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Adaptive resource allocation in NOMA-enabled backscatter communications systems

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ABSTRACT

The integration of NOMA with Backscatter communication (BackCom) is a promising solution for developing a green future wireless network. However, system performance degrades with the deployment of multiple backscatter devices (BDs) in a network. Hence, energy efficiency (EE) maximization with proper resource allocation is among the primary concerns. In this regard, this paper proposes an adaptive resource allocation method for maximizing EE by simultaneously optimizing the transmission power from the base station (BS), power allocation coefficients, and reflection coefficients under the constraints of maximum allowable transmission power and minimum achievable data rate. Specifically, an iterative method based on a parametric transformation approach is adopted for maximizing EE by jointly optimizing the coefficients, in which the power allocation problem to the BDs is solved by an adaptive method that is based on improved proportionate normalized least mean square (IPNLMS) algorithm. Then, the system performance is evaluated, and the impact of different parameters is also studied it is observed that EE is significantly improved as compared to the existing scheme, and maximum at η=-0.5.

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1. INTRODUCTION

Wireless communication is one of the most rapidly growing and successful technologies, with spectacular expansion in a variety of application sectors [1]. These days the explosive growth of the internet of things (IoT) and massive connectivity led to increasing demand for the spectrum. Further, the next generation in wireless technology is expected to offer high spectral efficiency and data rate with lower latency. The significant features of non-orthogonal multiple access (NOMA) enable multiple users to access the same spectral resources for data transmission by allocating different power levels to the users. NOMA is designed to be the next generation of multiple access, allowing for very effective and efficient handling of large networks of users without compromising the users' quality of service (QoS) [2], [3]. Compared to traditional orthogonal multiple access technologies, it increases spectral efficiency significantly [4]. The receiver applies the successive interference cancellation (SIC) technique to recover the users' information. The high compatibility and lower implementation complexity of NOMA inspired the researchers for integrating this technology with the other technologies for designing a spectrally efficient, energy-efficient, and of-course cost-effective technology that is meant for the futuristic wireless network [5], [6].

Meanwhile, Backscatter communication (BackCom) has grabbed the research interests as energy-efficient technology to build green IoT systems [7]. It allows the Backscatter devices (BDs) to communicate with the surrounding users by modulating and reflecting the radio frequency (RF) signals. The different architecture of BackCom system is discussed in [8]. The integration of NOMA and BackCom can have great potential for enhancing the energy efficiency (EE), transmission reliability, and data rate of the communication network as compared to the Non-cooperation NOMA [9].

However, proper resource allocation is essential for maintaining communication quality in such a BackCom network. There has been extensive research on the BackCom-NOMA network, and their contributions focus on different approaches for evaluating the system performance under different scenarios. A NOMA-enabled BackCom network consisting of a single backscatter tag and multiple users is considered in [10]. The system capacity maximization problem is formulated by convex optimization and is solved by applying the KKT solution for optimizing the transmission power coefficient and reflection coefficient. Then, the authors extended the research work by considering multiple-colluding eavesdroppers [11], [12]. The secrecy rate is enhanced by optimizing the power allocation coefficient and reflection coefficient under the constraint of BS transmit power. The maximization problem is formulated as nonconvex one and is solved by applying Lagrangian dual method. Xu et al. investigate the maximization of EE in the BackCom NOMA network by jointly optimizing the transmission power of the base station (BS) and reflection coefficient of the BD under the constraints of the minimum required signal-to-interference-plus-noise ratio (SINR) and maximum transmission power [13]. The optimization problem is solved by using an iterative Dinkelbach method with a quadratic transformation approach. The problem of sum-rate maximization problem in a BackCom NOMA system under imperfect SIC decoding is considered in [14]. The closed-form solutions for obtaining optimal transmission power coefficient and reflection coefficient are derived by exploiting KKT conditions on the Lagrangian function. Khan *et al.* [15], the authors investigate the spectral efficiency (SE) maximization problem in a multi-cell NOMA with BackCom network considering the imperfect decoding of SIC. The transmission power of BS and the reflection coefficient of BD are jointly optimized to maximize SE. The decomposition method with KKT condition is applied to obtain the suboptimal solution to the objective function. A power-domain NOMA with the time division multiple access (TDMA) technique is adopted to enhance the system performance. Resource allocation is an important metric in NOMA-enabled multiple cells with BackCom network in the presence of inter-cell interference. Khan *et al.* [16], the data rate of the network is maximized by jointly optimizing the transmission power allocation coefficient of the BS and the reflection coefficient of the BD under the constraints of the maximum reflection coefficient and the BS transmit power. The optimization problem is decoupled into two sub-problems, and the dual decomposition approach is used to solve each sub-problem. The research work is further extended for maximizing EE considering multiple cell scenario in [17]. The problem is first transformed into Dinkelbach method, which is then solved by employing Lagrangian dual method and KKT condition.

The max-min EE is maximized under the influence of large-scale fading by jointly optimizing transmission power from the BS and reflection coefficient of the backscatter device [18]. The sum-rate maximization is obtained by jointly optimizing the BD allocation strategy, reflection coefficient and decoding order of BDs at the reader end as discussed in [19]. To achieve this, the authors derive a low-complexity solution for both static and dynamic BD grouping strategies. Yang *et al.* [20], multiple backscatter devices are considered which are transmitting to a backscatter receiver. The minimum throughput is maximized by jointly optimizing devices' backscatter time and power reflection coefficient under the constraint of minimum SINR and the minimum energy required. An iterative algorithm is proposed by applying block-coordinated decent and successive convex optimization techniques to find the optimal solution. The superior performance of backscatter NOMA over backscatter-OMA is also discussed considering the imperfect successive interference cancellation and residual hardware impairments [21].

