Joint Resource Allocation for Full-Duplex Ambient Backscatter Communication: A Difference Convex Algorithm

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Abstract

In this paper, a Full-duplex Ambient Backscatter Communication (FAmBC) network is considered, including a full-duplex Access Point (AP), a Legacy User (LU), and multiple Backscatter Devices (BDs). The AP transmits downlink orthogonal frequency division multiplexing (OFDM) signals to LU and concurrently energy signals to multiple BDs, while simultaneously receiving uplink backscattered information from BDs. For such networks, maximizing the minimum BD's throughput while improving the overall BDs' throughput is the targeted design issue to achieve maximum network efficiency. This study employs a Multi-objective Lexicographical Optimization Problem (MLOP) to overcome the challenge posed jointly optimizing minimum BD's throughput maximization and overall BDs' throughput maximization, subject to the AP's subcarrier power, backscatter time, and BDs' reflection coefficients allocation. Since the proposed MLOP is a non-convex optimization problem, we propose Difference Convex Algorithm (DCA) using Exterior Penalty Function Method (EPFM)—an innovative approach in nonconvex optimization to compute the optimal solution. The application of DCA using EPFM offers the advantage of finding a globally optimal solution. Simulation results backed by theoretical analysis

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confirm that the proposed method is superior to the network performance compared to some of the investigated suboptimal algorithms while their computational complexity is similar.

Index Terms

Ambient backscatter communication, Resource allocation, Wireless-powered IoT, Multi-objective optimization problem, Non-convex problem, Difference Convex Programming.

I. INTRODUCTION

Internet-of-Things (IoT) is one of the most critical application scenarios of the fifth-generation (5G) mobile communication systems. One of the significant challenges facing the IoT is the sustainable energy supply of IoT devices. On the one hand, due to the difficulty of periodically replacing the batteries, IoT devices have a strict limitation on the lifetime with fixed power sources (batteries). On the other hand, practically, energy, cost, and complexity are among the limiting factors in these devices. Hence, this highlights the importance of the design of energy- and spectrum efficient communication technologies. To meet these demands, Radio Frequency (RF) signals have become a potential energy source as they can charge IoT devices by Energy Harvesting (EH) techniques [1]. Both Simultaneous Wireless Information and Power Transfer (SWIPT) and Wireless-Powered Communication (WPC) networks use the RF signals based on EH techniques in such a way that devices require oscillators for carrier signal generation and Analogue-to-Digital Converters (ADCs) for signal modulation [2]. To deal with this issue, Ambient Backscatter Communication (AmBC) networks have recently emerged as a promising technology that does not require oscillators and ADCs [3]. Generally, AmBC networks include an Access Point (AP), often known as a reader, multiple Backscatter Devices (BDs), and Legacy[1] Users (LUs). In particular, AmBC enables the wireless-powered BDs to harvest power from ambient RF signals (e.g., TV signal and WiFi signal) and, at the same time, to modulate information over the ambient RF carriers. Finally, they transmit modulated incident RF signals to nearby receivers (e.g., reader and smart-phone) without costly and power-hungry RF transmitters [4]. AmBC does not need the dedicated spectrum transmission due to the spectrum sharing between ambient transmission and backscatter transmission [5]. Unlike traditional backscatter

[1]The term “legacy” refers to any available wireless communication systems such as WiFi

communication such as Radio-Frequency-Identification (RFID) systems, AmBC also does not require any active RF components, thus enabling low-cost and energy-efficient ubiquitous communications [6]. Recent studies have also confirmed the adequacy of the harvested power from ambient RF signals to power a high throughput battery-less sensor [7], [8]. In this way, Full-duplex AmBC is a promising solution to IoT, which has recently drawn significant interest from academia and industry [9].

One of the critical challenges for AmBC networks is addressing the resource allocation problem to improve the network's performance, as APs are assigned to power the whole network and communicate with all BDs. Furthermore, the optimal allocation of resources has a significant effect on improving the efficiency of energy harvesting, and at the same time to meet throughput requirements. Hence, how to optimize the AmBC network's performance under resource allocation remains a challenge.

A. *Related Works*

Let us now review the current literature on AmBC networks in several aspects. Generally, AmBC systems can be classified into three types: Traditional AmBC (TAmBC) systems, Cooperative AmBC (CAmBC) systems, and Full-duplex AmBC (FAmBC) systems. Throughout this paper, the model system refers to the wireless-powered FAmBC system.

The existing TAmBC systems have a separated backscatter receiver and ambient transmitter. Their main challenge is to deal with received interference as a direct-link from the ambient transmitter at the backscatter receiver. Such a way that, this issue has been well investigated in some studies. In some of these studies, the main focus is on designing receivers for single-BD TAmBC networks to tackle the direct-link interference from the ambient RF source. For instance, Yang *et al.* [10] proposed a novel joint design for the BD waveform and receiver detector, in which direct-link interference was canceled using the specific feature of the ambient signals. In [11], a frequency-shifting method was presented to avoid direct-link interference. Aside from these studies, other researches have focused on resource allocations to improve single-BD TAmBC system performance, for example, in [5], [12], [13]. Kang *et al.* [5] analyzed a spectrum sharing system's performance under fading channels for a TAmBC system to maximize the ergodic capacity of the secondary system by jointly optimizing the transmit power of the primary signal and the reflection coefficient of the secondary ambient backscatter. For example, the authors in [12] have introduced and investigated a novel concept of integrating TAmBC into RF-powered cognitive radio networks with the aim of improving the performance of the secondary system in terms of the overall data transmission rate. Wang *et al.* [13], investigated the problem of signal detection and BER performance analysis at the reader for a TAmBC that adopts the differential encoding to eliminate the necessity of channel estimation. Also, a data detection approach was proposed in [13] that eliminates the need for Channel State Information (CSI).

In contrast, CAmBC systems are the systems with co-located backscatter receiver and LU, in which the ambient transmitters signals are recovered at the backscatter receiver instead of being treated as interference. Some of the researches in this category also focus on receiver design in single-BD CAmBC networks. For example, Liu *et al.* [14] investigated the achievable rate region of the backscatter multiplicative multiple-access channel. They also studied the detection error rates for coherent and noncoherent modulation schemes for a single-BD CAmBC system. In [15], the sum rate of the legacy and backscatter communication with multiple antennas at each node under both perfect and imperfect CSI was investigated. In [16], a CAmBC system is proposed in which the reader recovers information from the single-BD and the RF source. The authors derived the optimal maximum-likelihood detector, sub-optimal linear detectors, and the successive interference cancellation based detectors.

In FABC systems, the backscatter receiver and ambient transmitter are co-located. By exploiting the signal cancellation principles of full-duplex systems, the ambient transmitter's signals can be canceled out in FAmBC systems. In particular, for a FAmBC system over the ambient Orthogonal Frequency Division Multiplexing (OFDM) carrier, the capacity performances of backscatter and legacy communication were investigated in [17]. Also, in such a network, the asymptotic capacity bounds in closed form were obtained for many subcarriers. In [18], a FAmBC system prototype was designed as received backscattered signal and decoded by WiFi AP while simultaneously transmitted WiFi packages to its LU. Qian *et al.* [19] analyzed and derived the closed-form capacity expression and the achievable rate for AmBC system with one BD under three different channels. Such that, threshold maximizing the achievable capacity is almost the same as that of the Maximum-likelihood detector. This while that, only one BD is intended in the system model of [17]–[19]. Although this simplifies analysis and implementation, it limits its application in practice.

Studies mentioned so far mostly concentrate on hardware prototyping for diverse single-BD AmBC systems and the transceiver design. Whereas, in any practical deployment of an AmBC, an AP usually serves multiple-BDs. Our in-depth survey of relevant literature finds that only a few works address fundamental analysis and performance optimization for a general FAmBC network with multiple-BDs. For instance, Lyu *et al.* [20] investigated resource allocation policies for multi-tags FAmBC networks by considering cases of both passive and semi-passive tags. In [20], a Block Coordinate Descent (BCD)-based sub-optimal algorithm is proposed to maximize the two cases' total system throughput for the FAmBC system without considering any legacy communication system. Also, the authors in [21] presented an iterative algorithm by leveraging BCD and successive convex approximation optimization to maximize the minimum throughput and ensure fairness and security incurred in wireless powered backscatter communication network by injecting artificial noise. In [22], the throughput maximization problem in a multiple-BDs FAmBC network -which is a non-convex problem- is solved through a suboptimal iterative algorithm by leveraging the BCD and Successive Convex Optimization (SCO) techniques. In fact [20]–[22] address performance optimization for general FAmBC networks with multiple-BDs, but all of them have utilized an approximate technique to solve the non-convex problem. Although the system model in [22] considers both multiple-BDs FAmBC network and legacy communication system, the proposed method in [22] still has a considerable drawback. The SCO technique has been applied to solve the non-convex optimization problem in the BCD algorithm in [22]. Although the SCO technique allows solving convex subproblems with exponential constraints, which should be avoided by simpler constraints, it is approximate and does not reach an optimal global solution. Also, it reaches to near optimum very slower than more sophisticated methods, and the subproblems can't be solved in parallel since the current sub-iteration depends on the previous sub-iteration. Among optimization algorithms for the non-convex problems, algorithms based on Difference Convex (DC) programming have appeared to be very efficient.

