_k I_k \\ \text{s.t. } &\mathrm{C1}: 0 \le \alpha_k \le 1, \forall k \\ &\mathrm{C2}: \sum_{i=0}^{K} \tau_i \le 1, \\ &\mathrm{C3}: \left(\tfrac{a|h_{1k}|^2 (1-\alpha_k) P + b}{|h_{1k}|^2 (1-\alpha_k) P + c} - \tfrac{b}{c} \right) \tau_k \\ &\quad + \left(\tfrac{aP|h_{1k}|^2 + b}{P|h_{1k}|^2 + c} - \tfrac{b}{c} \right) \sum_{i=0, i\neq k}^{K} \tau_i \ge p_{c,k}\tau_k, \forall k \\ &\mathrm{C4}: \tfrac{|g|^2 P}{\alpha_k P |h_{1k}h_{2k}|^2 + \sigma^2} \ge \gamma_{\mathrm{th}}, \forall k \\ &\mathrm{C5}: 0 \le P \le P_{\max}, \end{aligned} \tag{8}$$

where $\gamma_{\rm th}$ denotes the minimum QoS requirement of PT, $p_{c,k}$ denotes the circuit energy consumption of the k-th BD.

In $\mathbf{P1}$, C1 and C2 are practical constraints for reflection coefficients and time slots. C3 denotes the energy causality-constraints for BDs. C4 guarantees the PT's QoS requirement. The optimization problem is non-convex due to the challenging subjective function and the coupled variables in constraints. In what follows, we attempt to transform the non-convex problem into convex and solve it.

B. Problem transformation

In $\mathbf{P1}$, the subjective function I_k involves the expectation over n, which implies computationally intensive integral operations. Therefore, we approximate I_k as

$$I_{k(1)} = \frac{1}{2}\tau_k \log_2 M - \frac{1}{2M}\tau_k * \left(\sum_{i=1}^{M}\log_2\sum_{j=1}^{M}\exp\left(\frac{-\left|h_{1k}h_{2k}\sqrt{\alpha_k P}(c_i-c_j)\right|^2}{2\sigma^2}\right)\right), \tag{9}$$

which is an accurate approximation proposed in [13] to reduce the computational complexity.

For the non-convex objective function, we introduce a slack variable $\theta = \min\limits_{k\in K} I_k$ to transform it into linear one as follows.

$$\begin{aligned} \mathbf{P2}: &\max_{\tau_0,P,\alpha_k,\tau_k} \quad \theta \\ &\text{s.t. C1} \sim \text{C5}, \\ &\quad \text{C6}: I_{k(1)}^{\min} \geq \theta, \forall k, \end{aligned} \tag{10}$$

where $I_{k(1)}^{\min}$ is the minimum throughput of the k-th BD, and C6 ensures the communication quality of BDs.

The problem $\mathbf{P2}$ with linear objective function is still non-convex because the variables P, α_k and τ_k are coupled in constraints. To cope with this, we first introduce the following Theorem 1 to transform the problem.

Theorem 1. The optimal P that maximizes the minimum throughput, denoted by P^*, is given by $P^* = P_{\max}$.

Proof. From $\mathbf{P2}$, we can observe that the variable P exists in C3, C4, C5 and C6. In C3, the energy harvested function is an incremental function on P, which means a larger P should have a higher probability to satisfy the energy-causality constraints. Similarly, from C4, it is easy to conclude that a larger P can lead to better QoS conditions for PT. Lastly in C6, the $\log_2\sum\exp\left(-a_3 P\right)$ decreases with the increased P, where $a_3 = \frac{\left|h_{1k}h_{2k}\sqrt{\alpha_k}(c_i-c_j)\right|^2}{2\sigma^2}$. Thus $I_{k(1)}$ increases with the increasing P. Put the above together with C5 and the optimal P can be determined by $P_{\max}$.