It is obvious that the BackCom-NOMA system is an appealing solution for achieving a higher transmission rate with lower power consumption. Further, the novel pairing of nodes along with the adaptive power reflection coefficient allocation in NOMA combinedly can improve the performance over the time-varying channel conditions. Under heavily doped users, a grouping of multiple users based on their power level can outperform the static pairing schemes [22]. Most of the aforementioned research works have considered a BD with two NOMA users. However, resource allocation in BackCom network in different scenarios is still an open challenge before its successful adaptation. In this regard, we consider a network consisting of multiple BDs, and multiple NOMA-enabled users. The system performance is evaluated in the presence of interference from other BDs. Table 1 summarizes a few research works and the type of scenario considered.

The novel contributions of our paper are:

- A single cell BackCom NOMA system is considered. The BDs act as relays to the users which are deployed at distant places from the BS.

- The SINRs at the user's end are derived in the presence of interference. Accordingly, the EE of the network is derived.
- Different reflection coefficients are considered for near and far users, and are derived based on the minimum SINR required at the users end.
- An iterative Dinkelbach method is proposed for maximizing EE by jointly optimizing the reflection coefficient, power allocation coefficient and transmission power allocation to the multiple BDs.
- Further, an adaptive power allocation algorithm based on improved proportionate normalized least mean square (IPNLMS) algorithm is proposed for assigning power to the BDs.

The rest of the paper is organized as follows. Section 2 presents the system model with detailed derivation of received signals at the users' end. The objective of this paper is presented in Section 3. Section 4 elaborates on our proposed solution approaches. The performance of the system is evaluated, and the numerical results are presented in Section 5. Finally, the paper is concluded in Section 6.

Table 1. Literature table discussing a few existing schemes

Ref.	Problem Formulation	Parameter optimized	Scenario (in BackCom-NOMA system)
Khan *et al.* [10]	Sum capacity maximization	Transmission power allocation coefficient and reflection power coefficient	Single backscatter tag and 2 users
Khan *et al.* [11]	Secrecy rate maximization	Reflection coefficient	Single backscatter tag and two users with multiple eavesdroppers
Khan *et al.* [12]	Secrecy rate maximization	Transmission power allocation coefficient and reflection power coefficient	Single backscatter tag and two users with multiple eavesdroppers
Xu *et al.* [13]	EE maximization	Transmission power allocation and reflection coefficient	One backscatter device with two users
Khan *et al.* [14]	Sum rate maximization	Transmission power allocation coefficient and reflection coefficient	One backscatter tag and two users under imperfect SIC decoding
Khan *et al.* [15]	Spectral efficiency maximization	Transmission power allocation and reflection coefficient	Multi-cell BackCom-NOMA network under imperfect SIC decoding
Khan *et al.* [16]	Data rate maximization	Transmission power allocation coefficient and reflection coefficient	Multi-cell BackCom-NOMA network with intercell interference
Ahmed *et al.* [17]	EE maximization	Transmission power allocation coefficient and reflection coefficient	Multi-cell BackCom-NOMA network with intercell interference

2. SYSTEM MODEL

In this section, we consider a downlink backscatter NOMA model as shown in Figure 1. The users are assumed to be located at a farther distance from the BS. Therefore, multiple BDS are deployed as relays for sending the information from the BS to the users. Each BD is assigned to two users; one is located nearer to the BD having stronger channel gain and the other is far from the BD with a weaker channel gain. Hence, the BD transmits the received messages to both users with different power. The set of BDs is denoted as $I = \{i|1,2,3, \dots, I\}$ where i is referred as the index of ith BD. The assigned near user user1 and the far user user2 to the ith BD are denoted as ${u_i}^n$ and ${u_i}^f$, respectively. All I BDs simultaneously receive the RF signals from the BS. It is assumed that, all the BDs consist of omnidirectional antennas to receive and transmit the information from the BS to the users. The end users adopt the NOMA protocol, where the strong user applies the SIC strategy, and decodes the information of the weak user before decoding its own information. With this principle, the weak user decodes only its own information.

The channel responses from the BS to the BDs are assumed to be Rayleigh fading channels, are denoted as $\{g_1, g_2, \dots, g_I\}$. The channel gains from the BDs to the end users are considered in the indoor environment. The reflected signals from the BDs may suffer from reflection and diffraction due to the presence of other objects and partition walls. Therefore, we adopt the following path-loss model for the channel from the ith BD to the users [23].

$$P_L(dB) = P_L(d_0) + \varphi log_{10}\left(\frac{d}{d_0}\right) + L_F(\rho) \quad (1)$$

Where φ is the distance power loss coefficient. $L_F(\rho)$ denotes the floor penetration loss factor (dB), and ρ is the number of floors between the BD and the users. d and d_0 are the distance between the BD and the user (d>1m) and reference distance (1m), respectively. The parameters are referred from the indoor propagation channel model given in International Telecommunication Union (ITU) considering the office scenario [23]. It is assumed that the BS has the knowledge of all assigned users to I BDs. Accordingly, the BS sends information of those users to BDs in I different channels simultaneously. It is assumed that the I channels are orthogonal to each other to avoid interference between the channels. The superposition signal sent from the BS is denoted as:

$$x = \sum_{i=1}^{I} x_i \tag{2}$$

where $x_i = \sqrt{\alpha_i P_i} x_i{}^n + \sqrt{(1-\alpha_i)P_i} x_i{}^f$. x_i is the transmitted signal to ith BD. Here $x_i{}^n$ and $x_i{}^f$ are the transmitted messages for the strong and weak users assigned to ith BD, respectively, and $E[|x_i{}^n|^2] = 1$ and $E\left[\left|x_i{}^f\right|^2\right] = 1$. P_i is the transmission power allocated to ith BD with power allocation coefficient α_i, where $0 \leq \alpha_i \leq 1$.

