Energy Efficient Resource Management in SWIPT Enabled Heterogeneous Networks with NOMA

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Abstract—Non-orthogonal multiple access (NOMA) in heterogeneous network (HetNet) is a very promising scheme to meet the exponential growth of mobile data in the next years. However, since wireless networks are becoming more and more dense, the energy consumption problem becomes increasingly severe. Therefore, it is necessary to design novel energy efficiency (EE) maximization technologies under the constraint of limited energy supply. This paper investigates the resource optimization problem of NOMA heterogeneous small cell networks with simultaneous wireless information and power transfer (SWIPT). By decoupling subchannel allocation and power control, a low-complexity subchannel matching algorithm is designed. Furthermore, to maximize the energy efficiency, a power optimization algorithm is proposed using the Lagrange dual theory. Aiming at the power allocation problem, the original non-convex and non-linear energy efficiency optimization problem is transformed into a standard one. Simulation results demonstrate the effectiveness and convergence of the proposed optimization scheme in terms of system energy efficiency.

Index Terms—Energy efficiency, energy harvesting, HetNets, resource allocation, NOMA.

I. INTRODUCTION

The widespread adoption of mobile devices has led to an enormous increase in data traffic and number of mobile users. However, due to the limited resources of wireless networks, it is difficult to meet the huge service requirements of massive users. Therefore, the concept of heterogeneous small cell networks is one of the major objectives in the design of future wireless networks. Compared to traditional cellular networks, they increase the system spectral efficiency (SE) by adding small cells in the macro cell area [1]. The macro cell can guarantee the coverage of the HetNets, while small cells can improve their throughput [2]. Small base stations (SBSs), which are convenient to deploy, can well fit to the different service requirements [3]. In a HetNet environment, where multiple types of wireless nodes coexist, users choose to access the appropriate network in order to improve the quality of service (QoS) [4]. However, the coexistence of various types of networks will cause serious interference, while a large number of SBSs and users will also increase the energy consumption [5].

In a HetNet, the transmission power of SBS is generally small, which makes the users to be highly susceptible to interference [6]. Considering that some SBSs can be used for a specific period of time (such as workdays), these BSs are still in operation out of these time periods, which consumes unnecessary energy [7]. According to [8], most of the energy in the wireless network is consumed by the BSs. Therefore, reducing interference and improving energy efficiency are very important aspects for HetNets.

In order to improve the network energy efficiency, several emerging technologies and effective resource allocation schemes have been proposed. Taking into account environmental and financial factors, the authors in [9] explored the characteristics of energy-saving design by distributing backhaul bandwidth resources in HetNets. Furthermore, the BS sleep mode was proposed in [10], where partial spectrum reuse was applied to increase the coverage of HetNets and improve network EE. In [11], the EE and content caching in heterogeneous networks were studied, by using the concept of maximum distance separable in order to code to achieve the trade-off between backhaul rate and energy consumption.

For jointly maximizing SE and EE, the authors in [12] proposed the inter-layer frequency division multiplexing and adopted the proportional fair resource allocation in order to ensure fairness among the users. Furthermore, non-orthogonal multiple access technology (NOMA) enabled multi-user multiplexing on the power domain [13], that is, one channel can be occupied by multiple users simultaneously, thereby improving the network EE [14]. In order to separate the users on the same channel, NOMA used successive interference cancelation (SIC) at the receiver, where the signals were ranked according to the power or channel gain [15]. Existing research was show that adopting NOMA in HetNets can optimize the network performance [16]. By exploiting the non-cooperative game theory, the authors in [17] proposed a low complexity channel allocation algorithm and transformed the power allocation problem into a convex one, while it was proved that NOMA provided higher EE. In [18], the authors analysed the coverage and throughput for cooperative and non-cooperative schemes and proposed non-cooperative coordinated joint transmission NOMA, which can improve...
coverage and throughput in HetNets.