B. Contributions and Organization

Although the recently reviewed literature provides fundamental analysis and performance optimization for a general FAmBC system with multiple-BDs, previous works have not considered a mathematical algorithm for solving the non-convex optimization in improving resource allocation in such networks. To fill this gap, for the first time, this paper presents a mathematical algorithm that offers the advantage of finding a globally optimal solution. Furthermore, in the multiple-BDs FAmBC networks, improving fairness among BDs is usually at the expense of the reduced overall BDs' throughput. It can be concluded achieving minimum BD's throughput maximization and the improvement of the overall BDs' throughput at the same time are two major bottlenecks in such networks. Motivated by this issue's critical role and considering that - to the best of our knowledge, there is no article to tackle this, we aim to take up this challenge and formulate a Multi-objective Lexicographical Optimization Problem (MLOP).

This paper considers a FAmBC network over ambient OFDM carriers consisting of multiple-BDs and a full-duplex AP with two antennas for simultaneous signal transmission and reception. OFDM is a widely used modulation scheme in current wireless systems such as WiFi, DVB, and LTE, due to its unique features; thus, it is a readily available ambient RF source. In such networks, the AP transmits the downlink signal that carries information to the LU while also transferring energy to the BDs. Simultaneously, all BDs alternately perform uplink information transmission through backscattering in a Time-Division-Multiple-Access (TDMA) manner. Since the backscattered signal interferes with the LU's received information signal directly from the AP, this proposed FAmBC network differs from the conventional full-duplex WPC network. Such that WPC networks work in two phases: first, the AP transmits only downlink energy signal to all BDs, and then, each BD sends an uplink information signal by utilizing its harvested energy via an additional RF transmitter. To improve the performance and ensure fairness of the FAmBC network, a novel MLOP is formulated to maximize the minimum throughput across all BDs while enhancing the overall throughput. This is created by jointly searching over the backscatter time, AP's subcarrier power allocation, and reflection coefficients of the BDs, subject to the LU's throughput constraint, the BDs' harvested-energy constraints, and other practical constraints. Since the MLOP investigated in this study is a non-convex optimization problem, we propose a Difference Convex Algorithm (DCA) using Exterior Penalty Function Method (EPFM). The application of DCA offers the advantage of finding a globally optimal solution. This algorithm is a descent method without line search but with global convergence, and every limit point of its generated sequence is a critical point of the related DC program. The main contributions of this paper are summarized as follows:

- A novel MLOP is formulated that jointly optimizes the two major objectives, simultaneously, by jointly optimizing the BDs' backscatter time allocation, the BDs' power reflection coefficients, and the FAP's subcarrier power allocation, subject to the LU's throughput requirement and the BDs' harvested energy constraints, together with other practical limitations. The two objectives have a hierarchical structure: the fairness objective has the highest priority to be optimized, and among the feasible solutions, the overall BDs' throughput is further maximized. This MLOP is nontrivial to solve since the variables are mutually coupled and result in non-convex constraints, due to the system's benefit from setting parameters in multiple dimensions optimization such a problem seems attractive in practice.

- The proposed MLOP is a non-convex optimization problem. Due to the distinction between local and global optimum non-convex problems, finding a global optimum solution is often a complicated task. Fortunately, by presenting a DCA using EPFM, which will be described later, the optimal solution is achieved. Applying the proposed algorithm to the formulated MLOP contains two steps. First, the proposed MLOP be formulated into a Difference Convex Problem (DCP). Then in the second step, the resulting DCP to be converted into its exterior penalty problem equivalent.
- Both theoretical and numerical analyses confirm this novel approach's superiority in terms of network performance over investigated suboptimal algorithms while their computational complexity is the same. Furthermore, simulation results show desirable overall BDs' throughput-LU throughput trade-off, BDs' throughput-energy trade-off, and BDs-LU throughput trade-off.

The rest of the paper is organized as follows: The system model is described in Section II. In Section III, the proposed MLOP for a multiple-BDs FAmBC network is formulated; a novel algorithm applying DCP using EPFM to solve the joint resource allocation problem in the mentioned network is derived. Then at the end of Section III, the complexity of the proposed algorithm is evaluated. In Section IV, simulation results are presented, and also comparisons are made to evaluate the proposed solution against some of the popular models investigated. The paper is concluded in Section V highlighting the study's main contributions.

II. System Model

The system model is shown in Fig. 1, where the FAmBC network over ambient OFDM carriers comprises two coexisting systems: AmBC system and Legacy Communication (LC) system. As

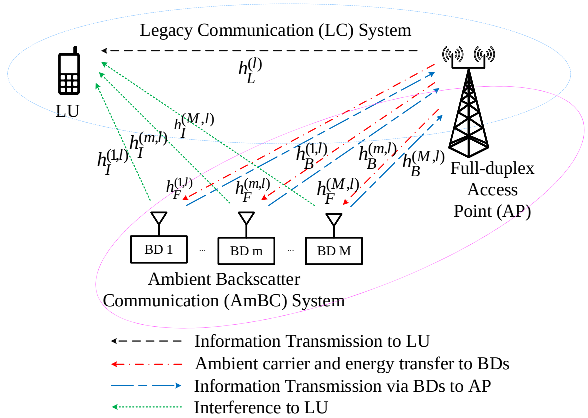

Fig. 1: a FAmBC network

can be seen, both systems include a full-duplex AP with two antennas for simultaneous data transmission and reception. Besides, M $(M \geq 1)$ BDs and only one LU are considered in the AmBC system and LC system, respectively. The AP simultaneously transmits OFDM signals to the LU and energy to all BDs; meanwhile, the AP continuously receives uplink information transmission via backscattering in a TDMA manner from all BDs over the incident OFDM carriers. We are only interested in the AmBC system in which each BD transmits its modulated signal back to the AP over its received ambient OFDM carrier from the AP. Each BD comprises a single backscatter antenna, a backscatter transmitter (i.e., a switched load impedance), an energy harvester, and other modules (e.g., sensors, memory, battery). Generally, the BDs are semi-passive devices in AmBC systems that harvest energy from the incident signals and store it in a battery for subsequent circuit operations. The BD modulates its received ambient OFDM carrier by intentionally switching the load impedance to vary the amplitude and/or phase of its backscattered signal, and the backscattered signal is received and finally decoded by the AP. Considering a common assumption in backscatter communication systems, the full-duplex AP can completely separate its received signals from the transmitted signals [23].

The channels are modeled as block fading, and we assume that the channel block length is much longer than the OFDM symbol period. Parameters $h_F^{(m,l)}$ and $h_B^{(m,l)}$ shown in Fig. 1 denote the l_F-path forward channel gain from the AP to the m-th BD $(m = 1, ..., M)$ and the l_B-path backward channel gain from the m-th BD to the AP, respectively. Furthermore, let $h_L^{(l)}$ and $h_I^{(m,l)}$ respectively be the l_L-path legacy channel gain from the AP to the LU and the l_I-

path interference channel gain from the m-th BD to the LU. The $H_F^{(m,n)}$, $H_B^{(m,n)}$, $H_I^{(m,n)}$ and $H_L^{(n)}$ $(n = 0, ..., N-1)$ are frequency responses at the n-th subcarrier for forward, backward, interference, and legacy channel, respectively, which are obtained by:

$$\begin{aligned} H_F^{(m,n)} &= \sum_{l=0}^{l_F-1} h_F^{(m,l)} e^{\frac{-j2\pi nl}{N}}, \\ H_B^{(m,n)} &= \sum_{l=0}^{l_B-1} h_B^{(m,l)} e^{\frac{-j2\pi nl}{N}}, \\ H_I^{(m,n)} &= \sum_{l=0}^{l_I-1} h_I^{(m,l)} e^{\frac{-j2\pi nl}{N}}, \\ H_L^{(n)} &= \sum_{l=0}^{l_L-1} h_L^{(l)} e^{\frac{-j2\pi nl}{N}}, \end{aligned} \tag{1}$$

where $N(N \geq 1)$ is the number of subcarriers of the transmitted OFDM signals.

