Energy Efficiency Maximization in Downlink Multi-Cell Multi-Carrier NOMA Networks with Hardware Impairments

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ABSTRACT In this paper, we investigate energy efficiency (EE) maximization in multicell multicarrier non-orthogonal multiple access (MCMC-NOMA) networks with hardware impairments (HIs). We formulate the optimization problem as a mixed integer nonlinear NP-hard problem, which is difficult to solve efficiently. To solve this problem, we decompose it into two subproblems. The first subproblem is the user and base station (BS) association and subchannel assignment problem, where binary whale optimization algorithm (BWOA) is proposed to handle it. For the second subproblem of the non-convex power allocation problem, successive pseudo-convex approximation (SPCA) is employed to establish the problem's pseudo-convexity. The approximate problem is separable into a sequence of equivalent problems that can be easier to solve. Each problem of the obtained sequence has a stationary point solution and is guaranteed to converge. The simulation results demonstrate that the proposed algorithm achieves a performance comparable to that of the successive lower bound maximization (SLBM) algorithm and outperforms both fractional transmit power allocation (FTPA) benchmark for NOMA and the conventional orthogonal multiple access (OMA).

INDEX TERMS Binary whale optimization algorithm (BWOA), energy efficiency (EE), hardware impairments (HIs), multi-cell multi-carrier (MCMC), non-orthogonal multiple access (NOMA).

I. INTRODUCTION

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NON-orthogonal multiple access (NOMA) is considered as one of the promising technologies for the fifth-generation mobile networks (5G) and beyond 5G (B5G) [1]–[5] and has received great attention from researchers due to its excellent connectivity. NOMA gains its superiority over the conventional orthogonal multiple access (OMA) due to its spectral efficiency (SE). In the power domain NOMA, two users can concurrently occupy the same subchannel and successive interference cancellation (SIC) is applied to extract the desired signal at the receiver [1]. In contrast, each user can solely occupy one subchannel in OMA. Therefore, the spectrum resources can be efficiently exploited using NOMA, and this leads to enhancing the throughput of the network [5], [6]. During this concurrent utilization of the spectrum resources, NOMA considers the users' channel conditions

and prioritizes the users with different channel conditions. Thus, fairness can be guaranteed and the throughput of the entire system can be improved [7], [8].

As a key measure of the next generation networks, energy efficiency (EE) in NOMA systems has been investigated in several studies. EE maximization for single cell NOMA systems was investigated in [9], [10], multicarrier NOMA (MC-NOMA) [11]–[15], multi-cell multi-carrier NOMA (MCMC-NOMA) networks [16]. Weighted EE maximization with user's fairness were considered in [17]–[20].

Although some studies in the above literature considered only power allocation to enhance, joint resource allocation is significant to improve system performance. For instance, the authors in [21] considered joint subchannel and power optimization to maximize the EE for downlink NOMA heterogeneous network. Convex relaxation was used to solve the subproblem of subchannel allocation while fractional programming and Lagrange dual method are used to obtain the closed-form solution for the power allocation. Joint ener-

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gy efficient user-resource block (RB) association and power allocation were investigated for uplink hybrid NOMA-OMA in [22] by considering the tradeoffs between the feasibility and the complexity of the solution. Joint user scheduling and power allocation were studied in [23]. The authors formulated the EE maximization problem as a multi-objective optimization (MOO) problem. For the solution, the problem was decoupled into two single-objective optimization (SOO) problems. A non-cooperative game and global optimal search (GOS) were used to solve the scheduling subproblem, while successive convex approximation (SCA) was used to allocate the power across subchannels.

All the above studies in [9]–[14], [16]–[23] have assumed perfect channel conditions at the transceivers. However, in practice, wireless systems experience hardware impairments (HIs) due to quantization problems, phase imbalances and non-linearities of the amplifier [24]. To alleviate the impact of HIs, some algorithms have been introduced such as compensation and calibration algorithms. However, those algorithms have not guaranteed the elimination of HIs effect and have been suffering from some problems such as the inaccuracy of calibration, estimation errors as well as correlation with noise types [25]. Consequently, there are still residual HIs in NOMA systems [26].

The impact of HIs on NOMA systems has been investigated in several studies. The performance in terms of outage probability has been studied in [26]–[31] and the throughput was investigated in [33], [34]. In [35], the authors studied the secrecy performance of a NOMA energy harvesting (EH) network in the presence of residual hardware impairments with an untrusted relay. The secrecy outage probability was used to evaluate the performance of the system. The study in [36] used outage probability and ergodic rate to evaluate the performance of full duplex NOMA networks with HIs over Rician fading channels. Outage probability and ergodic rate were also used in [37] to investigate the effect of residual hardware impairments (RHIs), channel estimation errors (CEEs) and imperfect SIC on cooperative NOMA system over Nakagami-m channels. HIs impact on two way multiple relay NOMA networks was investigated in [38], the opportunistic relay selection was applied to improve the spectral efficiency. The authors also studied the EE of the system.

In addition to the above research, some studies have been dedicated to investigating the impact of HIs on the EE in NOMA systems. The study in [33] considered EE maximization and throughput improvement in EH NOMA. The authors proposed transmit time-switching based algorithm to handle both problems. The authors proposed a joint design to optimize power splitting ratio and beamforming vectors to maximize EE of the system. The authors in [39] investigated the EE maximization in cooperative NOMA systems with HIs. The authors designed an algorithm of power and amplification gain allocation for EE maximization problem based on fractional programming (FP), Lagrange dual method and Dinkelback's method.

From the above literature, there are few studies focused on HIs impact on EE of wireless NOMA networks. Moreover, since our focus here on EE maximization in MCMC-NOMA networks, we realized a lack of literature focusing on this topology. Most of the aforementioned works were focusing on single-cell. In practice, wireless networks are usually multi-cell deployed networks. Motivated by the above, we consider MCMC-NOMA networks topology with HIs. We investigate the performance with regard to EE maximization. The formulated EE maximization problem is mixed integer NP-hard problem due to the existence of binary variables related to the users and the base stations (BSs) association via the multicarrier and the intra-cell and inter-cell interference. Thus, we give a novel algorithm to handle it. Our main contributions are summarized as follows:

- Different from the existing works in [33] and [39], we consider the downlink MCMC-NOMA network with HIs working in the non-cooperative mode, where the BS sends the signal directly to the users. We derive the EE maximization problem by representing the effect of HIs as a distortion in the transceiver signal. The problem is a mixed-integer nonlinear programming (MINLP) problem, which is non-convex and NP-hard. Obtaining the solution to this problem is usually challenging.
- The optimization problem is decomposed into two subproblems. The first problem is user-BS association and subchannel assignment, and the second problem is the energy-efficient power allocation. The first subproblem is handled using the binary whales optimization algorithm (BWOA). For power allocation, we designed successive pseudo-convex approximation (SPCA) based framework to perform the power allocation.
- Different from the power allocation schemes proposed in [12], [23] and [40], our proposed power allocation scheme has the advantage of parallelizing the solution process by converting the problem into separable subproblems, where each subproblem has a closed-form solution. Thus, the proposed power allocation scheme is more suitable for MCMC topology compared to other schemes such as successive lower bound maximization (SLBM) [41].
- The simulation results have shown comparable performance to that of the SLBM method in terms of EE. Moreover, the simulation results demonstrate the superiority of the proposed algorithm over fractional transmit power allocation (FTPA) benchmark for NOMA as well as OMA scheme.