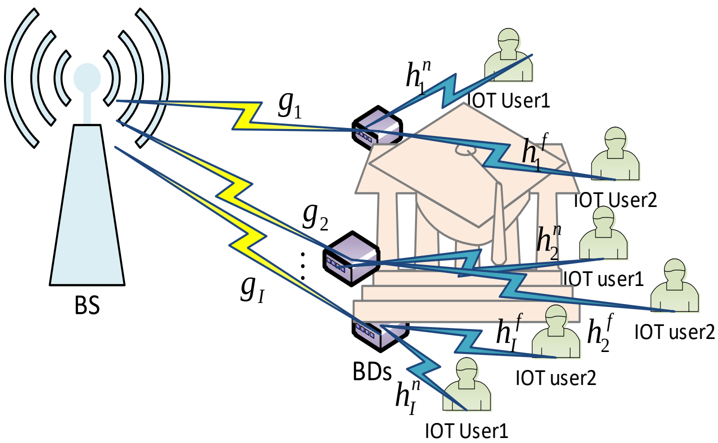

Figure 1. System model showing the distribution of users

2.1. The Received signal at $u_i{}^n$

The ith BD modulates the received information, and backscatters to user 1. Thus, the received signal at $u_i{}^n$ is given by (1).

$$y_i{}^n = \sqrt{\beta_i{}^n} g_i x_i h_i{}^n + \sum_{i'=1, i' \neq i}^{I} h_{i'}{}^n g_{i'} \sqrt{\beta_{i'}{}^n} x_{i'} + n_i{}^n \tag{3}$$

The first term represents the desired backscattered signal, the second term denotes the interference received from the other $(I-1)$ BDs, and the term $n_i{}^n$ is the additive white Gaussian noise (AWGN) with mean zero and variance σ^2. $\beta_i{}^n$ is the reflection coefficient of the ith BD for near user. $h_i{}^n$ represents the pathloss between the ith BD and its assigned user 1, and is obtained from (1). Being the strong user, user 1 applies the SIC technique to decode the information of the weak user, and then, recovers its own signal. Assuming priori knowledge of the perfect channel state information, the SINR at $u_i{}^n$ for decoding $x_i{}^f$ is given by:

$$\gamma_i{}^{n,f} = \frac{P_i(1-\alpha_i)|h_i{}^n|^2 |g_i|^2 \beta_i{}^n}{P_i \alpha_i |h_i{}^n|^2 |g_i|^2 \beta_i{}^n + \Gamma_i{}^n + \sigma^2} \tag{4}$$

where $\Gamma_i{}^n = \sum_{i'=1, i' \neq i}^{I} P_{i'} \alpha_{i'} |g_{i'}|^2 |h_{i'}{}^n|^2 \beta_{i'}{}^n$. After successful decoding, $x_i{}^f$ is subtracted from $y_i{}^n$, and then, the SINR of decoding its own signal $x_i{}^n$ at user 1 is given by (5).

$$\gamma_i{}^{n,n} = \frac{P_i \alpha_i |h_i{}^n|^2 |g_i|^2 \beta_i{}^n}{\Gamma_i{}^n + \sigma^2} \tag{5}$$

2.2. The Received Signal at $u_i{}^f$

The signal received at $u_i{}^f$ is given by:

$$y_i{}^f = \sqrt{\beta_i{}^f} g_i x_i h_i{}^f + \sum_{i'=1, i' \neq i}^{I} h_{i'}{}^f g_{i'} \sqrt{\beta_{i'}{}^f} x_{i'} + n_i{}^f \tag{6}$$

where $\beta_i{}^f$ is the reflection coefficient for user 2. $h_i{}^f$ and $h_{i'}{}^f$ denote the pathloss from ith BD to user 2, and interference channel gain from the other $(I-1)$ BDs, respectively. $n_i{}^f$ is the AWGN with zero mean and variance σ^2. User 2 decodes its own signal in the presence of interference from $u_i{}^n$ and $\Gamma_i{}^f$, where $\Gamma_i{}^f = \sum_{i'=1,i'\neq i}^{I} P_{i'}(1-\alpha_{i'})|g_{i'}|^2 \left|h_{i'}{}^f\right|^2 \beta_{i'}{}^f$. Hence, SINR at $u_i{}^f$ for decoding its own signal is given by (7).

$$\gamma_i{}^{f,f} = \frac{P_i(1-\alpha_i)\left|h_i{}^f\right|^2 |g_i|^2 \beta_i{}^f}{P_i\alpha_i\left|h_i{}^f\right|^2 |g_i|^2 \beta_i{}^f + \Gamma_i{}^f + \sigma^2} \tag{7}$$