With Theorem 1, $\mathbf{P2}$ can be rewritten as

$$\begin{aligned} \mathbf{P3}: &\max_{\tau_0,\alpha_k,\tau_k} \quad \theta \\ &\text{s.t. C1, C2}, \\ &\quad \text{C3}-1: \left(\frac{a|h_{1k}|^2(1-\alpha_k)P_{\max}+b}{|h_{1k}|^2(1-\alpha_k)P_{\max}+c} - \frac{b}{c}\right)\tau_k \\ &\quad + \left(\frac{aP_{\max}|h_{1k}|^2+b}{P_{\max}|h_{1k}|^2+c} - \frac{b}{c}\right)\sum_{i=0,i\neq k}^{K}\tau_i \geq p_{c,k}\tau_k, \forall k \\ &\quad \text{C4}-1: \frac{|g|^2 P_{\max}}{\alpha_k P_{\max}|h_{1k}h_{2k}|^2+\sigma^2} \geq \gamma_{\rm th}, \forall k \\ &\quad \text{C6}-1: \frac{1}{2}\tau_k\log_2 M - \frac{1}{2M}\tau_k * \\ &\left(\sum_{i=1}^{M}\log_2\sum_{j=1}^{M}\exp\left(\frac{-\left|h_{1k}h_{2k}\sqrt{\alpha_k P_{\max}}(c_i-c_j)\right|^2}{2\sigma^2}\right)\right) \geq \theta, \forall k. \end{aligned} \tag{11}$$

Compared to $\mathbf{P2}$, $\mathbf{P3}$ has a less number of optimization variables and is more simple. However, it is still a non-convex problem since the variable α_k and τ_k are coupled. To resolve this, the auxiliary variables $X_k = \alpha_k\tau_k$ are constructed. By using $\frac{X_k}{\tau_k}$ to replace α_k in $\mathbf{P3}$, the optimization problem is converted to

$$\begin{aligned} \mathbf{P4}: &\max_{\tau_0,X_k,\tau_k} \quad \theta \\ &\text{s.t. C1}-1: 0 \leq X_k \leq \tau_k, \\ &\quad \text{C2}: \sum_{i=0}^{K}\tau_i \leq 1, \forall k, \\ &\quad \text{C3}-2: \left(\frac{a|h_{1k}|^2\left(1-\frac{X_k}{\tau_k}\right)P_{\max}+b}{|h_{1k}|^2\left(1-\frac{X_k}{\tau_k}\right)P_{\max}+c} - \frac{b}{c}\right)\tau_k \\ &\quad + \left(\frac{aP_{\max}|h_{1k}|^2+\ b}{P_{\max}|h_{1k}|^2+c} - \frac{b}{c}\right)\sum_{i=0,i\neq k}^{K}\tau_i \geq p_{c,k}\tau_k, \forall k, \\ &\quad \text{C4}-2: X_k \leq \left(\frac{|g|^2}{|h_{1k}h_{2k}|^2\gamma_{\rm th}} - \frac{\sigma^2}{P|h_{1k}h_{2k}|^2}\right)\tau_k, \forall k, \\ &\quad \text{C6}-2: \frac{1}{2}\tau_k\log_2 M - \frac{1}{2M} * \tau_k \\ &\left(\sum_{i=1}^{M}\log_2\sum_{j=1}^{M}\exp\left(\frac{-P_{\max}X_k|h_{1k}h_{2k}(c_i-c_j)|^2}{2\sigma^2\tau_k}\right)\right) \geq \theta, \forall k. \end{aligned} \tag{12}$$

Theorem 2. $\mathbf{P4}$ is convex.

Proof. Please see Appendix A.

Although the problem $\mathbf{P4}$ is convex, the fractional form in constraints $\text{C3}-2$ and $\text{C6}-2$ can not be directly recognized due to the rigorous form of CVX [14]. Therefore, we propose an iterative algorithm based on the block coordinate descent (BCD) technique to solve the problem.