In order to achieve the efficient utilization of energy resources and simultaneously to ensure the QoS, we use simultaneous wireless information and power transfer (SWIPT) in NOMA based HetNets. SWIPT is a technique which can decrease the energy cost of wireless networks and significantly reduce the network energy expenditure, through energy harvesting [19], [20]. In [21], the authors considered the application of energy harvesting in HetNets with imperfect channel state information. Then, they introduced a non-cooperative game to optimize the resource allocation problem. In [22], the authors combined SWIPT with multi-hop wireless transmission by proposing an energy-aware routing algorithm, which could effectively utilize the resources and reduce energy consumption. Finally, a resource allocation scheme for Device-to-Device communication networks with energy harvesting was proposed in [23] and an algorithm that could optimize the average link energy efficiency was designed, through Dinkelbach and Lagrange dual methods. However, to the best of the author’s knowledge, the subchannel allocation and power optimization with consideration of cross-tier interference mitigation and system EE, have not been investigated in SWIPT enabled NOMA heterogeneous networks. Therefore, in this paper, we investigate the resource allocation in NOMA based HetNets, by considering energy harvesting and taking into account the cross-tier interference from the SBSs to the macro base station (MBS). In order to solve this problem, we use the Lagrangian dual decomposition theory and derive a closed-form expression for the user power allocation. Then, an iterative method is utilized to optimize the system EE, and a distributed subchannel matching and power optimization algorithm is proposed. Specifically, in this paper, we extend the system modeling and resource optimization presented in [24] and analyze the complexity of the optimization algorithm. Finally, we provide a detailed complexity analysis and more simulation results.

The main contributions of this paper can be summarized as follow:

- We formulate the energy efficient optimization problem for a NOMA based HetNets with energy harvesting. Because of the limited available energy at the BS nodes, we consider the use of energy harvesting from the environment. At the same time, we consider the factors which affect the system EE, including QoS requirements, maximum power constraints, and cross-tier interference. Moreover, an EE maximization framework with multiple constraints is proposed.
- A low-complexity distributed subchannel and power allocation scheme is designed for energy efficiency maximization. Considering that the initial energy efficiency optimization problem is non-convex and non-linear, an approximate convex transformation is introduced, which can convert the objective function into an equivalent subgradient form. The subchannel matching problem and the power allocation problem are separately optimized, thereby reducing the computational complexity.
- We propose a HetNet energy-efficient optimization algorithm with quick convergence. According to the quality of the channel condition and Lagrangian dual decomposition theory, the subchannel and power allocation are optimized. Then, an iterative method is used to update the energy efficiency. The energy efficiency can converge through several iterations. Finally, the simulation results verify the convergence of the proposed algorithm.

The rest of this paper is organized as follows: The model of NOMA HetNets with energy harvesting and the problem of energy efficiency optimization are presented in Section II. In Section III, the algorithm for subchannel allocation and energy optimization is provided, while in Section IV, an iterative energy optimization algorithm is proposed and its complexity is analyzed. Section V shows the simulation results of the proposed algorithms, and this paper is summarized in Section VI.

The following notation is adopted in the rest of the paper. Let lowercase bold font and uppercase bold font denote vectors and matrices, respectively. |·| denotes the absolute value of a complex-valued scalar. (·)\(\ast\) denotes the value of the variable under the \(z\)-th iteration, where \(\cdot\)\(\ast\) denotes the optimal solution of the variable.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Next, we formulate the energy efficiency optimization problem for a NOMA based HetNet with energy harvesting. The system model is shown in Fig. 1.

A single macro cell including one MBS and \(J\) SBSs is considered. We assume that each terminal is equipped with hardware facilities capable of energy harvesting. The BSs including MBS and SBSs are denoted as \(b \in \{1, 2, \cdots, B + 1\}\), where the \((B + 1)\)th BS is MBS. The \(U_b \in \{U_{1, b}, U_{2, b}, \cdots, U_{B+1, b}\}\) is the user’s number of the BS \(b\) and the system bandwidth is \(BW\), divided into \(S\) subchannels equally, and expressed as \(s \in \{1, 2, \cdots, S\}\), and the subchannel bandwidth is \(BW_s = BW/S\). Let \(h_{b, r, u, s}\) denote the channel gain of user \(u\) of BS \(b\) to BS \(r\) on subchannel \(s\), where \(u \in \{1, 2, \cdots, U_b\}\). We denote \(M_{b, u, s}\) to be an exponent to the subchannel allocation. If the user \(u\) of the channel condition and Lagrangian dual decomposition theory, the subchannel and power allocation are optimized. Then, an iterative method is used to update the energy efficiency. The energy efficiency can converge through several iterations. Finally, the simulation results verify the convergence of the proposed algorithm.