In this paper a frame-based protocol is considered for backscatter transmission, such that the time duration of each frame is given as T seconds and is within the channel block length. Each frame includes M slots in which m-th BD is allocated with $\tau^m T$ time duration $(0 \leq \tau^m \leq 1)$ and can only work during its allocated duration. The backscatter time allocation vector for all BDs is denoted as $\tau = [\tau^1, ..., \tau^m, ..., \tau^M]^T$. As different BDs may have different distances to AP, the τ requires to be properly allocated to meet each BD's throughput demand. During each BD duration, the AP transmits downlink OFDM signals to the LU, incident signals to BDs, and concurrently receives backscattered signals modulated by the BD. It should be noted that in addition to reflecting a portion of its incident signal for transmitting information to the AP in its allocated slot, each BD also harvests energy from the remaining incident signal. While at the same time, all other BDs only harvest energy from their received OFDM signals.

Let $P^{(m,n)}$ be the signal power allocated to the m-th BD at the n-th subcarrier. Suppose the subcarrier power allocation matrix is $P = [p^1, ..., p^m, ..., p^M]$, in which p^m is the subcarrier power allocation vector to the m-th BD. From [3], when m-th BD is in backscatter communication, a proportion λ^m of the incident power is reflected backward, while the remaining part $(1 - \lambda^m)$ propagates to the energy harvester. Hence, $\lambda = [\lambda^1, ..., \lambda^m, ..., \lambda^M]^T$ represents the power reflection coefficient vector. Given how to harvest energy by the m-th BD and the other BDs in the mentioned protocol and from [2], the total EH by the m-th BD in all slots is thus:

$$E^m(\tau,\lambda^m,P)=\gamma^m\sum_{n=0}^{N-1}|H_F^{(m,n)}|^2[\tau^m P^{(m,n)}(1-\lambda^m)+\sum_{q=1,q\neq m}^{M}\tau^q P^{(q,n)}], \quad (2)$$

where γ^m $(0\leq\gamma^m\leq 1)$ is the EH efficiency constant of m-th BD. where the first term indicates the energy harvested in the m-th slot, and the second term for all other slots.

In m-th slot, the incident signal at BD m is $x_s^{(m,t)}(k)\otimes h_F^{(m,l)}$ ($\otimes$ is the convolution operation). Let $x_s^{(m,t)}(k)$ be the transmitted signal in time-domain at the k-th OFDM symbol period of the m-th slot for the time index t $(t=0,...,N-1)$, which is obtained after Inverse-Discrete-Fourier-Transform (IDFT) at AP by:

$$x_s^{(m,t)}(k)=\frac{1}{N}\sum_{n=0}^{N-1}\sqrt{P^{(m,n)}}X_s^{(m,n)}(k)e^{\frac{j2\pi nt}{N}}, \quad (3)$$

where $X_s^{(m,n)}(k)\in\mathcal{CN}(0,1)$ ($\mathcal{CN}(0,1)$ is the circularly symmetric complex Gaussian distribution with zero mean and variance 1) denotes the AP's information symbol at the n-th subcarrier in the k-th OFDM symbol period of the m-th slot. Without loss of generality, in this paper, it is assumed that $E[|x_s|^2]=1$.

The backscattered wave observed at the AP is composed of two different components: structural mode (load-independent) and antenna mode (load-dependent) [24]. Structural mode scattering depends on only the antenna geometry and material, while antenna mode scattering depends on the antenna's load impedance. A back signal with a different phase and amplitude is backscattered to the AP by changing the BD's antenna impedance loading. The AP utilizes the received backscattered signal to estimate the different modulation states at the BD.

In practice, via some methods like the scheme that employs the repeating structure of CP [10], each BD can estimate the arrival time of the OFDM signal. Consequently, we suppose that the m-th BD can adjust the transmission of its own symbol $X^m(k)$ with its received OFDM symbol. Where $X^m(k)\in\mathcal{C}$ (convex set) is the m-th BD's information symbol, such that its duration is designed to be equal to the OFDM symbol period. Given that the structural mode component is fixed for each BD, it can be reconstructed and subtracted from the received signal at AP. Thus, for convenience, this component is ignored; this is while the antenna mode component is defined as $-\sqrt{\lambda^m}X^m(k)$ [17]. From now on, the backscattered signal is denoted as:

$$x_r^{(m,t)}(k)=\sqrt{\lambda^m}x_s^{(m,t)}(k)\otimes h_F^{(m,l)}X^m(k). \quad (4)$$

Let us assume that the full-duplex AP is enabled by employing the perfect Self-Interference Cancellation (SIC), due to that $x_s^{(m,t)}(k)$ is known with the AP receiving chain and it can be reconstructed and subtracted from the received signal at the AP. Hence, the received backscattered signal from the m-th BD in the time-domain after applying SIC can be expressed as follows:

$$y^{(m,t)}(k) = \sqrt{\lambda^m} x_s^{(m,t)}(k) \otimes h_F^{(m,l)} \otimes h_B^{(m,l)} X^m(k) + \omega^{(m,t)}(k), \tag{5}$$

where $\omega^{(m,t)}(k) \sim \mathcal{CN}(0, \sigma^2)$ represents the time-domain additive white Gaussian noise (AWGN) with mean 0 and variance σ^2. The counterpart of $y^{(m,t)}(k)$ in the frequency-domain after the CP removal and DFT at the AP is:

$$Y^{(m,n)}(k) = \sqrt{\lambda^m P^{(m,n)}} H_F^{(m,n)} H_B^{(m,n)} X_s^{(m,n)}(k) X^m(k) + W^{(m,n)}(k), \tag{6}$$

where $W^{(m,t)}(k) \sim \mathcal{CN}(0, \sigma^2)$ is the frequency-domain additive white Gaussian noise (AWGN).

In order to recover the BD symbol $X^m(k)$, the AP applies maximum-ratio-combining (MRC) [25]. Thus, the reconstructed information symbol of BD is as follows:

$$\hat{X}^m(k) = \frac{1}{N} \sum_{n=0}^{N-1} \frac{Y^{(m,n)}(k)}{\sqrt{\lambda^m P^{(m,n)}} H_F^{(m,n)} H_B^{(m,n)} X_s^{(m,n)}(k)}. \tag{7}$$

It can be concluded from points mentioned that the decoding Signal-to-Noise Ratio (SNR) for the m-th BD and the average receive SNR at AP are derived, respectively as:

$$\Upsilon_{BD}^m(\lambda^m, p^m) = \frac{\lambda^m}{\sigma^2} \sum_{n=0}^{N-1} |H_F^{(m,n)} H_B^{(m,n)}|^2 P^{(m,n)},$$

$$\bar{\Upsilon}_{AP} = \frac{P_{total}}{\sigma^2} \sum_{l=0}^{l_F-1} E[|h_F^{(1,l)} h_B^{(1,l)}|^2], \tag{8}$$

where P_{total} is the maximum total transmission power.

By the assumption that the BDs' symbols $X^m(k)$ follow Gaussian distribution, the normalized throughput -with unit of bits-per-second-per-Hertz (bps/Hz)- for the m-th BD is:

$$R_{BD}^m(\tau^m, \lambda^m, p^m) = \frac{\tau^m}{N} \log(1 + \Upsilon_{BD}^m). \tag{9}$$

Since the AmBC is carried out at the same frequency band as the downlink signal in the legacy OFDM system, the entire FAmBC system shown in Fig. 1 can be considered as a spectrum sharing system [5]. Hence, the LU's received signal results from the superposition of two signals:

the backscattered signal from BD and the downlink legacy OFDM signal. Nevertheless, the power of this resulting interference is typically much lower than that of the received signal from the AP, even if the LU and the BDs are close to each other. Accordingly, it is treated with the backscattered signal from BD as interference and the received signal of LU in the frequency-domain is given by:

$$Y_{LU}^{(m,n)}(k) = \sqrt{P^{(m,n)}} H_L^n X_s^{(m,n)}(k) + \sqrt{\lambda^m P^{(m,n)}} H_F^{(m,n)} H_I^{(m,n)} X_s^{(m,n)}(k) X^m(k) + \tilde{W}^{(m,t)}(k). \tag{10}$$

As a result, the total throughput of LU can be expressed as:

$$R_{LU}(\tau, \lambda, P) = \sum_{m=1}^{M} \frac{\tau^m}{N} \sum_{n=0}^{N-1} \log(1 + \frac{|H_L^n|^2 P^{(m,n)}}{\lambda^m |H_F^{(m,n)} H_I^{(m,n)}|^2 P^{(m,n)} + \sigma^2}). \tag{11}$$

Now let us move on to the next section and formulate the main problem of the mentioned FAmBC system model based on the given E^m, R_{BD}^m and R_{LU} equations.