Our work's scope mainly focuses on solving user association and subchannel assignment and power allocation. Since obtaining the optimal solution for the power allocation is complicated and entails very high complexity, we focus on the problem approximation. Those can be considered as a significant delimitation.

The remainder of the paper is organized as follows. Section II presents the system model and problem formulation.

Section III discusses user-BS association and subchannel assignment. Section IV discusses the energy-efficient power allocation for MCMC-NOMA networks. Section V shows the simulation results and Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION
A. SYSTEM MODEL
We consider a non-cooperative downlink MCMC-NOMA network with M BSs communicating with N_{ue} users via N_{sc} subchannels and defined as $\mathbb{M} = \{1, 2, ..., M\}$, $\mathbb{U} = \{1, 2, ..., N_{ue}\}$ and $\mathbb{K} = \{1, 2, ..., N_{sc}\}$, respectively. The system bandwidth B is divided into subchannels such that the bandwidth of the subchannel n is $B_n = \frac{B}{N_{sc}}$. We assume each user is equipped with one antenna. The BS m sends a superposition symbol $x_{m,n}$ to the associated user i via the subchannel n, this signal is given as

$$x_{m,n} = \sum_{i=1}^{N_{ue}} v_{m,i,n}\sqrt{p_{m,i,n}}\left(s_{m,i,n} + \chi_{m,i,n}\right) \qquad (1)$$

where $v_{m,i,n} \in \{0, 1\}$ is the user-BS and subchannel-BS indicator. $v_{m,i,n} = 1$ indicates the user i is associated with BS m and assigned with the subchannel n and $v_{m,i,n} = 1$ if otherwise. $p_{m,i,n}$ is the allocated power to the user i served by BS m via subchannel n. $s_{m,i,n}$ is the transmit signal of BS m in the subchannel n with $E\left[\left|s_{m,i,n}\right|^2\right] = 1$. $\chi_{m,i,n}$ is the distortion noise due to the hardware impairments between the BS m and the user i on the subchannel n with zero mean and variance $\phi_{m,i,n}^2 p_{m,i,n}$, $\phi_{m,i,n}$ is the level of hardware impairments.

The received signal at the user i served by BS m through subchannel n is given as

$$y_{m,i,n} = h_{m,i,n}x_{m,n} + I_{m,i,n} + \eta_{m,i,n} \qquad (2)$$

where $h_{m,i,n} = g_{m,i,n}d_{m,i}^{-\alpha}$ is the channel coefficient between the BS m and its associated user i, $g_{m,i,n}$ is the Rayleigh fading channel gain between the BS m and the user i on the subchannel n. $d_{m,i}$ is the distance between the user i and BS m and α is the pathloss exponent. $\eta_{m,i,n}$ is AWGN with zero means and variance σ^2. $I_{m,i,n}$ is the accumulated intercell interference received by the user i from other BSs on subchannel n except BS m

$$I_{m,i,n} = \sum_{t \neq m}^{M} h_{t,i,n}\sqrt{P_{t,n}}x_{t,n} \qquad (3)$$

where $P_{t,n}$ is the total allocated power by BS t on subchannel n and given by

$$P_{t,n} = \sum_{n=1}^{N_{sc}} v_{t,i,n}p_{t,i,n} \qquad (4)$$

Let $H_{m,i,n}$ represents the channel response to noise and interference ratio (CRNIR)

$$H_{m,i,n} = \frac{\left|h_{m,i,n}\right|^2}{\sigma^2 + \sum\limits_{t \neq m}^{M} \left|h_{t,i,n}\right|^2 P_{t,n}} \qquad (5)$$

Without loss of generality, we assume the following order

$$H_{m,1,n} \leq H_{m,2,n} \leq ... \leq H_{m,N_{ue},n} \qquad (6)$$

According to NOMA protocol, SIC is carried out by the user to retrieve its intended signal. Then, signal-to-interference-plus-noise ratio (SINR) for the user i served by BS m via the subchannel n is expressed as

$$\gamma_{m,i,n} = \frac{v_{m,i,n}\left|h_{m,i,n}\right|^2 p_{m,i,n}}{\sigma^2 + \phi_{m,i,n}^2 p_{m,i,n} + I_{m,i,n}^{aggr}} \qquad (7)$$

where $I_{m,i,n}^{aggr}$ is the aggregated interference experienced by the user i associated with the BS m through the subchannel n and it's defined as

$$I_{m,i,n}^{aggr} = \sum_{j=1,j \neq i}^{N_{ue}} v_{m,i,n}\left|h_{m,i,n}\right|^2 p_{m,j,n}\left(1 + \phi_{m,j,n}^2\right)$$
$$+ \sum_{t \neq m}^{M} \left|h_{t,i,n}\right|^2 P_{t,n}\left(1 + \phi_{t,n}^2\right) \qquad (8)$$

The achievable data rate of the user i served by the BS m via the subchannel n is defined as

$$r_{m,i,n} = B_n\log_2\left(1 + \gamma_{m,i,n}\right) \qquad (9)$$

Then, the sum rate of the network can be expressed as

$$R = \sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} r_{m,i,n} \qquad (10)$$

Hence, the network's total energy efficiency is given as

$$EE = \frac{R}{P_T} \qquad (11)$$

where P_T represents the total power and given by

$$P_T = \sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} + p_c \qquad (12)$$

where p_c is the circuit power consumption excepted transmit power part [42].