For a given $X_k^{(l)}$, the time duration τ_o and τ_k can be obtained by solving the following problem.

$$\begin{aligned} \mathbf{P5}: &\max_{\tau_0,\tau_k} \quad \theta \\ &\text{s.t. C1}-1: 0 \leq X_k^{(l)} \leq \tau_k, \text{C2}, \\ &\quad \text{C3}-3: E_k^{total'}\left(X_k^{(l)},\tau_k,\tau_0\right) \geq p_{c,k}\tau_k, \forall k \\ &\quad \text{C4}-3: X_k^{(l)} \leq \left(\frac{|g|^2}{|h_{1k}h_{2k}|^2\gamma_{\rm th}} - \frac{\sigma^2}{P|h_{1k}h_{2k}|^2}\right)\tau_k, \forall k, \\ &\quad \text{C6}-3: I_{k(1)}\left(X_k^{(l)},\tau_k\right) \geq \theta, \forall k. \end{aligned} \tag{13}$$

For a given $\tau_k^{(l)}$, the reflection coefficient α_k can be obtained by solving $\mathbf{P6}$.

$$\begin{aligned} \mathbf{P6}: &\max_{X_k} \quad \theta \\ &\text{s.t. C1, C2}-1: \sum_{i=0}^{K}\tau_i^{(l)} \leq 1, \\ &\quad \text{C3}-4: E_k^{total'}\left(X_k,\tau_k^{(l)},\tau_0\right) \geq p_{c,k}\tau_k^{(l)}, \forall k \\ &\quad \text{C4}-4: X_k \leq \left(\frac{|g|^2}{|h_{1k}h_{2k}|^2\gamma_{\rm th}} - \frac{\sigma^2}{P|h_{1k}h_{2k}|^2}\right)\tau_k^{(l)}, \forall k, \\ &\quad \text{C6}-4: I_{k(1)}\left(X_k,\tau_k^{(l)}\right) \geq \theta, \forall k. \end{aligned} \tag{14}$$

$\mathbf{P5}$ and $\mathbf{P6}$ are convex problems which can be directly solved by CVX, and the convergence of the proposed iterative algorithm is guaranteed [15]. The BCD-based procedure is summarized in Algorithm 1 as shown at the top of the next page.

Algorithm 1 The BCD-based algorithm for resource allocation scheme

Input: K BDs;

Output: τ_0^*, τ_k^*, α_k^*;

1: Initialize the reflection coefficients $X_k^{(l)}$; Set the convergence precision δ;
2: Let l=0;
3: **Repeat**;
4: Solve **P5** for given $X_k^{(l)}$ and obtain the optimal $\tau_0^{(l+1)}$, $\tau_k^{(l+1)}$ by using CVX tools;
5: Solve **P6** for given $\tau_k^{(l)}$ and obtain the optimal $X_k^{(l+1)}$ by using CVX tools;
6: Update the iteration number $l = l + 1$;
7: **Until** $\theta^{l+1} - \theta^l < \delta$;
8: **return** $\tau_0^* = \tau_0^l$, $\tau_k^* = \tau_k^l$ and $\alpha_k^* = \frac{X_k^l}{\tau_k^l}$;

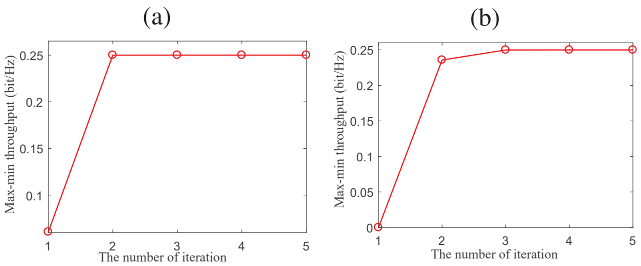

Fig. 3: Convergence of Algorithm 1. (a) $P_{\max}$=1dBm; (b) $P_{\max}$=2dBm.

IV. Simulation Results

In this section, simulation results are provided to verify the performance of the proposed resource allocation scheme and investigate the influence by related parameters. Assume that small-scale fading is Rayleigh fading with unit variance and large-scale fading is distance exponential fading with the path loss exponential υ, the channel gains is modeled as $|g|^2 {d_p}^{-\upsilon}$, $|h_{1k}|^2 {d_{1k}}^{-\upsilon}$ and $|h_{2k}|^2 {d_{2k}}^{-\upsilon}$, in which d_p and d_{1k} are the distance from PT to CRx and the k-th BD, and d_{2k} is the distance from the k-th BD to CRx respectively. We assume the input follows 2-symbol equip probable discrete distribution since BD always performs simple modulation in practice. For ease of description, the circuit power consumption are assumed same for each BD, i.e., $p_{c,k} = p_c$. Unless otherwise specified, the other parameters are set as a=2.463, b=1.735, c=0.826, $\delta = 10^{-3}$, $\upsilon = 2$, $K = 2$, $\gamma_{\text{th}} = 3$dB, $p_c = 0.05$mv, $\sigma^2 = -10$dBm, $d_{\text{p}} = 0.6$m, $d_{11} = 0.8$m, $d_{12} = 0.9$m, $d_{21} = 1.1$m, $d_{22} = 0.9$m.