III. Problem Formulation and Proposed Method

From the point of view of the "doubly near-far" problem [26] in multiple-BDs FAmBC systems, the AP will allocate more resources to close BDs than the far BDs, which leads to an unfair performance among various BDs. In such networks, improving fairness among BDs is usually at the expense of the reduced overall BDs' throughput. This paper investigates both fairness and efficiency issues to come up with a joint optimization to balance the throughputs among different BDs in the network while maximizing the overall throughput. Different from the single-objective optimization in most of the literatures, we formulate a novel MLOP to jointly determine the BDs' backscatter time allocation, the BD's power reflection coefficients, and the AP's subcarrier power allocation while satisfying the requirements of the LU's throughput constraint, the BDs' harvested-energy constraints, and other practical constraints. The two objectives have a hierarchical structure: the fairness objective has the highest priority to be optimized, and among the feasible solutions, the overall throughput is further maximized. We adopt the fairness definition in [27], where the maximum fairness is achieved when all BDs have the same throughput. The maximum fairness can be obtained by solving the max-min problem to maximize the worst BD's throughput. The optimal value of the proposed MLOP is obtained by maximizing the functions sequentially, starting with the most crucial one and moving on to the next one based on the order of importance of the objective functions. Additionally, the computed optimal value of each objective is added as a constraint for subsequent optimizations. This proposed MLOP can be formulated as follows:

$$\mathit{lex} \quad \max_{\tau,\lambda,P}(\min_{m} R_{BD}^{m}, \mathcal{R}) \tag{12a}$$

s.to :

$$\sum_{m=1}^{M}\frac{\tau^m}{N}\sum_{n=0}^{N-1}\log(1+\frac{|H_L^n|^2P^{(m,n)}}{\lambda^m|H_F^{(m,n)}H_I^{(m,n)}|^2P^{(m,n)}+\sigma^2})\geq D \tag{12b}$$

$$\gamma^m\sum_{n=0}^{N-1}|H_F^{(m,n)}|^2[\tau^mP^{(m,n)}(1-\lambda^m)+\sum_{q=1,q\neq m}^{M}\tau^qP^{(q,n)}]\geq E_{min}^m, \forall m \tag{12c}$$

$$\sum_{m=1}^{M}\sum_{n=0}^{N-1}\tau^mP^{(m,n)}\leq P_{total} \tag{12d}$$

$$\sum_{m=1}^{M}\tau^m\leq 1, \forall m \tag{12e}$$

$$\tau^m\geq 0, \forall m \tag{12f}$$

$$0\leq P^{(m,n)}\leq P_{peak}, \forall m,n \tag{12g}$$

$$0\leq\lambda^m\leq 1, \forall m. \tag{12h}$$

where the $\mathcal{R}$ denotes the sum of all BDs' throughput, i.e., $\mathcal{R}=\sum_{m=1}^{M}R_{BD}^m$. We define $R_{BD}^m = \psi^m\mathcal{R}$, so that, ψ^m is a member of the throughput-profile vector $\boldsymbol{\psi}=[\psi^1,...,\psi^m,...,\psi^M]^T$ by considering to $\sum_{m=1}^{M}\psi^m=1$ and $\psi^m\geq 0$. Additionally, D, E_{min}^m, P_{total}, and P_{peak} indicate the minimum throughput required for LU's throughput, the requirement of lowest energy-harvested for each BD's throughput, maximum total transmission power and maximum subcarrier power, respectively.

Note that the above joint optimization problem is appealing from two points of view. First, from the perspective of the "doubly near-far" problem, to overcome the effect of this problem in FAmBC systems, more backscatter time can be allocated to far BDs to further enhance their throughput performance, by applying a proper power reflection allocation policy to the close BDs. Second, from the perspective of subcarrier power allocation, by properly allocating subcarrier power at the AP, the BDs-LU throughput trade-off and the BDs' throughput-HE trade-off can be improved. In general, the proposed MLOP is challenging to solve since the backscatter time allocation variables, the power reflection coefficient variables, and the subcarrier power variables are coupled in the first three constraints. Furthermore, the logarithm function in the first constraint is a non-convex function of the subcarrier power variables. Thus, the proposed MLOP can be categorized as a non-convex optimization problem, which is generally difficult to find the desired globally optimal solution. And there often is no standard and straightforward method for optimally and efficiently solving it. Hence, this MLOP can be formulated as a DCP, which is explained later. DCP has directed researchers' attention to non-convex wireless communication problems in recent years.

Now, as discussed before, we proceed to deal with the optimization of the two objectives through the following two steps:

Step1: Maximizing the minimum BD's throughput: In this step, the first single-objective optimization problem is optimized to maximize the minimum BD's throughput by jointly resources allocation optimizing for multiple-BD, which is a non-convex optimization problem. This problem can be converted into its optimization problem with a linear objective by utilizing a lower-bound minimum BD's throughput (Θ) as a slack variable. Hence, the first single-objective optimization problem, as given in the proposed MLOP can be simplified to generate the following mathematical programming:

$$\max_{\Theta,\tau,\lambda,P} \quad \Theta \tag{13a}$$

s.to :

$$\frac{\tau^m}{N}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)}) \geq \Theta, \forall m \tag{13b}$$

$$\sum_{m=1}^{M}\frac{\tau^m}{N}\sum_{n=0}^{N-1}\log(1+\frac{|H_L^n|^2P^{(m,n)}}{\lambda^m|H_F^{(m,n)}H_I^{(m,n)}|^2P^{(m,n)}+\sigma^2}) \geq D \tag{13c}$$

$$\gamma^m\sum_{n=0}^{N-1}|H_F^{(m,n)}|^2[\tau^mP^{(m,n)}(1-\lambda^m)+\sum_{q=1,q\neq m}^{M}\tau^qP^{(q,n)}] \geq E_{min}^m, \forall m \tag{13d}$$

$$\sum_{m=1}^{M}\sum_{n=0}^{N-1}\tau^mP^{(m,n)} \leq P_{total} \tag{13e}$$

$$\sum_{m=1}^{M} \tau^m \leq 1, \forall m \tag{13f}$$

$$\tau^m \geq 0, \forall m \tag{13g}$$

$$0 \leq P^{(m,n)} \leq P_{peak}, \forall m, n \tag{13h}$$

$$0 \leq \lambda^m \leq 1, \forall m. \tag{13i}$$

Since the objective functions are characterized in incomparable units, which bring conflict among them, all of the objective functions should be normalized first for making a fair comparison of all of them. Herein, the minimum BD's throughput function should be normalized using the Lemma 1.

Lemma 1. *The Upper Bound (UB) of the minimum BD's throughput function* Θ *is evaluated by* $\frac{P_{peak}}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2$.