3. PROBLEM FORMULATION

The information $x_i{}^f$ can be successfully recovered at $u_i{}^n$ if the following condition is satisfied:

$$\gamma_i{}^{n,f} \geq \gamma_{th} \tag{8}$$

where γ_{th} is the minimum required SINR. Similarly, the condition for the $u_i{}^n$ to extract its own information must satisfy $\gamma_i{}^{n,n} \geq \gamma_{th}$. $x_i{}^f$ can be recovered at $u_i{}^f$ if $\gamma_i{}^{f,f} \geq \gamma_{th}$ is satisfied. Therefore, the system performance is evaluated by obtaining the sum-rate of the communication network between the BDs and the assigned users. The data rate at $u_i{}^n$ connected to ith BD is given by:

$$R_i{}^n = log_2(1+\gamma_i{}^{n,n}) \tag{9}$$

the data rate at $u_i{}^f$ assigned to ith BD is given by:

$$R_i{}^f = log_2(1+\gamma_i{}^{f,f}) \tag{10}$$

then, the total data rate of the network can be formulated as:

$$R_T = \sum_{i=1}^{I}\left(R_i{}^n + R_i{}^f\right) \tag{11}$$

from (9) and (10), it is clearly observed that maximization of data rate depends on three important factors such as transmission power P_i, transmission power allocation coefficient α_i, and the reflection coefficients $\beta_i{}^n$ and $\beta_i{}^f$. If P_{MAX} is the maximum power transmitted from the BS, then the EE maximization problem of the entire network is formulated as:

$$\max_{P_i,\alpha_i,\beta_i{}^n,\beta_i{}^f} \frac{R_T}{\sum_{i=1}^{I} P_i} \tag{12}$$

$$\text{st.} \quad 0 \leq \alpha_i \leq 1 \tag{12a}$$

$$P_i\alpha_i \leq P_i(1-\alpha_i) \tag{12b}$$

$$\sum_{i=1}^{I} P_i \leq P_{MAX} \tag{12c}$$

$$0 \leq (\beta_i{}^n, \beta_n{}^f) \leq 1 \tag{12d}$$

$$R_i{}^n \geq R_{th} \tag{12e}$$

$$R_i{}^f \geq R_{th} \tag{12f}$$

the optimization problem (12) describes the EE maximization in the BackCom NOMA network under the constraints (12a) to (12f). The (12a) and (12d) show the maximum limit of α_i and $\beta_i{}^n$, $\beta_i{}^f$, respectively. In NOMA technique, power allocation to the near user must be less than the power allocated to the far user, which is described in (12b). The maximum allowable transmitted power from the BS is represented in (12c). The data rates of $u_i{}^n$ and $u_i{}^f$ must be greater than the minimum achievable data rate R_{th} which are given in (12e) and (12f), respectively.

4. PROPOSED SOLUTION APPROACHES

The objective problem (12) is a mixed integer problem and non-convex due to all the variables $P_i, \alpha_i, \beta_i{}^n$ and $\beta_i{}^f$. This makes the problem difficult to solve. Hence, we propose an approach to solve the above maximization problem (12) in three steps. Firstly, the reflection coefficients $\beta_i{}^n$ and $\beta_i{}^f$ are evaluated based on the power allocation coefficient α_i. Then, we propose an iterative Dinkelbach algorithm to maximize EE of the network by simultaneously optimizing the P_i, $\beta_i{}^n$ and $\beta_i{}^f$, where the power allocation to the ith BD P_i is obtained for maximizing the sum-rate of the network R_T while satisfying the conditions (12e) and (12f).

3.1. Derivation of reflection coefficients

The constraints (12e) and (12f) represent the minimum achievable data rates of $u_i{}^n$ and . $u_i{}^f$, respectively. The minimum required data rate R_{th} is same for both near and far users. So, the minimum SINR required at each user is $\gamma_{th} = 2^{R_{th}} - 1$. If $P_{imin}{}^n$ is the minimum transmission power required at $u_i{}^n$ to achieve the constraint (12e), then $P_{imin}{}^n$ is derived as (13).

$$P_{imin}{}^n = \frac{(2^{R_{th}}-1)(\Gamma_i{}^n+\sigma^2)}{\alpha_i |h_i{}^n|^2 \beta_i{}^n |g_i|^2} \tag{13}$$

Similarly, if $P_{imin}{}^f$ is the minimum transmission power required at $u_i{}^f$ to achieve the constraint (12f), then $P_{imin}{}^f$ is derived as (14).

$$P_{imin}{}^f = \frac{(2^{R_{th}}-1)\left(\Gamma_i{}^f+\sigma^2\right)}{\left|h_i{}^f\right|^2 \beta_i{}^f |g_i|^2 \{1-\alpha_i-(2^{R_{th}}-1)\alpha_i\}} \tag{14}$$

From (13) and (14), the minimum transmission power required for ith BD is obtained by (15).

$$P_{imin} = max\left\{P_{imin}{}^n, P_{imin}{}^f\right\} \tag{15}$$

If we consider the reflection coefficient assigned to $u_i{}^n$, then from (4) and (8), minimum $\beta_i{}^n$is derived as (16).

$$\beta_i{}^n \geq \frac{\gamma_{th}(\Gamma_i{}^n+\sigma^2)}{P_i |h_i{}^n|^2 |g_i|^2 (1-\alpha_i-\gamma_{th}\alpha_i)} \tag{16}$$

Similarly, $\gamma_i{}^{n,n} \geq \gamma_{th}$. Therefore, $\beta_i{}^n$can also be obtained from (5) as (17).

$$\geq \frac{\gamma_{th}(\Gamma_i{}^n+\sigma^2)}{P_i \alpha_i |h_i{}^n|^2 |g_i|^2} \tag{17}$$

Equating (16) and (17), α_i is obtained as $\alpha_{imin} = \frac{1}{\gamma_{th}+2}$. Hence, the relationship of $\beta_i{}^n$ and α_i can be derived as (18).

$$\beta_i{}^n = \begin{cases} (16), & \alpha_i \geq \alpha_{imin} \\ (17), & \alpha_i < \alpha_{imin} \end{cases} \tag{18}$$

Then, depending on the conditions (16) and (17), and considering (7), $\beta_i{}^f$ can be obtained as (19).