B. PROBLEM FORMULATION
Based on the above analytical derivation, our objective is to maximize the network EE of the network. The optimization problem can be formulated as follows

$$\max_{v,p} \quad EE$$

$$\text{s.t.} \quad C1: H_{m,i,n} \geq H_{m,j,n}, \forall i > j, \forall m \in \mathbb{M}, \forall n \in \mathbb{K},$$

$$C2: \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} v_{m,i,n}p_{m,i,n} \leq P_m^{max}, \forall m \in \mathbb{M},$$

$$C3: \sum_{m=1}^{M} \sum_{n=1}^{N_{sc}} B_n\log_2\left(1 + \frac{v_{m,i,n}\left|h_{m,i,n}\right|^2 p_{m,i,n}}{\sigma^2 + \phi_{m,i,n}^2 p_{m,i,n} + I_{m,i,n}^{aggr}}\right)$$
$$\geq R_{\min}, \forall i \in \mathbb{U},$$

$$C4: p_{m,i,n} \geq 0, \forall m \in \mathbb{M}, \forall i \in \mathbb{U}, n \in \mathbb{K},$$

$$C5: v_{m,i,n} \in \{0, 1\}, \forall m \in \mathbb{M}, \forall i \in \mathbb{U}, n \in \mathbb{K},$$

$$C6: \sum_{m=1}^{M} \sum_{n=1}^{N_{sc}} v_{m,i,n} \leq 1, \forall i \in \mathbb{U},$$

$$(13)$$

where constraints C1 is to guarantee the successful performance of SIC in specific order. Constraints C2 is the total power constraints of the BS limited by the maximum transmit power of m-th BS P_m^{max}. Constraints C3 is the data rate requirements for each user. C4 is the nonnegativity of user's power. Constraints C5 represent the user-BS association and subchannel assignment indicator. Constraints C6 to assert that the user can associate with only one BS through only one subchannel.

Since EE maximization problem for a single cell is NP-hard [12], it can be observed that the problem is MINLP problem which is also NP-hard problem and difficult to solve. To effectively tackle this problem, we decompose it into two subproblems. First, user-BS association and subchannel assignment subproblem. Second, energy efficient power allocation in MCMC-NOMA networks. Even after the decomposition, obtaining the optimal solution is difficult and this is another limitation drawn up the nature of the problem. The details are presented in section III and section IV.

III. USER-BS ASSOCIATION AND SUBCHANNEL ASSIGNMENT

In this section, we investigate the user-BS association and subchannel assignment subproblem. We assume that equal power is allocated to each user then we propose a metaheuristic algorithm to tackle this subproblem. The subproblem is defined as follows

$$\max_{v} \frac{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} r_{m,i,n}}{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} + p_c}$$

s.t. $C5 : v_{m,i,n} \in \{0,1\}, \forall m \in \mathbb{M}, \forall i \in \mathbb{U}, n \in \mathbb{K},$

$$C6 : \sum_{m=1}^{M} \sum_{n=1}^{N_{sc}} v_{m,i,n} \leq 1, \forall i \in \mathbb{U}, \tag{14}$$

Metaheuristic optimization algorithms have many advantages such as the simplicity of the concepts, can be exploited to solve wide range of problems and can bypass local optima [43]. Generally, metaheuristic optimization methods have two processing phases, exploration and exploitation [45], [46]. In exploration phase, the optimizer utilizes operators to explore the search space and determine the areas of interest. This phase usually depends on the random generation of the variables. In the exploitation phase, the detailed search in the areas of interest takes place.

The proposed algorithm is BWOA which imitates the hunting behavior of the humpback whales [47]. BWOA was tested with different problems and has shown competitive performance compared to state-of-the-art optimization methods. Humpback whales use a hunting technique called bubblenet. In this technique, humpback whales move in a shrinking circle while blowing bubbles under their favorite small preys forcing them to the top water [43]. The algorithm includes

three elements, encircling the prey, bubble-net attacking and searching the prey.

A. ENCIRCLING THE PREY

To formulate the procedural behavior, the define the following equations [47]

$$\vec{D} = \left| \vec{C} \cdot \vec{X}^* (t) - \vec{X} (t) \right| \tag{15}$$

where $\vec{X}^* (t)$ is the position of the best search agent, t is the current iteration and the symbol $\cdot$ is to indicate the element-wise product. $\vec{C}$ is a coefficient vector and calculated by

$$\vec{C} = 2 \cdot \vec{r} \tag{16}$$

where $\vec{r}$ is a random vector in $[0,1]$. The positions of the agents are updated by

$$\vec{X} (t+1) = \vec{X}^* (t+1) - \vec{A} \cdot \vec{D} \tag{17}$$

where $\vec{A}$ is a coefficient vector calculated as follows

$$A = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{18}$$

where $\vec{a}$ is a control parameter linearly decreased from 2 to 0 with iterations during exploration and exploitation phases (i.e. $\vec{a} = 2 \left(1 - t/T \right)$) where, T represents the maximum number of iterations. Equations (16) and (18) are to balance the exploitation and exploration. To enhance the exploration and exploitation over the course of the optimization, the parameter C can be random in [0,1].

B. BUBBLE-NET ATTACKING

The humpback whales swim around the prey in shrinking circle and move in spiral-shaped path (shrinking encircling and spiral updating position mechanisms). First the step size for shrinking and encircling is defined as the following transfer function

$$\varphi_{SE} = \frac{1}{1 + \exp \left(-10 \left(\vec{A} \cdot \vec{D} - 0.5 \right) \right)} \tag{19}$$

The value of φ_{SE} is used to toggle between zero and one. The position of the search agent is updated as

$$\vec{X} (t+1) = \begin{cases} \mathbb{C} \left(\vec{X} (t) \right), & \text{if } p_B < \varphi_{SE} \\ \vec{X} (t), & \text{if } p_B \geq \varphi_{SE} \end{cases} \tag{20}$$

where p_B is a uniform random number in $[0,1]$ and $\mathbb{C} (\cdot)$ indicates the complement operation. For the spiral updating position, first the step size is defined as

$$\varphi_{SUP} = \frac{1}{1 + \exp \left(-10 \left(\vec{A} \cdot \vec{D} - 0.5 \right) \right)} \tag{21}$$

Then, then the position is updated by

$$\vec{X} (t+1) = \begin{cases} \mathbb{C} \left(\vec{X} (t) \right), & \text{if } p_B < \varphi_{SUP} \\ \vec{X} (t), & \text{if } p_B \geq \varphi_{SUP} \end{cases} \tag{22}$$

C. SEARCHING THE PREY

Applying similar mechanism as shrinking encircling, the searching for prey is performed with the coefficient vector $\left|\vec{A}\right| > 1$, where $|\cdot|$ represents the absolute value. Then, replacing the position of the best agent $\vec{X}^*(t)$ with randomly selected position of a whale $\vec{X}_{rand}$. This helps in extending the search space. The step size is defined as

$$\varphi_{SP} = \frac{1}{1 + \exp\left(-10\left(\vec{A}\cdot\vec{D} - 0.5\right)\right)} \quad (23)$$