Proof. It can be seen that since $\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})$ is an increasing function of $P^{(m,n)}$ and λ^m, these variables can be set to their maximum values P_{peak} and 1, respectively. We will get an UB as:

$$\begin{aligned}
\Theta &\leq \frac{1}{N}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P_{peak}) \\
&\leq \frac{1}{N}\log(1+\frac{1}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P_{peak}) \\
&\leq \frac{1}{N}(\frac{1}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P_{peak}) \\
&\leq \frac{NP_{peak}}{N\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2.
\end{aligned} \tag{14}$$

Thus, we have

$$\Theta^{UB} = \frac{P_{peak}}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2. \tag{15}$$

The proof is complete. ■

Mathematically, we can rewrite the normalized the minimum BD's throughput as $\Theta_n = \frac{\Theta}{\Theta^{UB}}$. By this approach, the range of the objective function is always within 0 and 1. So, problem (13) can be expressed as follows:

$$\max_{\Theta_n,\tau,\lambda,P} \quad \Theta_n \tag{16a}$$

s.to :

$$\frac{\tau^m}{N}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)}) \geq \Theta, \forall m \tag{16b}$$

$$\sum_{m=1}^{M}\frac{\tau^m}{N}\sum_{n=0}^{N-1}\log(1+\frac{|H_L^n|^2P^{(m,n)}}{\lambda^m|H_F^{(m,n)}H_I^{(m,n)}|^2P^{(m,n)}+\sigma^2}) \geq D \tag{16c}$$

$$\gamma^m\sum_{n=0}^{N-1}|H_F^{(m,n)}|^2[\tau^mP^{(m,n)}(1-\lambda^m)+\sum_{q=1,q\neq m}^{M}\tau^qP^{(q,n)}] \geq E_{min}^m, \forall m \tag{16d}$$

$$\sum_{m=1}^{M}\sum_{n=0}^{N-1}\tau^mP^{(m,n)} \leq P_{total} \tag{16e}$$

$$\sum_{m=1}^{M}\tau^m \leq 1, \forall m \tag{16f}$$

$$\tau^m \geq 0, \forall m \tag{16g}$$

$$0 \leq P^{(m,n)} \leq P_{peak}, \forall m,n \tag{16h}$$

$$0 \leq \lambda^m \leq 1, \forall m. \tag{16i}$$

Considering that (16c) is a non-convex function of the variables $P^{(m,n)}$'s, the objective function of the problem (16) is a linear function with non-convex constraints. Hence, working out a globally optimal solution is directly impractical and difficult. At the end of this section, a DCA using EPFM is proposed for solving this type of optimization problem, which does offer an optimal solution as Θ_n^*.

Step2: Maximizing the sum of all BDs' throughput: In this step, we try to maximize the sum of all BDs' throughput that is denoted as $\mathcal{R}$ by jointly resources allocation optimizing for multiple-BD, subject to the constraints mentioned before as well as the condition evaluated from step1 as $\psi^m\mathcal{R} \geq \Theta_n^*$. Hence, the second single-objective optimization problem will be as follows:

$$\max_{\mathcal{R},\tau,\lambda,P} \quad \mathcal{R} \tag{17a}$$

s.to :

$$\frac{\tau^m}{N}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})\geq\psi^m\mathcal{R},\forall m \tag{17b}$$

$$\sum_{m=1}^{M}\frac{\tau^m}{N}\sum_{n=0}^{N-1}\log(1+\frac{|H_L^n|^2P^{(m,n)}}{\lambda^m|H_F^{(m,n)}H_I^{(m,n)}|^2P^{(m,n)}+\sigma^2})\geq D \tag{17c}$$

$$\gamma^m\sum_{n=0}^{N-1}|H_F^{(m,n)}|^2[\tau^mP^{(m,n)}(1-\lambda^m)+\sum_{q=1,q\neq m}^{M}\tau^qP^{(q,n)}]\geq E_{min}^m,\forall m \tag{17d}$$

$$\sum_{m=1}^{M}\sum_{n=0}^{N-1}\tau^mP^{(m,n)}\leq P_{total} \tag{17e}$$

$$\sum_{m=1}^{M}\tau^m\leq 1,\forall m \tag{17f}$$

$$\tau^m\geq 0,\forall m \tag{17g}$$

$$0\leq P^{(m,n)}\leq P_{peak},\forall m,n \tag{17h}$$

$$0\leq\lambda^m\leq 1,\forall m \tag{17i}$$

$$\psi^m\mathcal{R}\geq\Theta_n^*,\forall m. \tag{17j}$$

Lemma 2. *The UB of the overall BD's throughput function $\mathcal{R}$ is evaluated by* $\frac{MP_{peak}}{\sigma^2}\sum_{m=1}^{M}\sum_{n=0}^{N-1}(|H_F^{(m,n)}H_B^{(m,n)}|^2)$.

Proof. Similar to Lemma 1, since $\mathcal{R}=\sum_{m=1}^{M}\frac{\tau^m}{N}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})$ is an increasing function of $P^{(m,n)},\lambda^m$ and τ^m. It will give a UB as:

$$\begin{aligned}\mathcal{R}&=\sum_{m=1}^{M}\frac{\tau^m}{N}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})\\&\leq\frac{1}{N}\sum_{m=1}^{M}\log(1+\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})\\&\leq\frac{1}{N}\sum_{m=1}^{M}(\frac{\lambda^m}{\sigma^2}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})\\&\leq\frac{1}{N\sigma^2}\sum_{m=1}^{M}(\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2P^{(m,n)})\\&\leq\frac{MNP_{peak}}{N\sigma^2}\sum_{m=1}^{M}\sum_{n=0}^{N-1}|H_F^{(m,n)}H_B^{(m,n)}|^2.\end{aligned} \tag{18}$$

Thus, we have

$$\mathcal{R}^{UB} = \frac{MP_{peak}}{\sigma^2} \sum_{m=1}^{M} \sum_{n=0}^{N-1} |H_F^{(m,n)} H_B^{(m,n)}|^2. \tag{19}$$

The proof is complete. ∎

Mathematically, we can rewrite the normalized overall BD's throughput as $\mathcal{R}_n = \frac{\mathcal{R}}{\mathcal{R}^{UB}}$. So, problem (17) can be rewritten as follows:

$$\max_{\mathcal{R}_n, \tau, \lambda, P} \quad \mathcal{R}_n \tag{20a}$$

s.to :

$$\frac{\tau^m}{N} \log(1 + \frac{\lambda^m}{\sigma^2} \sum_{n=0}^{N-1} |H_F^{(m,n)} H_B^{(m,n)}|^2 P^{(m,n)}) \geq \psi^m \mathcal{R}, \forall m \tag{20b}$$

$$\sum_{m=1}^{M} \frac{\tau^m}{N} \sum_{n=0}^{N-1} \log(1 + \frac{|H_L^n|^2 P^{(m,n)}}{\lambda^m |H_F^{(m,n)} H_I^{(m,n)}|^2 P^{(m,n)} + \sigma^2}) \geq D \tag{20c}$$

$$\gamma^m \sum_{n=0}^{N-1} |H_F^{(m,n)}|^2 [\tau^m P^{(m,n)} (1 - \lambda^m) + \sum_{q=1, q \neq m}^{M} \tau^q P^{(q,n)}] \geq E_{min}^m, \forall m \tag{20d}$$

$$\sum_{m=1}^{M} \sum_{n=0}^{N-1} \tau^m P^{(m,n)} \leq P_{total} \tag{20e}$$

$$\sum_{m=1}^{M} \tau^m \leq 1, \forall m \tag{20f}$$

$$\tau^m \geq 0, \forall m \tag{20g}$$

$$0 \leq P^{(m,n)} \leq P_{peak}, \forall m, n \tag{20h}$$

$$0 \leq \lambda^m \leq 1, \forall m \tag{20i}$$

$$\psi^m \mathcal{R} \geq \Theta_n^*, \forall m. \tag{20j}$$

Similar to that mentioned in step 1, it is clear that this problem belongs to the class of non-convex programming problems with the linear objective function and the non-convex constraints. Thus, through the application of the technique used in step1, the optimum value of the $\mathcal{R}_n$ is evaluated, which is denoted as $\mathcal{R}_n^*$.

The following subsection describes the technique used to solve both the steps mentioned above in more detail.