$$\beta_i{}^f \geq \frac{|h_i{}^n|^2 \beta_i{}^n \left(\Gamma_i{}^f+\sigma^2\right)}{\left|h_i{}^f\right|^2 (\Gamma_i{}^n+\sigma^2)} \tag{19}$$

3.2. Iterative Dinkelbach algorithm

Applying parametric transformation method, the optimization problem is formulated as $\omega^* = \frac{R_T(P_i{}^*,\alpha_i{}^*,\beta_i{}^*)}{P_T(P_i{}^*)}$. $\max\limits_{P_i,\alpha_i,\beta_i} \left\{\frac{R_T(P_i,\alpha_i,\beta_i)}{P_T(P_i)}\right\}$ can be derived by considering $R_T(P_i{}^*, \alpha_i{}^*, \beta_i{}^*) - \omega^* P_T(P_i{}^*) = 0$ [24]. Here, $P_i{}^*, \alpha_i{}^*$ and $\beta_i{}^*$ are the optimal power allocated to the ith BD, power allocation coefficient and reflection coefficients of ith BD for near and far users. Algorithm 1 presents the pseudocode for joint optimization of P_i^*, α_i^* and β_i^*.

Algorithm 1: Iterative Dinkelbach algorithm for parameters allocation
Input:
Randomly generate P_i satisfying the constraints (15) and (12c).
Evaluate α_i, $\beta_i{}^n$ and $\beta_i{}^f$.
Dinkelbach parameter ω ←0;
Accepted tolerance value $\xi \leftarrow 10^{-4}$;
Current iteration $it \leftarrow 1$;

Output:
Optimal P_i, α_i, $\beta_i{}^n$ and $\beta_i{}^f$.

1. ***while*** $|\omega(it) - \omega(it-1)| \geq \xi$ do
2. With the given α_i, $\beta_i{}^n$ and $\beta_i{}^f$, find P_i from **Algorithm 2**
$$P_i = \underset{P_i}{\operatorname{argmax}}\left\{R_T\left(P_i, \alpha_i, \beta_i{}^n, \beta_i{}^f\right) - \omega(it) P_T\left(P_i, \alpha_i, \beta_i{}^n, \beta_i{}^f\right)\right\};$$
3. Given P_i, obtain $\beta_i{}^n$ and $\beta_i{}^f$ considering (18) and (19);
4. $it \leftarrow it + 1$;
5. $\omega(it) \leftarrow \frac{R_T\left(P_i, \alpha_i, \beta_i{}^n, \beta_i{}^f\right)}{P_T\left(P_i, \alpha_i, \beta_i{}^n, \beta_i{}^f\right)}$;
6. ***end while***

In Algorithm 1, power allocation to the ith BD is obtained from Algorithm 2. Algorithm 1 describes the steps of maximizing EE by simultaneously optimizing α_i, $\beta_i{}^n$ and $\beta_i{}^f$, while Algorithm 2 emphasizes on enhancing sum-rate of the network by properly allocating $P_i, \forall I$ BDs.

3.3. Adaptive power allocation

The objective of maximizing R_T under the constraints (12e) and (12f) is a mixed integer and nonlinear problem. Hence, the objective problem of maximizing $\left(R_i{}^n + R_i{}^f\right)$ with associated constraints (12e) and (12f) is equivalently represented as the maximization of $\left(log_2\left(\frac{\gamma_i{}^{n,n}\gamma_i{}^{f,f}}{\gamma_{th}{}^2}\right)\right)$. Thus, the modified power allocation problem is reduced to:

$$\max_{P_i} \sum_{i=1}^{I} log_2\left(\frac{\gamma_i{}^{n,n}\gamma_i{}^{f,f}}{\gamma_{th}{}^2}\right) \tag{20}$$

the (20) is further reduced to the maximization of:

$$\max_{P_i} \sum_{i=1}^{I} log_2\left(P_i{}^2 \widetilde{W}_i\right) \tag{21}$$

where $\widetilde{W}_i = \frac{\left(\tilde{\Gamma}_i{}^n + \sigma^2\right)\left(P_{imin}\alpha_i\left|h_i{}^f\right|^2 \beta_i{}^f |g_i|^2 + \tilde{\Gamma}_i{}^f + \sigma^2\right)}{P_{imin}{}^2\left(\Gamma_i{}^n + \sigma^2\right)\left(P_{imin}\alpha_i\left|h_i{}^f\right|^2 \beta_i{}^f |g_i|^2 + \Gamma_i{}^f + \sigma^2\right)}$. Here, $\tilde{\Gamma}_i{}^n = \sum_{i'=1, i' \neq i}^{I} P_{i'min}\alpha_{i'}|g_{i'}|^2 |h_{i'}{}^n|^2 \beta_{i'}{}^n$ and $\tilde{\Gamma}_i{}^f = \sum_{i'=1, i' \neq i}^{I} P_{i'min}(1-\alpha_{i'})|g_{i'}|^2 \left|h_{i'}{}^f\right|^2 \beta_{i'}{}^f$. Let n be the current iteration, then the power allocation problem at nth iteration is formulated as:

$$\left\{\sum_{i=1}^{I} log_2\left(P_i{}^2 \widetilde{W}_i\right)\right\}(n) \geq \left\{\sum_{i=1}^{I} log_2\left(P_i{}^2 \widetilde{W}_i\right)\right\}(n-1) \tag{22}$$

then, taking the equality constraint in the equation (22), we have:

$$\left\{\sum_{i=1}^{I} log_2\left(P_i{}^2 \widetilde{W}_i\right)\right\}(n) + \chi = \left\{\sum_{i=1}^{I} log_2\left(P_i{}^2 \widetilde{W}_i\right)\right\}(n-1) \tag{23}$$

where χ is a random variable of mean zero and variance $I\gamma_{th}{}^2$. Let us consider a matrix.