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is allocated to the BS $b$ on the subchannel $s$, then $m_{b,u,s} = 1$, otherwise, $m_{b,u,s} = 0$. Denote $p_{b,u,s}$ the transmission power of user $u$ of BS $b$ on subchannel $s$. The set of subchannnels and power allocations are represented by $M = \{m_{b,u,s}\}$ and $P = \{p_{b,u,s}\}$, respectively. According to Shannon formula the rate of user $u$ of BS $b$ on subchannel $s$ is given by:

$$r_{b,u,s} = B_s \log_2 (1 + SINR_{b,u,s}), \quad (1)$$

where $SINR_{b,u,s}$ denotes the signal-to-interference-plus-noise ratio (SINR) of user $u$ on subchannel $s$ of BS $b$.

NOMA can assign a subchannel to multiple users. It performs decoding at the receiver through SIC, which can reduce interference in a certain order according to the power or channel gain of different users [25]. In this paper, we assume that there are at most two users assigned to each subchannel of the BS. The user signal with higher channel gain is first decoded on the same subchannel. Therefore, the received SINR of user $u$ on subchannel $s$ of BS $b$ can be modeled as:

$$SINR_{b,u,s} = \frac{m_{b,u,s}p_{b,u,s}|h_{b,b,u,s}|^2}{\sum_{v=\{u+1\}} \sum_{v=1} U_v \sum_{r=1, r\neq b} R_{r,s} |h_{b,r,u,s}|^2 + \sigma^2}, \quad (2)$$

where $\sigma^2$ represents the additive white Gaussian noise (AWGN) and $p_{r,s} = \sum_{v=1} U_v m_{r,v,s}p_{r,v,s}$ is the total power of the BS $r$ on the subchannel $s$.

### B. Problem Formulation

With the aim of reducing the system energy consumption, this paper aims to maximize the system EE. While allocating the subchannel and power resource, we also consider the user equipment with the energy harvesting unit [26]. Under this assumption the sum rate is given by:

$$R(M, P) = \sum_{b=1}^{B+1} \sum_{u=1}^{U} \sum_{s=1}^{S} r_{b,u,s}. \quad (3)$$

The total transmit power of the system can be formulated as:

$$Q(M, P) = \sum_{b=1}^{B+1} \sum_{u=1}^{U} \sum_{s=1}^{S} m_{b,u,s}p_{b,u,s}. \quad (4)$$

The energy harvesting module on wireless devices can convert radio signals in the environment into energy signals. Therefore we assume that each user equipment can collect energy from subchannels of other BSs. According to [27], the energy harvested by user $u$ of BS $k$ on subchannel $n$ can be modeled as:

$$H_{b,u,s} = \sum_{r=1, r\neq b}^{B+1} \lambda_{r,s} m_{b,u,s}p_{b,u,s}|h_{b,r,u,s}|^2, \quad (5)$$

where $\lambda_{r,s}$ represents a constant parameter of energy harvesting efficiency.

Then, the total energy harvested by system can be denoted by

$$H(M, P) = \sum_{b=1}^{B+1} \sum_{u=1}^{U} \sum_{s=1}^{S} \sum_{r=1, r\neq b}^{B+1} \lambda_{r,s} m_{b,u,s}p_{b,u,s}|h_{b,r,u,s}|^2. \quad (6)$$

We note that the circuit power consumption of the BS is relatively small compared to the total harvested energy [19], so the total power consumption can be expressed as:

$$U(M, P) = Q(M, P) - H(M, P) = \sum_{b=1}^{B+1} \sum_{u=1}^{U} \sum_{s=1}^{S} m_{b,u,s}p_{b,u,s}(1 - \sum_{r=1, r\neq b}^{B+1} \lambda_{r,s}|h_{b,r,u,s}|^2). \quad (7)$$