A. Difference Convex Problem (DCP) and Difference Convex Algorithm (DCA) using Exterior Penalty Function Method (EPFM)

DCP and DCA constitute the backbone of smooth and non-smooth non-convex programming and global optimization. They play a vital role in these research areas because most real-world non-convex programs are DCPs. Their original key idea relies on the structure DC of the objective function and constraint functions in non-convex DCP, which are explored and exploited profoundly in the appropriate manner. Based on local optimality conditions and DC duality, DCA is one of the rare effective and efficient algorithms in the non-smooth non-convex programming framework. It is proved that it converges quite often to a global one with an appropriate starting point, and it is more robust and more efficient than appropriate standard methods. The resulting DCA introduces the elegant concept of approximating a non-convex DCP by a sequence of convex ones: each iteration of DCA requires a convex program solution. The popularity of DCP and DCA is due to their rich and deep and mathematical foundations, inexpensiveness and efficiency of DCA's compared to existing methods, and their ability to solve real-world, large-scale non-convex programs [28]. DCA attend to the problem of minimizing a function f which is a DC functions on the whole space $\mathbb{R}^n$ or on a convex set. Mathematically, a standard DCP is expressed as:

$$\varrho = inf\{f(x) := g(x) - h(x) : x \in \mathbb{R}^n\} \qquad (P_{dcp}) \tag{21}$$

where g, h are lower semi-continuous proper convex functions on $\mathbb{R}^n$. The convex constraint $x \in \mathrm{C}$ can be included in the objective function of (P_{dcp}) by using the indicator function denoted as χ_C, which is defined as follows:

$$\chi_C(x) = \begin{cases} 0 & x \in \mathrm{C}; \\ \infty & \text{otherwise.} \end{cases} \tag{22}$$

Hence,

$$inf\{g(x) - h(x) : x \in \mathrm{C}\} = inf\{\chi_C(x) + g(x) - h(x) : x \in \mathbb{R}^n\}. \tag{23}$$

Therefore, any convex constrained DCP can be written in the standard form (P_{dcp}) by adding the indicator function of the convex constraint set to the first difference convex component g. It should be mentioned that the foundation of DCA relies on the substantial relation of DCP

(P_{dcp}) and its duality (D_{dcp}). Let us define the dual program of (P_{dcp}) as:

$$\varrho_D = inf\{h^*(y) - g^*(y) : y \in \mathbb{R}^n\}, \qquad (D_{dcp}) \tag{24}$$

where h^* and g^* are the conjugate functions of h and g respectively. There is a perfect symmetry between (P_{dcp}) and its dual (D_{dcp}): the dual of (D_{dcp}) is exactly (P_{dcp}). Hence it can be proved that $\varrho = \varrho_D$ [29].

Note that DCA is based on local optimality conditions and duality in DCP and this relationship is perfectly expressed in the Appendix as Lemma 3 and Proposition 1. On the other hand, DCA has quite a simple interpretation: each iteration w of DCA approximates the concave part $-h$ by its affine majorization (which corresponds to taking $y_w \in \partial h(x_w)$) and minimizes the resulting convex function, (i.e., computing $x_{w+1} = \partial g^*(y_w)$, where ∂ is the sub-differential operation).

Mathematically, a DCP problem with a few constraints is expressed in the following.

Definition 1 (Definition of DCP)**.** *Programming problems dealing with the difference convex functions are called DCP problems. The standard form of the General DCP (P_{gdc}) with difference convex constraints is:*

$$\begin{aligned} (P_{gdc}): \quad \min \quad & f_0(x) \\ \textit{s.to}: \quad & f_i(x) \leq 0, \quad i = 1, ..., s \\ & x \in \mathbf{C}, \end{aligned} \tag{25}$$

where $f_i : \mathbb{R}^n \longrightarrow \mathbb{R} \cup \{+\infty\}, i = 0, 1, ..., s$ are difference convex functions, $C \subseteq \mathbb{R}^n$ is a non-empty closed convex subset of $\mathbb{R}^n$ and $F = \{x \in \mathbf{C} : f_i(x) \leq 0, i = 1, ..., s\}$ denotes the feasible set of P_{gdc}.

DCA's unique feature relies upon the fact that DCA deals with the convex DC components g and h but not with the DC function f itself. In general, a given DCP has many types of different convex decompositions so that each can directly impact the quality of DCAs (e.g., convergence speed, complexity, globality of computed solutions, etc.). Hence, finding a suitable DC decomposition that is vital and difficult depends on the particular structure of the considered problem. The flexible property of DCA motivates us to investigate the proposed DC formulations for the proposed problem. Some specific cases of different convex functions and representations used in this paper are fully explained in the Appendix (Proposition 2). Interestingly, with appropriate DC decompositions, DCA permits to recover, as special cases, all (resp. most) existing algorithms in convex (resp. non-convex) programming, e.g., the proximal and (sub)gradient algorithms.

Going back to P_{gdc}, we define $\Gamma(x)$ and $\Gamma^{+}(x)$ as follows:

$$\begin{aligned}\Gamma(x) :=& max\{f_1(x), ..., f_s(x)\},\\ \Gamma^{+}(x) :=& max\{\Gamma(x), 0\}.\end{aligned} \tag{26}$$

Let $f_i = g_i - h_i; \quad i = 1, ..., s$ be difference convex decomposition of f_i, such that g_i, h_i are finite convex functions on C. As the difference convex rule, the standard difference convex decomposition of $\Gamma(x)$ and $\Gamma^{+}(x)$ can be denoted as $\Gamma(x) := g(x) - h(x)$ and $\Gamma^{+}(x) := \max\{g(x), h(x)\} - h(x)$, respectively; so that, $g(x), h(x)$ are expressed as below:

$$\begin{aligned}g(x) :=& \max_{i=1,...,s}\{g_i(x) + \sum_{j=1,j\neq i}^{s} h_j(x)\},\\ h(x) :=& \sum_{j=1}^{s} h_j(x).\end{aligned} \tag{27}$$

The $\Gamma^{+}(x)$ can be rewritten with the replacement of $g(x), h(x)$ obtained in (27) as follows:

$$\Gamma^{+}(x) := \max\{\max_{i=1,...,s}\{g_i(x) + \sum_{j=1,j\neq i}^{s} h_j(x)\}, \sum_{j=1}^{s} h_j(x)\} - \sum_{j=1}^{s} h_j(x). \tag{28}$$

After transforming MLOP to P_{gdc} through the steps mentioned above, it is vital that P_{gdc} is converted to its equivalent Exterior Penalty Function Problem (P_{epf}) form in order to apply DCA to it using penalty function. Mathematically, we can derive the equivalent problem as:

$$\begin{aligned}(P_{epf}) : \min \quad & \Psi_w(x) := f_0(x) + \rho_w \Gamma^{+}(x)\\ \text{s.to}: \quad & x \in \boldsymbol{C},\end{aligned} \tag{29}$$

where ρ_w is the penalty parameters. Penalty relative to difference convex function Γ^{+} is said to be exact in (28) if there exists $\rho \geq 0$ such that for every $\rho_w > \rho$ (P_{gdc}) and (28) are equivalent in the sense that they have the same optimal value and the same solution set.

Let us suppose that the difference convex decompositions f_0 and Γ^{+} are given as follows:

$$\begin{aligned}f_0(x) :=& g_0(x) - h_0(x),\\ \Gamma^{+}(x) :=& \Gamma_1(x) - \Gamma_2(x),\end{aligned} \tag{30}$$

where $g_0(x), h_0(x), \Gamma_1(x), \Gamma_2(x)$ are convex functions defined on the whole space. Then, the difference convex decomposition for $\Psi_w(x)$ is shown:

$$\Psi_w(x) := G_w(x) - H_w(x), \tag{31}$$

Here,

$$\begin{aligned} G_w(x) :=& g_0(x) + \rho_w \Gamma_1(x), \\ H_w(x) :=& h_0(x) + \rho_w \Gamma_2(x). \end{aligned} \tag{32}$$

Algorithm 1 DCA using EPFM for solving MLOP

Input: $G_w(x)$, $H_w(x)$ and $\Gamma(x)$

Initialization : Take an initial point $x_1 \in C$; $\delta > 0$; an initial penalty parameter $\rho_1 > 0$ and set $w := 1$.

Repeat

1: Compute $y_w \in \partial H_w(x_w)$.

2: Compute $x_{w+1} \in \partial(G_w(x_w) + \chi_C)^*$ (χ_C is the indicator function of C, i.e.,$\chi_C(x) = 0$ if $x \in C$, $+\infty$ otherwise), i.e., x_{w+1} is a solution of convex program : $\min\{G_w(x_w) - \langle x, y_w \rangle : x \in C\}$.

3: Compute $r_w := \min\{\Gamma(x_w), \Gamma(x_{w+1})\}$, $d_w = \|x_{w+1} - x_w\|$ and update penalty parameter:

$$\rho_{w+1} = \begin{cases} \rho_w + \delta, & \text{if } \rho_w < d_w^{-1} \quad \& \quad r_w > 0, \\ \rho_w, & \text{if } \rho_w \geq d_w^{-1} \quad || \quad r_w \leq 0. \end{cases}$$

4: Set $w := w + 1$.

Until $x_w = x_{w+1}$ and $\Gamma(x_w) \leq 0$.