$$S(n) = \begin{pmatrix} {P_1}^{2(n)} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & {P_I}^{2(n)} \end{pmatrix} \tag{24}$$

Similarly,

$$Q(n) = \begin{pmatrix} {\widetilde{W}_1}^{(n)} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & {\widetilde{W}_I}^{(n)} \end{pmatrix} \tag{25}$$

let $Z(n)$ be the solution at the nth iteration then:

$$Z(n) = \sum_{i=1}^{I} P_i^2(n)\widetilde{W}_i(n) = \sum_{i=1}^{I} s_i(n)\big(q_i(n)\big)^T + \chi(n) \tag{26}$$

where $s_i(n)$ and $q_i(n)$ are the ith row of $S(n)$ and $Q(n)$ at nth iteration, respectively. Let,

$$U(n) = \sum_{i=1}^{I} s_i(n-1)\big(q_i(n)\big)^T \nu_i(n) \tag{27}$$

where $\nu_i(n)$ is the random variable with mean zero and variance γ_{th}. Then, the instantaneous error is given by:

$$e(n) = Z(n) - U(n) \tag{28}$$

let $s_i(n)$ be the component to decide the power allocation to the ith BDs at nth iteration, then, applying IPNLMS algorithm, $s_i(n)$ is updated as [25].

$$s_i(n) = s_i(n-1) + \frac{\mu s_i(n)^{(L)^T} C(n-1) e(n)^{(L)}}{s_i(n)^{(L)^T} C(n-1) s_i(n)^{(L)} + \delta_{PLNMS}} \tag{29}$$

Where μ is the overall step size and it ranges between 0 and 1. $C(n-1)$ is the step size control matrix, and $C(n-1) = diag\{c_1(n-1), c_2(n-1), \dots, c_l(n-1), \dots, c_L(n-1)\}$ which assigns different step sizes to different coefficients. Here, $c_l(n-1)$ is denoted as:

$$c_l(n-1) = \frac{1-\eta}{2L} + (1+\eta)\frac{|\widetilde{W}_l(n-1)|}{2\sum_{l=0}^{L}|\widetilde{W}_l(n-1)| + \varepsilon} \tag{30}$$

where $-1 \leq \eta \leq 1$. When $\eta = -1$, the IPNLMS algorithm works like NLMS algorithm. The IPNLMS algorithm becomes like PNLMS algorithm when η is close to 1. For, IPNLMS algorithm, we have taken $\eta = -0.5$. The signal length is assumed to be L. Let I_A and I_B be the iterations required to converge Algorithm 1 and Algorithm 2, respectively, then the over all complexity of the proposed algorithm is $O(I_A I_B)$.

Algorithm 2: Adaptive power allocation algorithm
Input:
Consider all the parameters including α_i, ${\beta_i}^n$ and ${\beta_i}^f$, those are evaluated from **Algorithm 1**.
$Diff \leftarrow 0$;
$R_{h1} \leftarrow \sum_{i=1}^{I} log_2\big({P_i}^2\widetilde{W}_i\big)$;
$R_h \leftarrow 1$;
Current iteration $n \leftarrow 1$;

Output:
P_i for $\forall I$ that maximizes R_T.

1. while $(Diff < R_h)$ do
2. $R_h \leftarrow R_{h1}$;
3. $n \leftarrow n + 1$;
4. $for\ i = 1{:}I$

$P_i \leftarrow [P_i(1), P_i(2), \dots \dots, P_i(L)]^T$;
$s_i \leftarrow (P_i).\hat{}2$;
$\widetilde{W}_i \leftarrow \left[\widetilde{W}_i(1), \widetilde{W}_i(2), \dots \dots, \widetilde{W}_i(L)\right]^T$;
$J \leftarrow s_i .* \widetilde{W}_i$;
end for
$e(n) = Z(n) - U(n)$
for $i = 1{:}\, I$
for $l = 1{:}\, L$
$c_l(n-1) \leftarrow \frac{1-\eta}{2L} + (1+\eta)\frac{|\widetilde{W}_l(n-1)|}{2\sum_{l=0}^{L}|\widetilde{W}_l(n-1)|+\varepsilon}$;
end for
$C(n-1) = diag\{c_1(n-1), c_2(n-1), \dots, c_l(n-1), \dots, c_L(n-1)\}$;
$s_i(n) \leftarrow s_i(n-1) + \frac{\mu s_i(n)^{(L)^T} C(n-1) e(n)^{(L)}}{s_i(n)^{(L)^T} C(n-1) s_i(n)^{(L)} + \delta_{PLNMS}}$;
end for
$R_{h1} \leftarrow \sum_{i=1}^{I} s_i(n).\widetilde{W}_i(n)$;
$Diff \leftarrow R_{h1}$;
end while

4. NUMERICAL RESULTS

This section provides the numerical results of our proposed resource allocation technique in BackCom-NOMA network. The system performance is evaluated by maximizing the sum-rate and EE of the network. The number of BDs is set at I=2. The channels between the BS and the BDs are modelled as Rayleigh fading. The communication between the BDs and the users are considered in Indoor environment. The center frequency in the indoor environment is set at 2.452 GHz. Accordingly, path-loss model is designed for indoor environment [23]. The key parameters are summarized in Table 2.