Thus, the position of search agent is updated as

$$\vec{X}(t+1) = \begin{cases} \mathbb{C}\left(\vec{X}(t)\right), & \text{if } p_B < \varphi_{SP} \\ \vec{X}(t), & \text{if } p_B \geq \varphi_{SP} \end{cases} \quad (24)$$

Before applying the above procedure, we use the penalty method to convert the constrained problem into an unconstrained problem by combining the objective function and the constraints together [44]. Then, the result is the fitness function. We define the fitness function as follows

$$fitness(v) = \frac{R}{P_T} + \sum_{i=1}^{N_{ue}} \mu_i F_i\left(f_i(v)\right) f_i^2(v) \quad (25)$$

where μ_i is a penalty factor used for the ease of implementation for all inequalities constraints, where $f_i(v) = \sum_{m=1}^{M} \sum_{n=1}^{N_{sc}} v_{m,i,n} - 1$. The index function $F_i(f_i(v)) = -1$ if $f_i(v) > 0$ and $F_i(f_i(v)) = 0$ if $f_i(v) \leq 0$. Algorithm 1 illustrates the the above procedures.

Initially, we start with a random set of solutions and calculate the corresponding fitness assuming there's a channel diversity and in this case. The search dimension is depending on the number of the BSs. The best searching agent is determined based on its fitness. Then, the position of the searching agent is updated either randomly or according to the best obtained solution in which the agents follow the best search agent. The random search agent is chosen to update the position of the searching agent when $|A| > 1$. Otherwise, the best solution is chosen. The exploration and exploitation are attained with the decrement of parameter a. Moreover, based on the value of p_B searching agent chose shrinking and encircling or spiral movement. If either of the termination conditions is satisfied, BWOA terminates.

It's noteworthy that there are two main parameters to be adjusted A and C. While decreasing A, as a consequence we can divide the iterations into two sets. When $|A| \geq 1$, the set of iterations are dedicated for exploration and the remaining iterations are dedicated for exploitation. Furthermore, the defined mechanism of the algorithm determines the search space in the surroundings of the best solution. Hence, BWOA is generally considered as a global optimizer [43].

Algorithm 1 BWOA-Based User-BS Association and Subchannel Assignment

1: Initialize whale population X_i, $i = \{1, ..., N\}$, $t = 1$, T, ϵ.
2: Calculate the fitness for each agent according to (25) and determine the best search agent $\vec{X}^*(t)$.
- **Procedure for user-BS association**
3: **while** $t < T$ or $\frac{|X^*(t)-X^*(t-1)|}{|X^*(t-1)|} \geq \epsilon$ **do**
4:   **for** each search agent (user) **do**
5:     Update a, A, C and generate p_B.
6:     **if** $p_B < 0.5$ **then**
7:       **if** $|A| < 1$ **then**
8:         Update $\vec{D}$ according to (15) and φ_{SE} according to (19).
9:         Update the position $\vec{X}(t)$ according to (20).
10:       **else**
11:         Select a random agent $\vec{X}_{rand}$ and update $\vec{D}$.
12:         Update φ_{SP} using (23) and $\vec{X}(t)$ by (24).
13:       **end if**
14:     **else**
15:       Update $\vec{D}$ as follows

$$\vec{D} = \left|\vec{X}^*(t) - \vec{X}(t)\right| \quad (26)$$

16:       Update φ_{SUP} by (21).
17:       Update the position $\vec{X}(t)$ according to (22).
18:     **end if**
19:   **end for**
20:   Calculate the fitness of each search agent by (25).
21:   Update $\vec{X}^*(t)$ of the best search agent.
22:   $t = t + 1$
23: **end while**
- **Procedure for subchannel assignment**
24: Repeat the above procedure for user multiplexing such that

$$i^* = \arg\max_i fitness(v) \quad (27)$$

Next, we give the complexity analysis for Algorithm 1. The complexity of computing the fitness is $\mathcal{O}(N_{ue}D)$, where N_{ue} is the number of whales (users) and D is the search dimension. The search dimension in our case depends on M and N_{sc}. The position of each searching vector is updated with each iteration; therefore, the complexity of this step is $\mathcal{O}(N_{ue}D)$. Since algorithm is doing the procedure twice with different search dimensions, then the computational complexity of Algorithm 1 is $\mathcal{O}(TN_{ue}(M + N_{sc}))$ where T is the maximum number of iterations.

IV. ENERGY-EFFICIENT POWER ALLOCATION IN MCMC-NOMA NETWORKS

After obtaining the user-BS association and subchannel assignment, we will introduce an iterative solution to solve our power allocation subproblem in this section. Although we have tackled the binary variable, yet the problem still non-

convex due to the presence of the interference as well as the existence of the constraints C1-C4. Thus, obtaining the optimal solution is difficult. Therefore, we will introduce an approximation to reduce the complexity of the calculations. The power allocation subproblem is defined as

$$
\begin{aligned}
\max_{p} \quad & EE \\
\text{s.t.} \quad & C1 : H_{m,i,n} \geq H_{m,j,n}, \forall m, i > j, \forall (i,j), \forall n, \\
& C2 : \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} v_{m,i,n} p_{m,i,n} \leq P_m^{max}, \forall m \\
& C3 : \sum_{m=1}^{M} \sum_{n=1}^{N_{sc}} B_n \log_2 \left(1 + \frac{v_{m,i,n} |h_{m,i,n}|^2 p_{m,i,n}}{\sigma^2 + \phi_{m,i,n}^2 p_{m,i,n} + I_{m,i,n}^{aggr}} \right) \\
& \qquad \geq R_{\min}, \forall i, \\
& C4 : p_{m,i,n} \geq 0, \forall i,
\end{aligned}
\tag{28}
$$

A. SUCCESSIVE PSEUD-CONVEX APPROXIMATION METHOD

Let $f(p)$ is an equivalent function to our objective function in (28) . Hence our problem is defined as

$$
\begin{aligned}
\max_{p} \quad & f(p) \\
\text{s.t.} \quad & C1 - C4,
\end{aligned}
\tag{29}
$$

Our objective is to propose introduce an approximate function of $f(p)$ that can be decomposed into subproblems that can exhibit closed-form solutions [48]. Let $\tilde{f}\left(p, p^{(t)}\right)$ represents the approximate iterative function of $f(p)$ over the iteration t around the point $p^{(t)}$. The approximate function is defined as

$$
\tilde{f}\left(p; p^{(t)}\right) = \frac{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} \tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right)}{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} + p_c}
\tag{30}
$$