Output: x_w

It should be noted that the penalty parameter plays a vital role in this algorithm, so that if the sequence $\{\rho_w\}$ is unbounded then $d_w \to 0$ and $r_w > 0$. Additionally, the DCA proposal mentioned above is particularly important when the exact penalty does not hold in P_{epf} or when the exact penalty occurs. However, the penalty parameter's upper bounds are computationally intractable. The initial penalty problem controls how severe the penalty is for violating the constraint. This value ρ_1 is small but increases over time so that unfeasible solutions found from the last iterations can be eliminated. The higher penalty increases accuracy. We continue to increase ρ values until the solutions converge. It should be mentioned that, based on EPFM, this algorithm chooses the initial point x_1 in violation of the constraint.

From a convergence point of view, if $g(x_{w+1}) - g(x_w) = h(x_{w+1}) - h(x_w)$, then x_w is a critical point of $g - h$, so that DCA terminates at the w-th iteration. As mentioned before, based

TABLE I

Computations of Proposed DCA using EPFM

Case	Executing order	Initialization and applying constraints	Computing objective functions	Computing in iterative DCA using EPFM
Addition	1	$N+M+MN-9$	MN	$N+M+MN+17$
Multiplication	1	$N+M+MN$	$M+MN$	$N+M+MN+23$
Division	1	$N+M+2$	M	$N+M+9$
Square	1	$N+MN$	MN	$N+MN$
Times of computing	1	–	–	$iteration$
Maximum order	1	MN	MN	$(MN)\times(iteration)$

on local optimality conditions and DC duality, DCA is successfully applied to a lot of different and various non-differentiable non-convex optimization problems. It should also be mentioned that the general DCA has a global linear convergence for DCP, which is presented in [30].

B. Complexity Analysis

Now, the complexity of our proposed DCA using EPFM is evaluated, and the result is compared with that of the iterative algorithm by leveraging the BCD and SCO techniques. Taking the number of BDs and subchannels as M and N, respectively, we compute the worst-case time complexity of the proposed DCA. Note that Tables II illustrates computations of our proposed DCA using EPFM. It can be concluded from Table I, the worst-case time complexity of DCA using EPFM is upper bounded by $\mathcal{O}(MN)\times iteration$. In DCA using EPFM, $iteration$ is the maximum number of times the algorithm has to be computed in order to reach to the optimum solution, which is a much lower number compared with N. Hence, the time complexity of the proposed DCA using EPFM is $\mathcal{O}(MN)$. According to [22] the time complexity of the iterative algorithm by leveraging the BCD and SCO techniques is polynomial. It can also be concluded, therefore, that the complexity of the proposed algorithm is the same as that of its counterpart. Moreover, in the next section it will be shown that the numerical results confirm the higher accuracy of the proposed algorithm over algorithms investigated in this study.

IV. Numerical results

In this section, numerical and simulation results are presented to evaluate the performance of the proposed problem and the proposed DCA using EPFM with optimal resource allocation

TABLE II

Simulation Parameters

Parameter	Value	Parameter	Value
M (#of BDs)	2	AP-to-LU distance	15m
N (#of subcarriers)	64	(BD1,BD2)-to-LU distance	15m
N_{cp} (#of cycle prefix)	16	P_{total}	1
$L_f = L_g$	4	γ_m	0.5 $\forall m$
L_h	8	E^m_{min}	10 μj $\forall m$
L_v	6	D	2 bps/Hz
AP-to-BD1 distance	2.5m	P_{peak}	$10P_{ave}$
AP-to-BD2 distance	4m	P_{ave}	$1/N$

for a FAmBC network. To illustrate the superiority of our proposed method in terms of the overall throughput improvement, we compare the throughput achieved by the optimal resource allocation in Algorithm 1 with the following three well-known suboptimal schemes:

- **Scheme1**: In this scheme, a FAmBC network with optimal resource allocation is designed, in which full-duplex AP transmits and receives information simultaneously and is optimized via an iterative algorithm by leveraging the BCD and SCO techniques in [22].
- **Scheme2**: The second scheme is a Half AmBC (HAmBC) network with optimal resource allocation. This network is comprised of a half-duplex AP that transmits and receives information in two phases and is optimized via an iterative algorithm by leveraging the BCD technique in [22].
- **Scheme3**: A FAmBC network with equal resource allocation is considered in the third scheme, in which both the backscatter time and subcarrier power are allocated equally. Also, all BDs adopt an average power reflection coefficient optimized via CVX.

In the simulation setup, we assume the first-path channel power gain for each channel link of independent Rayleigh fading channels is $10^{-3}d^{-2}$, where d denotes the transmitter-to-receiver distance in m. Note that all results are obtained based on 300 random channel realizations and all simulation parameters are summarized in Table II which are assumed unchanged during the simulation. In order to make a thorough evaluation, simulations are run on two types of parameters, namely, constant and variable. Variable parameters consist of E^m_{min}, P_{peak}, $\bar{\Upsilon}_{AP}$, and D which are different for each figure and other parameters are constant.

Let us begin with Fig. 2, which depicts the max-min throughput of all BDs versus the LU's throughput requirement D under different SNRs $\bar{\Upsilon}_{AP}$'s, for the proposed DCA using EPFM and

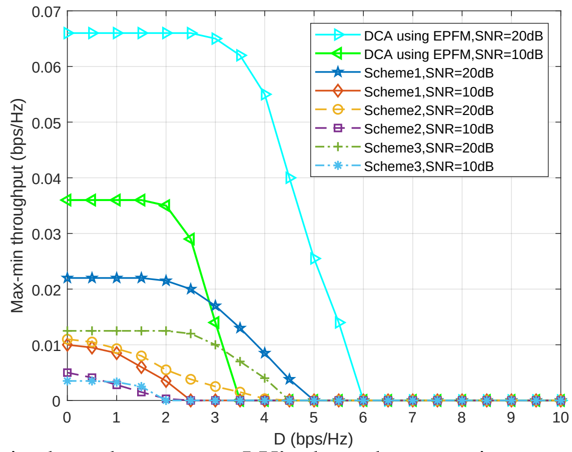

Fig. 2: Max-min throughput versus LU's throughput requirement at different SNRs.

three benchmark schemes mentioned. This Figure examines the effect of increasing the minimum throughput required for LU's throughput D on max-min BD throughput in the FAmBC network. Parameters were set to $E^{m}_{min} = 10\mu$J and $P_{peak} = 20P_{av}$ for all of the tested schemes. As is clear from Fig. 2, max-min throughput decreases as D increases resulting in throughput trade-offs between BDs and LU. As can be seen, the max-min throughput achieved by the proposed DCA using the EPFM approach is significantly higher than those of the competing solutions. For example, for: $D \leq 3$ bps/Hz and $\bar{\Upsilon}_{AP} = 20$ dB is 0.0668 bps/Hz, which is an increase of 242.7% over scheme 1, and of about five times over both schemes 2 and 3. It should be emphasized that superiority is gained despite the high processing complexity of AP due to the SIC operation. It is also worth noting that max-min throughput rises with increases in the received SNR at AP.

Fig. 3 plots the max-min throughput versus received SNR for different subcarrier peak-power values P_{peak}'s. In this scenario, parameters are set to $D = 1$ bps/Hz and $E_{min} = 10\mu$J. Again by increasing SNR, max-min throughput rises again a similar pattern of improvement is observed. For example, for $\bar{\Upsilon}_{AP} = 20$ dB and $P_{peak} = 5P_{av}$ displays 222.1% throughput which is about four times higher than those of schemes 1 and 2, respectively. Moreover, higher throughput is gained for higher subcarrier peak-power values P_{peak}'s with the given E_{min}.

To evaluate the performance of our proposed problem and algorithm in improving fairness as well as the overall BDs' throughput, we compare both the max-min throughput of all Bds and the average BDs' throughput achieved by Algorithm 1 with optimal resource allocation. Fig. 4 illustrates the max-min throughput versus the SNR under different BDs' energy requirements E_{min}'s, and Fig. 5 depicts the average BDs' throughput versus the SNR under the same require-

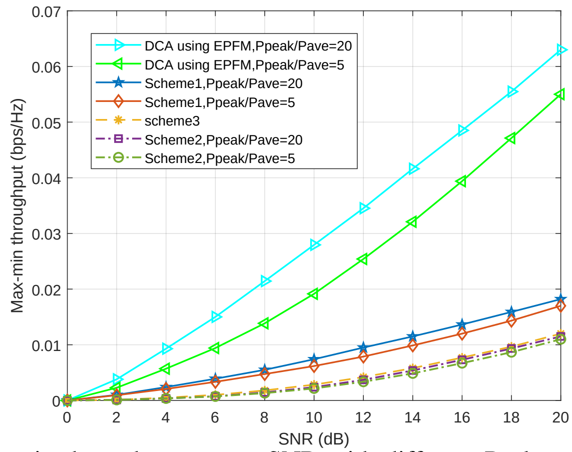

Fig. 3: Max-min throughput versus SNR with different Peak-power constraints.