The total system energy efficiency is given by

$$EE(M, P) = \frac{R(M, P)}{Q(M, P) - H(M, P)} = \frac{R(M, P)}{U(M, P)}. \quad (8)$$

The factors which affect the EE in NOMA based HetNets are also considered, including QoS requirements, maximum power constraints and cross-tier interference. In order to ensure a good experience for users in HetNets and maximizing the system EE, the optimization problem is subject to the following constraints:

- **Transmit power constraint:** The summation of the powers of all users on BSs must not exceed the maximum transmission power of this BS and the power value of each user cannot be a negative number. Therefore, the power constraint can be expressed as:

$$\sum_{u=1}^{U} \sum_{s=1}^{S} m_{b,u,s}p_{b,u,s} \leq P_{b,\text{max}}, \quad \forall b \quad (9)$$

$$p_{b,u,s} \geq 0, \quad \forall b, u, s, \quad (10)$$

where $P_{b,\text{max}}$ indicates the maximum transmission power of BS $b$. Power constraints ensure that user power is non-negative and not exceed the BS power.

- **Constraint on each subchannel:** A simple case is considered in which at most two users can be multiplexed on each subchannel of the BS. Under this assumption the error propagation and the complexity of the receiver can be limited [28]. Therefore, the user number constraint can be expressed as:

$$m_{b,u,s} \in \{0, 1\}, \quad \forall b, u, s \quad (11)$$

$$\sum_{u=1}^{U} \sum_{s=1}^{S} m_{b,u,s} \leq 2, \quad \forall b, s. \quad (12)$$

- **Heterogeneous QoS requirements:** For maintaining the communication system performance, we can express the QoS constraint as:

$$\sum_{u=1}^{U} \sum_{s=1}^{S} m_{b,u,s}r_{b,u,s} \geq R_{b,\text{min}}, \quad \forall b, \quad (13)$$

where $R_{b,\text{min}}$ denotes the minimal transmission rate requirement of each BS $b$.

- **Cross-tier interference constraint:** According to different traffic load conditions in HetNets, cross-layer interference constraints can dynamically coordinate interference to
improve system EE. Thus, cross-layer interference constraints can be formulated as:
\[
\sum_{b} \sum_{u=1}^{U_b} \sum_{s=1}^{S_b} m_{b,u,s} p_{b,u,s} |h_{b,B+1,s}|^2 \leq I_{\text{max}},
\]
(14)
where \( |h_{b,B+1,s}|^2 \) is the user’s gain from SBS to MBS on subchannel \( s \); and \( I_{\text{max}} \) is the maximal interference constraint.

To achieve the system EE maximization, subchannel matching and power are optimized in this paper. Thus, the corresponding EE optimization problem can be modeled as:
\[
\max_{M,P} EE(M,P) = \frac{\hat{R}(M,P)}{U(M,P)}
\]
(15)
\[
\text{s.t. } C1: \sum_{u=1}^{U_b} \sum_{s=1}^{S_b} m_{b,u,s} p_{b,u,s} \leq P_{b,\text{max}}, \quad \forall b
\]
\[
C2: p_{b,u,s} \geq 0, \quad \forall b, u, s
\]
\[
C3: m_{b,u,s} \in \{0,1\}, \quad \forall b, u, s
\]
\[
C4: \sum_{u=1}^{U_b} m_{b,u,s} \leq 2, \quad \forall b, s
\]
\[
C5: \sum_{s=1}^{S_b} m_{b,u,s} r_{b,s} \geq R_{b,\text{min}}, \quad \forall b
\]
\[
C6: \sum_{b=1}^{B} \sum_{u=1}^{U_b} \sum_{s=1}^{S_b} M_{b,u,s} p_{b,u,s} |h_{b,B+1,s}|^2 \leq I_{\text{max}}.
\]
(16)