Where $\tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right)$ is given by

$$
\begin{aligned}
\tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right) = \; & r_{m,i,n}\left(p_{m,i,n}; p_{m,-i,n}^{(t)}\right) \\
& + \sum_{j=1, j \neq i}^{N_{ue}} \left(p_{m,i,n} - p_{m,i,n}^{(t)}\right) \nabla_{p_{m,i,n}} r_{m,j,n}\left(p^{(t)}\right) \\
& + \sum_{t \neq m} \left(p_{m,i,n} - p_{m,i,n}^{(t)}\right) \sum_{i=1}^{N_{ue}} \nabla_{p_{m,i,n}} r_{t,i,n}\left(p^{(t)}\right)
\end{aligned}
\tag{31}
$$

Thus, we can reformulate our original power allocation in

the light of this approximation as

$$
\begin{aligned}
\max_{p} \quad & \tilde{f}\left(p; p^{(t)}\right) \\
\text{s.t.} \quad & C1 : H_{m,i,n} \geq H_{m,j,n}, \forall m, i > j, \forall (i,j), \forall n, \\
& C2 : \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} v_{m,i,n} p_{m,i,n} \leq P_m^{max}, \forall m \\
& C3 : \sum_{m=1}^{M} \sum_{n=1}^{N_{sc}} v_{m,i,n} \tilde{r}_{m,i,n} \geq R_{\min}, \forall i, \\
& C4 : p_{m,i,n} \geq 0, \forall i,
\end{aligned}
\tag{32}
$$

Suppose $\mathcal{P}$ is the solution set and it is closed and convex set and $\mathbb{B}p^{(t)}$ is the globally optimal point. Then, according to SPCA theory [48], the approximate function $\tilde{f}\left(p, p^{(t)}\right)$ is assumed to satisfy the following conditions:

1) $\tilde{f}\left(p, p^{(t)}\right)$ is pseud-convex for any $p^{(t)} \in \mathcal{P}$.
2) $\tilde{f}\left(p, p^{(t)}\right)$ is continuously differentiable in p for any $p^{(t)} \in \mathcal{P}$ and continuous in $p^{(t)}$ for any $p \in \mathcal{P}$.
3) $\nabla_p \tilde{f}\left(p^{(t)}; p^{(t)}\right) = \nabla_p f\left(p^{(t)}\right)\big|_{p=p^{(t)}}, \forall p^{(t)} \in \mathcal{P}$.
4) $\mathcal{P}$ is nonempty for $t = 1, ...,$.
5) For any convergent sequence $\{p^{(t)}\}_{t \in \mathcal{T}}$ where $\mathcal{T} \subseteq \{1, 2, ...\}$, the sequence $\{\mathbb{B}p^{(t)}\}_{t \in \mathcal{T}}$ is bounded.

First, to show the function $f\left(p, p^{(t)}\right)$ can exhibit pseudo-convexity, we show the numerator of the function is concave. The concavity of $\tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right)$ is preserved due the concavity of $r_{m,i,n}\left(p_{m,i,n}; p_{m,-i,n}^{(t)}\right)$. The concavity of $r_{m,i,n}\left(p_{m,i,n}; p_{m,-i,n}^{(t)}\right)$ can be verified by taking the second order derivative (see Appendix A).

Since $\tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right)$ and $p_{m,i,n} + p_c$ are continuously differentiable for any $p^{(t)}$, then the second condition is satisfied. The proof of fulfillment of the third condition in the Appendix B. Finally, since the power solution is bounded, the fourth and the fifth conditions are satisfied.

In each iteration t, the function maximizer for $f\left(p, p^{(t)}\right)$ is defined as

$$
\mathbb{B}p^{(t)} = \arg \max_{p} \frac{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} \tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right)}{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} + p_c}
\tag{33}
$$

Fractional programming is applicable on (33) since its numerator is concave and the denominator is linear. Applying Dinkelbach's algorithm [49], we get

$$
p\left(\lambda^{(t,\tau)}\right) = \arg \max_{p} \left[\begin{array}{c} \sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} \tilde{r}_{m,i,n}\left(p_{m,i,n}; p^{(t)}\right) \\ -\lambda^{(t,\tau)} \left(\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} + p_c \right) \end{array} \right]
\tag{34}
$$

Where, $\lambda^{(t,\tau)}$ is the auxiliary variable which is updated in iteration $\tau + 1$ as follows

$$\lambda^{(t,\tau+1)} = \frac{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} \tilde{r}_{m,i,n}\left(p_{m,i,n}; \mathrm{p}^{(t)}\right)}{\sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} + p_c} \quad (35)$$

The problem (34) can be decomposed into independent sub-problems that can be solved in parallel

$$p_{m,i,n}\left(\lambda^{(t,\tau)}\right) = \arg \max_{p \in \mathcal{P}} \left[\begin{array}{c} \tilde{r}_{m,i,n}\left(p_{m,i,n}; \mathrm{p}^{(t)}\right) \\ -\lambda^{(t,\tau)} p_{m,i,n} \end{array} \right] \quad (36)$$

Problem (36) is convex and $\mathcal{P}$ has a nonempty interior. The problem can be further decomposed into dual domain by relaxing the constraints. Hence, recalling back (34), we get the Lagrangian function (37) on the top of page 8.

Where, β , κ and π are Lagrange multipliers associated with the sum power constraint, QoS constraints and nonnegativity of power, respectively. They can be updated as follows

$$\beta^{(t+1,\tau)} = \left[\beta^{(t,\tau)} - \delta^{(t)} \left(P_{\mathrm{m}} - \sum_{m=1}^{M} \sum_{i=1}^{N_{ue}} \sum_{n=1}^{N_{sc}} p_{m,i,n} \right) \right]^{+} \quad (38)$$

$$\kappa_{m,i,n}^{(t+1,\tau)} = \left[\kappa_{m,i,n}^{(t,\tau)} - \delta_{\kappa}^{(t)} \left(\tilde{r}_{m,i,n}\left(p_{m,i,n}; \mathrm{p}^{(t)}\right) - R_{\min} \right) \right]^{+} \quad (39)$$

$$\pi_{m,i,n}^{(t+1,\tau)} = \left[\pi_{m,i,n}^{(t,\tau)} + \delta_{\pi}^{t} p_{m,i,n} \right]^{+} \quad (40)$$