Fig. 3 verifies the convergence of Algorithm 1 in different PT's transmit power cases. We can see that the algorithm converges very fast in few times both in the case $P_{\max}$=1dBm and $P_{\max}$=2dBm, which demonstrates the well convergence performance and generality of the Algorithm 1.

Fig. 4 shows the max-min throughput versus the optimal transmit power of PT under the different PT's QoS requirement. As can be observed, the max-min throughput increases with the increasing $P_{\max}$ and gradually achieves the upper throughput limit for any γ_{th}. This is because the throughput based on the discrete alphabet input distribution exists the

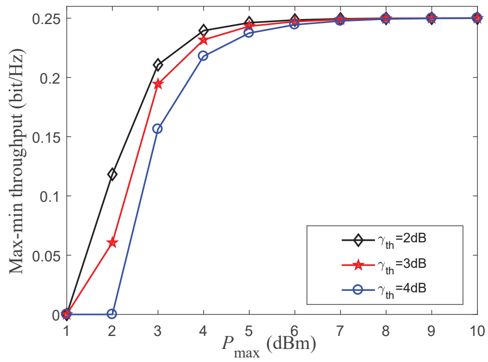

Fig. 4: Max-min throughput versus the optimal transmit power of the PT $P_{\max}$ for different interference thresholds γ_{th}.

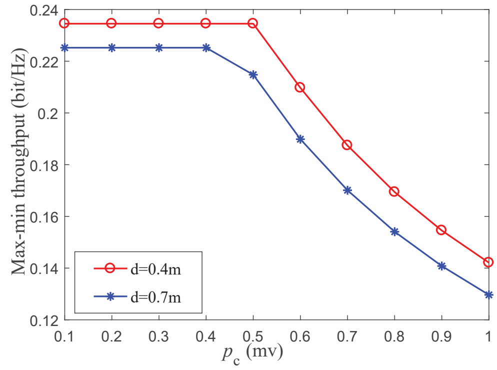

Fig. 5: Max-min throughput versus the minimum power consumption of the BD p_c for different channel gains.

upper bound $\frac{1}{2}\tau_k \log_2 M$ shown in eq.(9). It can also be seen that PT with higher interference threshold leads a lower max-min throughput of BD for given $P_{\max}$ before the upper bound. For example, the max-min throughput with $\gamma_{\text{th}} = 4$dB decreased 20% and 28% compared with the cases γ_{th}=2dB and 3dB for $P_{\max}$=3dBm, respectively. This is because the higher interference threshold means lower tolerance for BDs' communication, resulting in the decreased BDs' throughput.

Fig. 5 shows the max-min throughput versus the minimum power consumption of the BD p_c for different distance from PT to BD. During the curve down period with the increasing of p_c, BD has to reduce the α_k portion to transmit information, while keeps a larger portion to fulfill the circuit power consumption, which deteriorates the BD's performance. Additionally, we can see that the larger distance from PT to BD creates the max-min throughput degradation for given p_c. This is due to the fact that the large distance brings a worse channel gain and lower harvested energy to BD.

Take the sum throughput maximization scheme for comparison. Fig. 6 shows the comparison of the proposed max-min scheme with the max-sum scheme. For a given number of BDs, the left bars show the proposed max-min scheme, while the right bars show the max-sum scheme. The different colors denote the throughput of different BDs. We can observe that the max-sum scheme tends to allocate more resources to BD with better channel conditions to maximize the sum throughput, resulting in unfair throughput performance. For the max-