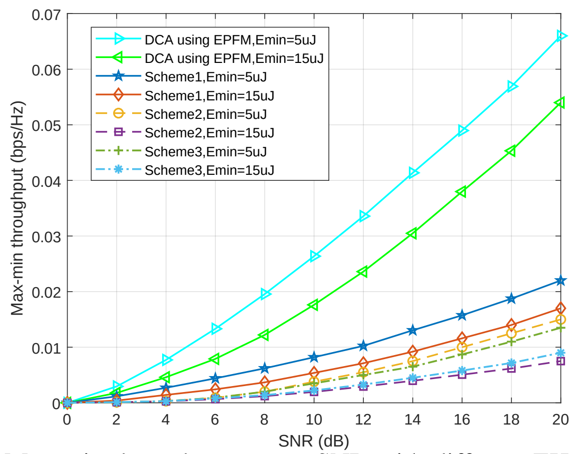

Fig. 4: Max-min throughput versus SNR with different EH constraints

ments. In the Fig. 4, parameters are set to $D = 1$ bps/Hz and $P_{peak} = 20P_{av}$ under all scenarios. Notice that in both figures, the max-min throughput achieved and average BDs' throughput achieved by the proposed Algorithm and by other schemes increase with increasing the SNR and decreasing E_{min}. From these figures, it can be seen that the proposed Algorithm achieves the highest throughput in both the $E_{min} = 15\mu$J case and $E_{min} = 5\mu$J case. Fig. 4 shows the max-min throughput of all BDs obtained by the four schemes. It can be seen that our proposed method can increase the minimum of BD's throughput drastically. For instance, for $\bar{\Upsilon}_{AP} = 20$ dB and $E_{min} = 5\mu$J the proposed DCA using EPFM achieves 214.2% throughput improvement over scheme 1, and about three times over schemes 2, and 3, respectively. Moreover, higher throughput is achieved for lower harvested-energy requirement E_{min} with the given P_{peak}, which points to the BDs' throughput energy trade-off. In terms of the average BDs' throughput which is shown

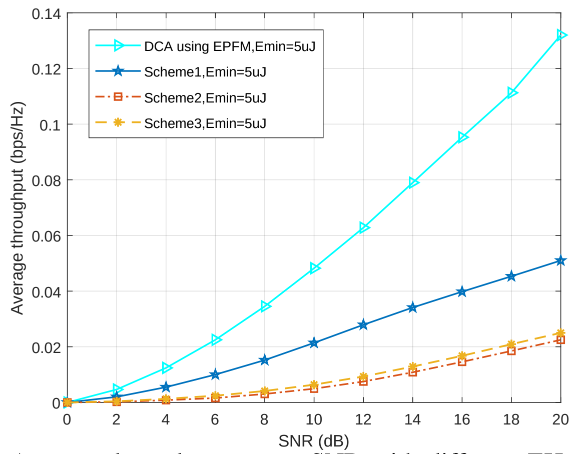

Fig. 5: Average throughput versus SNR with different EH constraints

in Fig. 6, the proposed algorithm can always outperform other schemes. Assume the parameters are set to $D = 1$ bps/Hz, $E_{min} = 5\mu$J, and $P_{peak} = 20P_{av}$ under all tested schemes in Fig. 5. As can be seen, the average BDs' throughput achieved by the proposed method at $\bar{\Upsilon}_{AP} = 20$ dB is 140% higher than scheme 1, and about five times higher than scheme 2, and 3. These results further prove the advantage of the proposed Algorithm in increasing the minimum throughput of all BDs and improving overall BDs' throughput simultaneously.

Finally, an evaluation of the average convergence behavior of the proposed algorithm in three cases is depicted in Fig. 6, comparing with the global optimal value through exhaustive search. Simulations were run on the basis of the optimal global value through the exhaustive search for $E_{min} = 5\mu$J, $D = 1$ bps/Hz and $P_{peak} = 20P_{av}$. In general, the proposed algorithm achieves the global optimality of about 5 iterations within an increment, which is smaller than a set threshold $\varepsilon = 10^{-4}$. Moreover, we can observe that the max-min throughput in the DCA using EPFM is larger than the other schemes. As expected, as the number of BDs goes up in such a network, the max-min throughput decreases. For all 2 BDs, 4 BDs, and 8 BDs cases, there is almost the same convergence speed. But in simulation, the 4 BDs, and 8 BDs cases need a little more time for CVX to solve the MLOP in each step since it has more variables in the problem with more BDs. All of these numerical result showed that the proposed method achieved a higher throughput in most of the simulation runs. In summary, we indicated that the proposed method makes it possible to design and implement an algorithm that yields global max-min throughput with acceptable computational complexity and convergence.

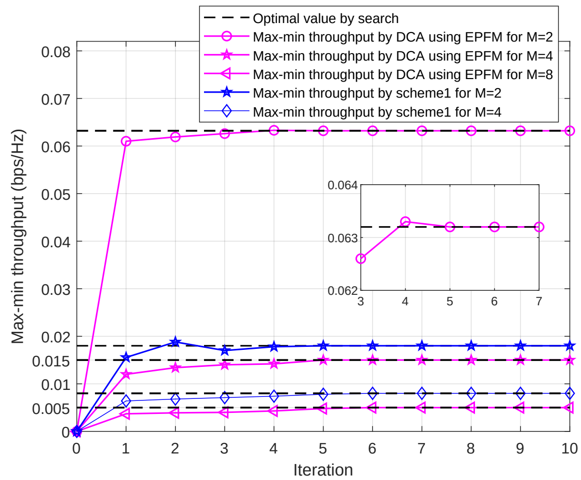

Fig. 6: Convergence behavior

V. Conclusion

In this study, we investigated the optimization problem for joint resource allocation in a FAmBC network with multiple BDs. We formulated a MLOP problem to guarantee max-min fairness as well as to improve the overall throughput by joint resource allocation. Due to the presence of non-convex constraints, MLOP was equivalent to a non-convex optimization problem, and there was no standard approach to work out an optimum solution. To compute globally optimum solutions we introduced an efficient DCA using EPFM. Both theoretical and numerical evaluations demonstrated that, in terms of network performance, the proposed method outperforms the suboptimal algorithms investigated in this study.

Appendix

The following are some of the principles to investigate DCP and DCA.

Lemma 3. *Let $x_w \in \mathbb{R}^n$ and $y_w \in \partial h(x_w)$. Then, $h^*(y_w) = \langle y_w, x_w \rangle - h(x_w)$ [29].*

proposition 1. *Let x^* be a local solution to Pdcp and let $y^* \in \partial h(x^*)$. If g^* is differentiable at y^*, then y^* is a local solution to D_{dcp}. Similarly, let y^* be a local solution to D_{dcp} and let $x^* \in \partial g(y^*)$. If h is differentiable at x^*, then x^* is a local solution to P_{dcp} [29].*

proposition 2. *Let $V_i : i = 1, ..., s$ and $U_1, U_2 : \mathbb{R}^n_+ \longrightarrow \mathbb{R}_+$ be DC and convex functions, respectively [31].*

- *$\sum_{i=1}^{s} \alpha_i V_i(x)$ is DC function for any real numbers α_i,*

- $V_{max}(x) = max\{V_1(x), ..., V_s(x)\}$ *is DC function,*
- $V^+(x) = max\{0, V(x)\}$ *is DC function,*
- $q(V(x))$ *is DC function for any convex non-decreasing function* $q : [0, a] \longrightarrow \mathbb{R}$ *such that* $0 \leq V(x) \leq a$ *and* $q'_-(a) < +\infty$*. Its DC representation is* $q(V(x)) = T(x) - \kappa[a - V(x)]$*, where the* $T(x) = q(V(x)) + \kappa[a - V(x)]$ *is a convex function and* κ *is a constant satisfying* $\kappa \geq q'_-(a)$*;*
- $U_1(x)U_2(x)$ *is DC function and its DC representation is* $U_1(x)U_2(x) = \frac{1}{2}[U_1(x) + U_2(x)]^2 - \frac{1}{2}[U_1^2(x) + U_2^2(x)]$.

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