Algorithm 2 Iterative Power Allocation for EE Maximization

Initialization: $R_{min}, \mathrm{p}^{(0)}, \beta^{(0,0)}, \kappa^{(0,0)}, \pi^{(0,0)}, \epsilon_p, \epsilon_\lambda, t = 0,$
$\quad \phi_{m,i,N}.$
1: **while** $\left| \left(\mathbb{B}\mathrm{p}^{(t)} - \mathrm{p}^{(t)} \right)^{T} \nabla f\left(\mathrm{p}^{(t)}\right) \right| \geq \epsilon_p$ **do**
2: $\quad \tau = 0$ and $\lambda^{(0,0)}$.
3: $\quad$ **while** $\left| \lambda^{(t,\tau+1)} - \lambda^{(t,\tau)} \right| \geq \epsilon_\lambda$ **do**
4: $\quad\quad$ Compute $p_{m,i,n}\left(\lambda^{(t,\tau)}\right)$ according to (42).
  $\quad\quad \bullet \quad$ Update $\beta^{(t+1,\tau)}$ according to (38).
  $\quad\quad \bullet \quad$ Update $\kappa^{(t+1,\tau)}$ according to (39).
  $\quad\quad \bullet \quad$ Update $\pi^{(t+1,\tau)}$ according to (40).
5: $\quad\quad$ Compute $\lambda^{(t,\tau+1)}$ according to (35).
6: $\quad\quad \tau \leftarrow \tau + 1$
7: $\quad$ **end while**
8: $\quad$ Compute $\mathbb{B}\mathrm{p}^{(t)}$ according to (33).
9: $\quad$ Determine the step size $\delta^{(t)}$ by successive line search.
10: $\quad$ Update $p^{(t)}$ as follows

$$\mathrm{p}^{(t+1)} = \mathrm{p}^{(t)} + \delta^{(t)} \left(\mathbb{B}\mathrm{p}^{(t)} - \mathrm{p}^{(t)} \right) \quad (41)$$

11: $\quad t \leftarrow t + 1$
12: **end while**

The closed form expression of the power is equivalent to finding the root of a polynomial with the second order and it can be expressed as in (42) on the top of page 8. Where,

TABLE 1. Simulation Parameters

Parameter	Value
Overall bandwidth	5MHz
Cell radius	500m
Path loss	$128.1 + 37.6\log_{10} d$ dB, d is in km
Users distribution scheme	Randomly uniform distribution
Shadowing	Log-normal, standard deviation 8 dB
Fading	Rayleigh fading with variance 1
Noise power spectral density	-174 dBm/Hz
Number of Users N	4 to 20 per BS
HIs level $\phi_{m,i,n}$	0, 0.01 and 0.02
μ	10^7
$\epsilon, \epsilon_p, \epsilon_\lambda$	0.001, 0.001, 0.001
Decay factor of NOMA-FTPA	0.2

$\rho = |h_{m,i,n}|^2$. $\omega_{m,i,n}\left(\mathrm{p}^{(t)}\right)$ and $I_{m,i,n}\left(\mathrm{p}^{(t)}\right)$ are given by (43) and (44), respectively on the top of page 8.

The power calculation procedures are illustrated in Algorithm 2.

Now, we provide the complexity analysis for Algorithm 2. Let I and T respectively represent the maximum number of iteration for both outer (Dinkelbach's algorithm) and inner loops which includes the subgradient method. The calculation of (42) requires $MN_{ue}N_{sc}$ operations while updating λ has computational complexity of $\mathcal{O}(N_{ue})$. Moreover, the initial value of λ and the method of step sizes calculations to update the multipliers and other parameters are greatly affecting the required number of iterations. Because T is a polynomial function of $\mathcal{O}\left(MN_{ue}^2 N_{sc}T\right)$, the total computational complexity of Algorithm 2 in the worst case is $\mathcal{O}\left(MN_{ue}^2 N_{sc}IT\right)$.

V. SIMULATION RESULTS

In this section, we present the simulation results and evaluate the performance of the proposed method. For the simulation, we consider MCMC-NOMA system with one BS in the center of each cell, the cell radius is 500m and the users are randomly distributed in the cell. The total bandwidth of the system is 5MHz equally divided by $N_{sc} = 20$ subchannels. We assume the small-scale Rayleigh fading channels between users and BSs. The levels of HIs $\phi_{m,i,n}$ are set to 0, 0.01 and 0.02. The noise power spectral density $N_0 = -174$ dBm/Hz. The error tolerance parameters ϵ, ϵ_p and ϵ_λ are set to 0.001 for each.

For the comparison part, same user-BS and subchannel assignment scheme is used with NOMA-FTPA scheme in [50], [51] and also with SLBM scheme in [48], [49]. However, for OMA each user is allocated in a separate subchannel. The decay parameter for NOMA-FTPA is set to 0.2. TABLE. 1 illustrates the simulation parameters.

Fig. 1 depicts the convergence of BWOA. The figure shows the user-BS association and the subchannel assignment. We selected the first BS and the first subchannel to show the performance. The number of BSs is $M = 7$ with 8 users for each and the number of subchannels is 20. It can be seen from that the fitness is improving with the number of iterations because the user tends to associated the base

$$L\left(p,\lambda,\beta,\kappa,\pi\right)=\underset{p\in\mathcal{P}}{\arg\max}\begin{bmatrix}\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\tilde{r}_{m,i,n}\left(p_{m,i,n};\mathrm{p}^{(t)}\right)-\lambda^{(t,\tau)}\left(\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}p_{m,i,n}+p_{c}\right)\\ -\beta^{(t,\tau)}\left(P_{\mathrm{m}}-\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}p_{m,i,n}\right)\\ -\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\kappa_{m,i,n}^{(t,\tau)}\left(\tilde{r}_{m,i,n}\left(p_{m,i,n};\mathrm{p}^{(t)}\right)-R_{\min}\right)\\ +\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\pi_{m,i,n}^{(t,\tau)}p_{m,i,n}\end{bmatrix} \quad (37)$$

$$p_{m,i,n}\left(\lambda^{(t,\tau)}\right)=\left[I_{m,i,n}\left(\mathrm{p}^{(t)}\right)\frac{\sqrt{\left(2\phi_{m,i,n}^{2}+\rho\right)^{2}-4\phi_{m,i,n}^{2}\left(\frac{\rho\left(1-\kappa_{m,i,n}^{(t,\tau)}\right)}{\left(\omega_{m,i,n}\left(\mathrm{p}^{(t)}\right)\left(1-\kappa_{m,i,n}^{(t,\tau)}\right)-\lambda^{(t,\tau)}-\beta^{(t,\tau)}+\pi_{m,i,n}^{(t,\tau)}\right)I_{m,i,n}\left(\mathrm{p}^{(t)}\right)}+1\right)}-1}{2\phi_{m,i,n}^{2}\left(\omega_{m,i,n}\left(\mathrm{p}^{(t)}\right)\left(1-\kappa_{m,i,n}^{(t,\tau)}\right)-\lambda^{(t,\tau)}-\beta^{(t,\tau)}+\pi_{m,i,n}^{(t,\tau)}\right)\left(\phi_{m,i,n}^{2}+\rho\right)}\right]^{+} \quad (42)$$