Figure 2 illustrates the comparison between the proposed and existing technique [10] taking different values of η. In [10], single BD is considered with two NOMA users. The reflection coefficient β is same for both near and far users. α and β are optimized for maximizing the sum-rate of the network. The Lagrangian method with KKT condition is adopted in [10] to optimize α and β of the BD. So, in the comparison result, we use the coefficients optimization technique described in [10], but the power allocations to BDs are obtained from our proposed adaptive methods, Algorithm 1 and Algorithm 2. In the proposed technique, we consider different reflection coefficients ${\beta_i}^n$ and ${\beta_i}^f$ for near and far user, respectively. Further, (18) and (19) are used to obtain the values of α_i, ${\beta_i}^n$ and ${\beta_i}^f$ for ith BD. From the figure, it is clearly observed that selection of α and β are equally important as power allocation in BackCom network. In the context of complexity comparison, two more iterations are required to update the Lagrangian variables according to [10], as compared to our proposed algorithm. Hence, the complexity of the algorithm is increased to $O(I_A I_B I_C I_D)$, where I_C and I_D are the iterations required to update the two Lagrangian variables for obtaing optimal α and β. Further, it is observed that our proposed algorithms performs better than the existing scheme, when η=-0.5. Hence, this value is used in subsequent simulations.

Figure 3 and Figure 4 illustrate the effect of minimum achievable data rate R_{th} on EE and sum-rate R_T, respectively. As R_{th} increases, P_{imin} increases. With increase in transmission power, sum-rate of the network initially increases from R_{th}=0.2 to R_{th}=1. For R_{th}>1, R_T slightly decreases due to more effect of interference power from the rest BD. Further, when P_{MAX} increases, power distributed to each BD P_i increases. Therefore, R_T is more for higher P_{MAX}. On the contrary, EE decreases with increase in R_{th} and P_{MAX}.

Table 2. Simulation parameters

Parameters	Value
$\boldsymbol{P_{MAX}}$	5 watts
$\boldsymbol{R_{th}}$	1 bits/s/Hz
$\boldsymbol{\sigma^2}$	-130 dB
$\boldsymbol{\mu}$	0.05
$\boldsymbol{\delta_{PLNMS}}$	0.01
$\boldsymbol{\varepsilon}$	0.01
$\boldsymbol{L}$	100

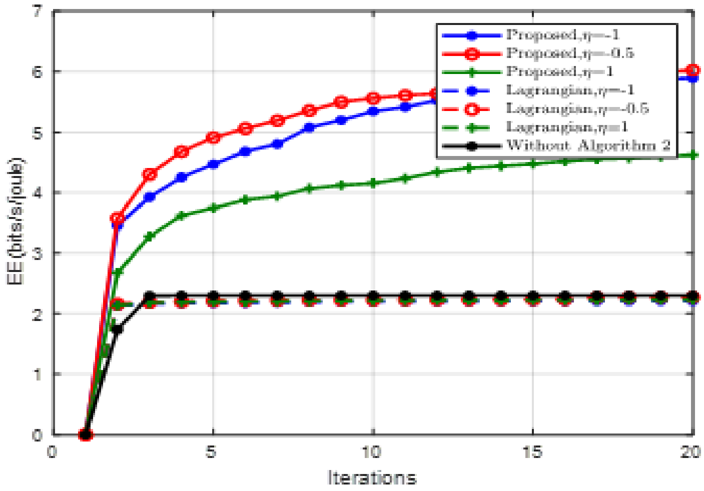

Figure 2. Convergence comparison of our proposed scheme for different values of η

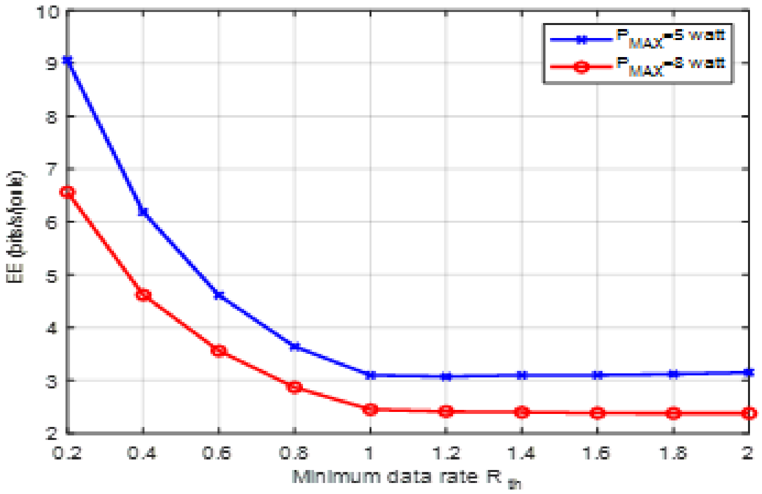

Figure 3. Variation of EE w.r.t R_{th}

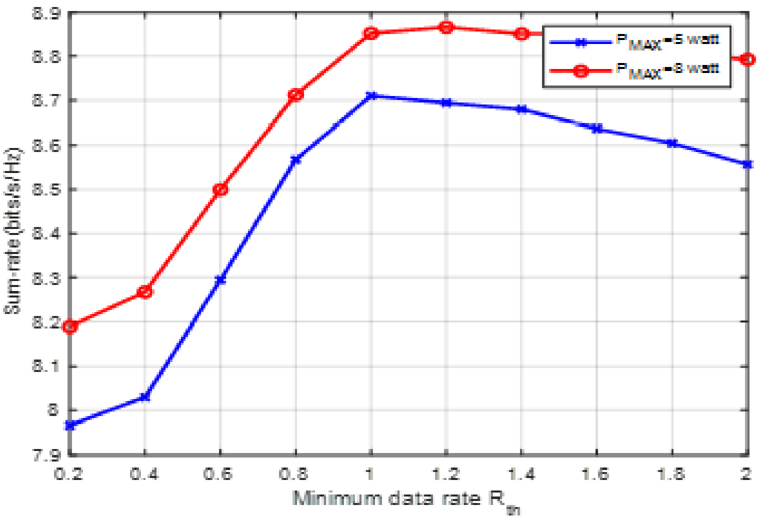

Figure 4. Variation of sum-rate R_T w.r.t R_{th}

Figure 5 shows the effect of applying IPNLMS algorithm for obtaining optimal power consumption at each user taking two different numbers of BDs. It is obvious that with increase in BDs and R_{th}, power consumption increases. Further, it is clearly observed that the Algorithm 2 along with Algorithm 1 help in reducing power consumption of the users while maintaining the required throughput.