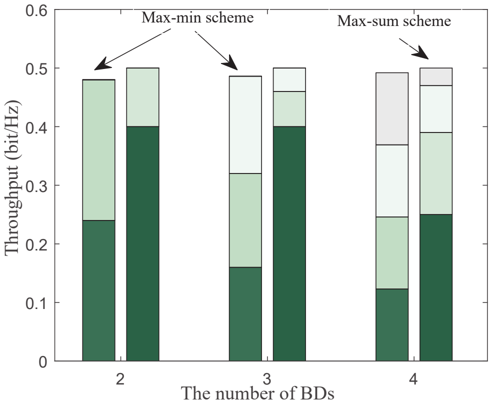

Fig. 6: Throughput versus the number of BDs K for $P_{\max}$=5dBm.

min scheme, the resources are allocated in fair manner that all K BDs achieve identical throughput to guarantee fairness. The reason is that the max-min scheme aims to maximize the throughput of BD with the worst channel condition, which drives the allocated resources for each BD to be as balanced as possible to ensure fairness.

V. Conclusions

In this paper, we proposed a fairness-aware resource allocation scheme for CBN with multiple BDs under the practical finite-alphabet inputs and energy harvesting model assumptions. In particularly, we formulated an optimization problem to maximize the minimum throughput by jointly optimizing the transmit power of PT, reflection coefficients and time scheduling of BDs to guarantee the fairness among BDs. To solve the non-convex optimization problem, we proposed a BCD-based iterative algorithm. Numerical simulation results were presented to verify the convergence performance of the proposed algorithm. In addition, our proposed max-min scheme was found to be more efficient than the max-sum scheme in terms of fairness.

Appendix A
Proof of the Theorem 2

In $\mathbf{P4}$, the objective function and the constraints C1-1, C2 and C4-2 are all linear, which means that the convexity of the $\mathbf{P4}$ is determined by whether the C3-2 and C6-2 are convex constraints or not. Then we prove the convexity for C3-2 and C6-2.

In C3-2, the second term of the left side is linear, the convexity of the second term $f(X_k, \tau_k) = \left(\frac{a|h_{1k}|^2 \left(1 - \frac{X_k}{\tau_k}\right) P_{\max} + b}{|h_{1k}|^2 \left(1 - \frac{X_k}{\tau_k}\right) P_{\max} + c} - \frac{b}{c} \right) \tau_k$ is the same as $f(X_k) = \frac{a|h_{1k}|^2 (1 - X_k) P_{\max} + b}{|h_{1k}|^2 (1 - X_k) P_{\max} + c}$ by using the perspective function with convexity preserving property. We note that the $f(X_k)$ have the same functional form and convexity with $f(x) = \frac{ax+b}{x+c} - \frac{b}{c}$, where x denotes the input power. The second-order derivative of $f(x)$ can be written as

$$\frac{\partial^2 f}{\partial x^2} = \frac{2(b-ac)}{(x+c)^3}. \tag{15}$$

It can be seen from eq.(13), the convexity of $f(x)$ relies on $b - ac$ and c. For a non-linear energy harvester, one we can obtained is that it exists a non-negative saturation threshold, i.e., $\lim\limits_{x \to \infty} \frac{ax+b}{x+c} - \frac{b}{c} > 0$, thus $a - \frac{b}{c} > 0$. The other is that the harvested energy is always greater than 0, i.e., $f(x) = \frac{b-ac}{x+c} - \frac{b-ac}{c} > 0$, thus $c > 0$ and $b - ac < 0$. To sum up, $\frac{\partial^2 f}{\partial x^2} < 0$, $f(x)$ is a concave function with respect to x.

In C6-2, by using the perspective function, $\frac{\tau_k}{2M} \left(\sum\limits_{i=1}^{M} \log_2 \sum\limits_{j=1}^{M} \exp\left(\frac{-P_{\max} X_k |h_{1k} h_{2k} (c_i - c_j)|^2}{2\sigma^2 \tau_k} \right) \right)$ have the same convexity with its perspective function $\frac{1}{2M} \left(\sum\limits_{i=1}^{M} \log_2 \sum\limits_{j=1}^{M} \exp\left(\frac{-P_{\max} X_k |h_{1k} h_{2k} (c_i - c_j)|^2}{2\sigma^2} \right) \right)$ which is proved convex in [16]. Therefore, $\mathrm{C}6-2$ is convex.

The objective function and all constraints in $\mathbf{P4}$ are convex. Therefore, $\mathbf{P4}$ is a convex problem. The proof is complete.

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