$$\omega_{m,i,n}\left(\mathrm{p}^{(t)}\right)=\sum_{j=1,j\neq i}^{N_{ue}}\nabla_{p_{m,i,n}}r_{m,j,n}\left(\mathrm{p}^{(t)}\right)+\sum_{t\neq m}\sum_{i=1}^{N_{ue}}\nabla_{p_{m,i,n}}r_{t,i,n}\left(\mathrm{p}^{(t)}\right) \quad (43)$$

$$I_{m,i,n}\left(\mathrm{p}^{(t)}\right)=\sigma^{2}+\sum_{j=1,j\neq i}^{N_{ue}}|h_{m,i,n}|^{2}p_{m,j,n}\left(1+\phi_{m,j,n}^{2}\right)+\sum_{t\neq m}|h_{t,i,n}|^{2}P_{t,n}\left(1+\phi_{t,n}^{2}\right) \quad (44)$$
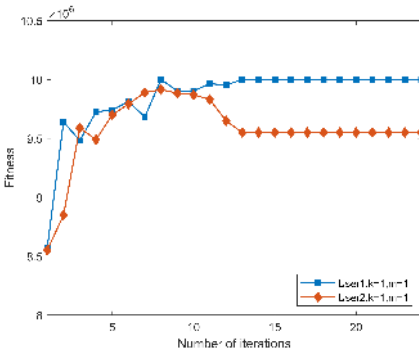

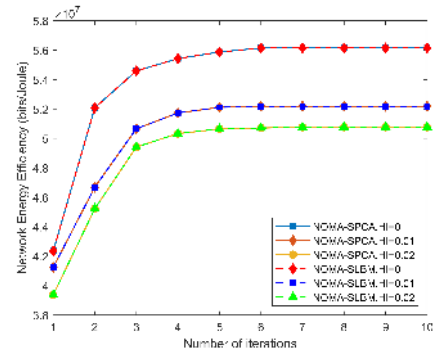**FIGURE 1.** Convergence of BWOA.

FIGURE 2. Convergence of the proposed power allocation algorithm.

station that achieves higher EE and the subchannel with better channel conditions. Moreover, the volatility in curves because the user tends to imitate the user with the best fitness.

To evaluate the performance of the iterative power allocation algorithm, Fig. 2 evaluates the performance with respect to the convergence speed for different HIs levels. We set the number of BS to $M=7$ and the number of users to 4 per BS. P_{m}^{max} is set to 40dBm, R_{min} is set to 0.1Mbit/s and p_{c} is 20dBm. One can notice the EE increases with each iteration until it converges in 6 iterations. Although both SPCA and SLBM have comparable convergence behaviour with regard to the number of iterations, the proposed SPCA method is superior than SLBM due to some reasons. First,

the approximate problem of the proposed method is in fact a set of independent subproblems that can be parallelly solved. Each subproblem has a closed-form solution as in (42). Conversely, when applying SLBM on (28), the approximate problem can only be solved by a general purpose solver [49]. The proposed scheme holds the same advantageous traits when compared with other well known methods such as SCA [12], [23].

Fig. 3 illustrates the performance of the proposed algorithm and other compared schemes for different maximum transmit power of BS P_{m}^{max} while R_{min} and p_{c} are set to 0.1Mbit/s and 20dBm respectively. The EE for the proposed algorithm, NOMA-SLBM and also for OMA grows with the
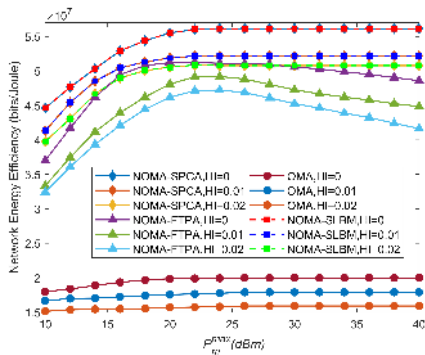
FIGURE 3. Network energy efficiency versus different P_m^{max} values.

increase of P_m^{max} and converges in a certain level. This means the increasing of P_m^{max} would not help in increasing the EE. For NOMA-FTPA, the EE increases with increasing of P_m^{max}, then this increment turns into decrement after specific level. It's noteworthy that the performance is impacted by the HIs level especially in the case of NOMA-FTPA and this impact is more obvious for higher values of P_m^{max}.
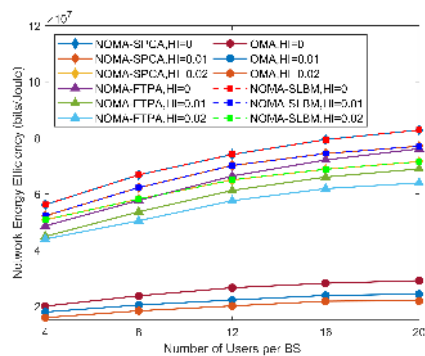

FIGURE 4. Network energy efficiency for different number of users per BS.

In Fig. 4, we evaluate the performance of the proposed method with the number of users per BS varies from 2 to 20. Obviously, the network EE rises with the number of users. The growth of EE becomes slower with a higher number of users due to the insufficiency of the allocated power to increase the EE for all users. For performance comparison, the proposed NOMA-SPCA scheme has comparable performance with NOMA-SLBM scheme, however when the number of users per BS equals 20, the EE of the proposed algorithm is 7.7% and 10.6% higher than NOMA-FTPA for HIs levels of 0, and 0.02, respectively. When comparing the performance with OMA, the number of users per BS is set to 20. The proposed method has 47% and 51% better performance than OMA for 0 HIs level and HIs level of 0.02.

The performance of the network EE for different values of circuit power p_c is shown in Fig. 5. The number of BSs is set to 7 with 4 users for per BS. The EE decreases with increasing of p_c. The proposed NOMA-SPCA scheme is achieving a comparable performance to that of the NOMA-SLBM scheme. For HIs level of 0.01, the performance of the proposed method is 24.9% better than NOMA-FTPA and 68.9% better OMA when p_c=27 dBm.
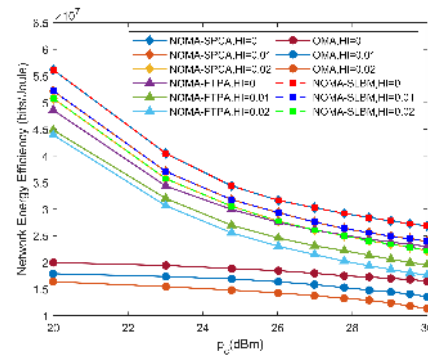

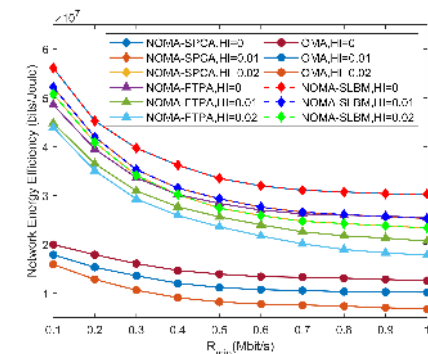**FIGURE 5.** Network energy efficiency versus p_c.