Figure 6 illustrates the effect of number of backscatter devices on EE and sum-rate of the network. A single BD in the network observes no interference from the surrounding. Also, power allocated to that BD is very less. A very small power can achieve the required data rate in the network. Therefore, both EE and sum-rate are high for BD=1. But EE decreases due to the effect of interference caused by the increase in the number of BDs. As BD increases, interference power increases. Hence, power allocated to each BD increases to achieve required data rate. So, sum-rate gradually increases but EE decreases. However, for fixed P_{MAX}, sometimes power allocation P_i to ith BD is not sufficient to achieve minimum required SINR under the effect of interference. Therefore, under the fixed maximum allowable transmission power P_{MAX} from the BS, optimal number of BD must be considered in a BackCom-NOMA network, so that SINR levels at all the users are higher than the minimum requirement. This will be our future scope of research work.

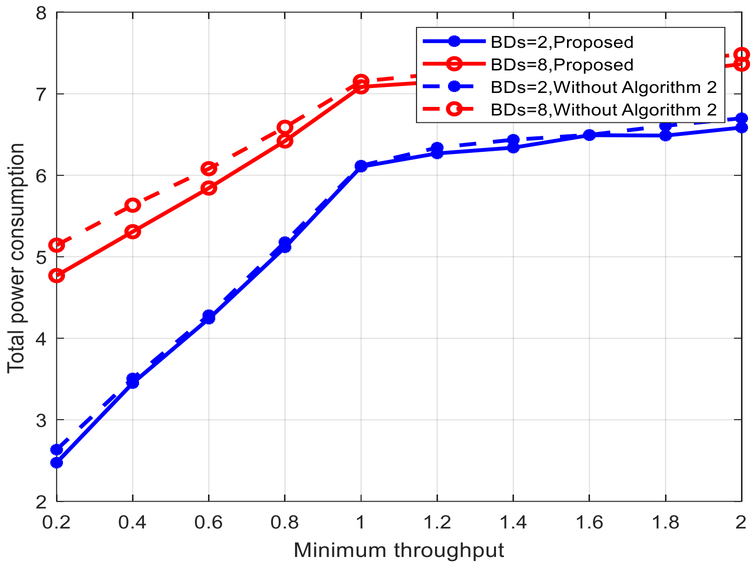

Figure 5. Effect of employing Algorithm 2 on total power consumption

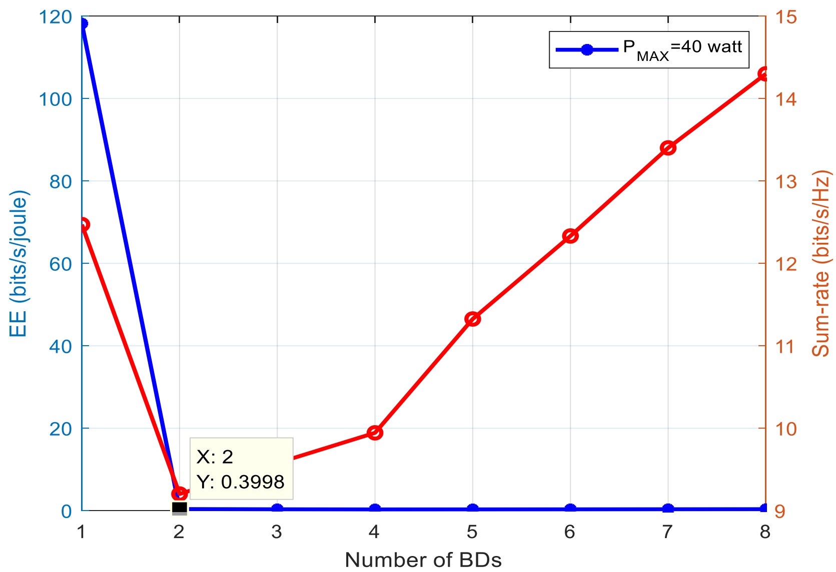

Figure 6. Effect of number of backscatter devices on EE and sum-rate of the network

5. CONCLUSIONS

This paper has presented an adaptive resource allocation method for maximizing EE in a Backcom-NOMA network under the effect of interference from surrounding BDs. The non-linear and non-convex optimization problem was formulated under the constraints of maximum allowable power from the BS and the minimum achievable data rate. More specifically, the problem was solved by an iterative approach for maximizing EE by simultaneously optimizing the power allocated to BD, power allocation coefficients and reflection coefficients, while the transmission power from the BS to BDs were obtained by an adaptive algorithm targeting the maximization of the sum-rate of the network. The efficacy of our algorithm was evaluated, and compared with the existing scheme. It was observed that EE increased by 165.25% by employing our proposed scheme over Lagrangian method at iteration 20 taking $\eta = -0.5$. Hence, proper adaptation of coefficients along with optimal power allocation can significantly improve the EE of a network. Our future work includes the finding of optimal number of backscatter devices in a BackCom-NOMA network for enhancing the system performance.

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