FIGURE 6. Network energy efficiency versus R_{min}.

Fig. 6 shows the performance of the network EE for different values of QoS constraints R_{min}. As R_{min} increases, the EE of the network decreases due to the growth of power consumption to meet the minimum rate requirements. While the EE of OMA tends to be static with the increasing of R_{min}, yet the proposed method still outperforms NOMA-FTPA and OMA and maintaining a performance comparable to that of the NOMA-SLBM scheme.

VI. CONCLUSION

In this paper, we studied EE maximization in MCMC-NOMA networks with HIs. We formulated our optimization problem and decoupled it into two subproblems. We adopted a metaheuristic algorithm, namely binary whale optimization algorithm (BWOA) to tackle user-BS association and subchannel assignment. For the power allocation subproblem, we utilized the SPCA method to approximate our original problem into a sequence of approximate problems that can be solved in parallel and exhibit closed-form solutions. The proposed scheme has shown efficiency in handling EE maximization and has surpassed the conventional OMA as well as NOMA-FTPA. In spite of that the proposed SPCA scheme has demonstrated a comparable performance to that of the NOMA-SLBM scheme, though SPCA scheme is advantageous due to the parallelization when solving the problem. Subsequent research on MIMO-NOMA network will be considered in which we shall try to prove the feasibility and efficiency of the proposed framework in such a scenario.

$$\frac{\partial r_{m,i,n}\left(p_{m,i,n};\mathrm{p}_{m,-i,n}^{(t)}\right)}{\partial p_{m,i,n}} = \frac{(1+c_1)\left(p_{m,i,n}+c_2\right)-(1+c_1)\,p_{m,i,n}+c_2}{\left((1+c_1)\,p_{m,i,n}+c_2\right)\left(p_{m,i,n}+c_2\right)} \tag{45}$$

$$\frac{\partial^2 r_{m,i,n}\left(p_{m,i,n};\mathrm{p}_{m,-i,n}^{(t)}\right)}{\partial p_{m,i,n}^2} = -\frac{2c_1 c_2 p_{m,i,n}\left(1+c_1\right)+\left(c_1^2+2c_1\right)c_2^2}{\left((1+c_1)\,p_{m,i,n}+c_2\right)\left(p_{m,i,n}+c_2\right)^2} \tag{46}$$

$$
\begin{aligned}
\nabla_{p_{m,i,n}} \tilde{f}\left(\mathrm{p};\mathrm{p}^{(t)}\right)\Big|_{\mathrm{p}=\mathrm{p}^{(t)}} &= \nabla_{p_{m,i,n}} \left(\frac{\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}} \tilde{r}_{m,i,n}\left(p_{m,i,n};\mathrm{p}^{(t)}\right)}{\sum_{m=1}^{M}\sum_{j=1}^{N_{ue}}\sum_{n=1}^{N_{sc}} p_{m,i,n}+p_c} \right) \\
&= \left(\frac{\left(\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\left(\nabla_{p_{m,i,n}}\left(\sum_{j=1}^{N_{ue}} r_{m,j,n}\left(\mathrm{p}^{(t)}\right)\right)\left(\sum_{j=1}^{N_{ue}}\mathrm{p}_{m,j,n}^{(t)}+p_c\right)\right)\right)-\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\left(\sum_{j=1}^{N_{ue}} r_{m,j,n}\left(\mathrm{p}^{(t)}\right)\right)}{\left(\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\left(\left(\sum_{j=1}^{N_{ue}}\mathrm{p}_{m,j,n}^{(t)}+p_c\right)\right)\right)^2} \right) \\
&= \nabla_{p_{m,i,n}} \left(\frac{\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\left(\sum_{j=1}^{N_{ue}} r_{m,j,n}(\mathrm{p})\right)}{\sum_{m=1}^{M}\sum_{i=1}^{N_{ue}}\sum_{n=1}^{N_{sc}}\left(\sum_{j=1}^{N_{ue}}\mathrm{p}_{m,j,n}^{(t)}+p_c\right)} \right)\Bigg|_{\mathrm{p}=\mathrm{p}^{(t)}}
\end{aligned}
\tag{47}
$$

APPENDIX A

Following similar steps as [49]. Considering the function $r_{m,i,n}\left(p_{m,i,n};\mathrm{p}_{m,-i,n}^{(t)}\right)$, for sake of simplicity, let $c_1 \triangleq |h_{m,i,n}|^2 / \phi_{m,i}^2 > 0$ and $c_2 \triangleq \left(\sigma^2 + I_{m,i,n}\right)/\phi_{m,i}^2 > 0$. Taking the first and the second derivatives with respect to $p_{m,i,n}$ as in (45) and (46) as on the top of page 10. Obviously $r_{m,i,n}\left(p_{m,i,n};\mathrm{p}_{m,-i,n}^{(t)}\right)$ is concave in $p_{m,i,n}$ because $\frac{\partial^2 r_{m,i,n}\left(p_{m,i,n};\mathrm{p}_{m,-i,n}^{(t)}\right)}{\partial p_{m,i,n}^2}$ for any $p_{m,i,n} \geq 0$.

APPENDIX B

To verify the third condition, we take the gradient of the approximate function $\tilde{f}\left(\mathrm{p};\mathrm{p}^{(t)}\right)$ and the original function $f(t)$ and show they are identical at $p_{m,i,n} = p_{m,i,n}^{(t)}$ (see (47)) on top of page 10. Where, putting into consideration that $\nabla_{p_{m,i,n}} \tilde{r}_{m,i,n}\left(\mathrm{p}^{(t)}\right) = \nabla_{p_{m,i,n}}\left(\sum_{j=1}^{N_{ue}} r_{m,j,n}\left(\mathrm{p}^{(t)}\right)\right)$ and $\tilde{r}_{m,i,n}\left(\mathrm{p}^{(t)}\right) = r_{m,i,n}\left(\mathrm{p}^{(t)}\right)$.

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