III. ENERGY-EFFICIENT RESOURCE ALLOCATION
Since the optimization problem in (15) is non-convex and the objective function is in fraction form, we use the inequality to approximate the convex transformation and to express the lower bound of the user data rate. According to [29], for any \( SINR_{b,u,s} \geq 0 \), we can get the following inequality:
\[
\alpha_{b,u,s} \log_2 (SINR_{b,u,s}) + \beta_{b,u,s} \leq \log_2 (1+\text{SINR}_{b,u,s}).
\]
(17)
The bound can be tight when
\[
\alpha_{b,u,s} = \frac{\text{SINR}_{b,u,s}}{\text{SINR}_{b,u,s} + 1}
\]
(18)
and
\[
\beta_{b,u,s} = \log_2 (1+\text{SINR}_{b,u,s}) - \frac{\text{SINR}_{b,u,s}}{1+\text{SINR}_{b,u,s}} \log_2 (\text{SINR}_{b,u,s})
\]
(19)
where \( \text{SINR}_{b,u,s} \) is the value of the last iteration of SINR. Due to the above inequality we can write the lower bound of the user’s rate as:
\[
\tilde{r}_{b,u,s} = B_{sc} \alpha_{b,u,s} \log_2 (\text{SINR}_{b,u,s}) + \beta_{b,u,s}.
\]
(20)
Therefore, the objective function (15) with constraints (16) can be written as:
\[
\max_{M,P} EE(M,P) = \max_{M,P} \frac{\hat{R}(M,P)}{U(M,P)}
\]
(21)
\[
\text{s.t. } C5': \sum_{u=1}^{U_b} \sum_{s=1}^{S_b} m_{b,u,s} \tilde{r}_{b,u,s} \geq R_{b,\text{min}}, \quad \forall b
\]
(22)
\[
C1-\text{C4}, C6.
\]
Since the objective function is a non-linear fraction, we transform the fractions into subtractions to decrease the computation complexity [30]. Here, a variable \( t \) that represents the energy efficiency need to be introduced.

We define
\[
t^* = \max_{M,P} \frac{\hat{R}(M,P)}{U(M,P)} = \frac{\hat{R}(M^*, P^*)}{U(M^*, P^*)},
\]
(23)
therefore
\[
\hat{R}(M^*, P^*) - t^* U(M^*, P^*) = 0.
\]
(24)
Objective function (21) with its constraints is rewritten as
\[
\max_{M,P} \hat{R}(M,P) - t U(M,P)
\]
(25)
\[
\text{s.t. } C1-C4, C5', C6.
\]

A. Energy-Efficient Subchannel Matching
In this subsection, we first associate users on BSs and subchannels. Referring to [28], by using DC programming and two-sided matching approach, a simpler and efficient subchannel matching algorithm is designed to determine matrix \( S \). Two main processes are included in this algorithm. First, the user is assigned to the subchannel according to the quality of the channel condition. In other words, the user who has the best channel state is assigned to the corresponding subchannel. Secondly, two users who can maximize the EE of the channel are selected. Then we can get the subchannel allocation scheme for each BS. Because the optimal subchannel allocation scheme, i.e. exhaustive method, needs to search all possible combinations of users, and select the user combinations from them to maximize the energy efficiency of the system, which greatly increases the complexity. The proposed subchannel allocation algorithm is suboptimal. However, compared with the optimal subchannel allocation scheme, the proposed subchannel allocation algorithm is simpler and can solve the subchannel allocation problem faster.

Let \( Z_0(s) \) denotes the set of users that are assigned to subchannel \( s \) on BS \( b \) and \( Z_0 \) is the set of users that are not assigned subchannels on the BS \( b \). The energy efficiency on BS \( b \) subchannel \( s \) can be written as:
\[
EE_{b,s} = \frac{1}{U_b} \sum_{u=1}^{U_b} \sum_{r=1}^{R_b} \sum_{n=1}^{N_b} \lambda_{j,n} m_{b,u,s} p_{b,u,s} |h_{b,r,u,s}|^2.
\]
(26)
The main idea of the subchannel matching algorithm is that each user sends the matching request to its optimal subchannel according to the channel state information. The subchannel also accepts or rejects users according to the energy efficiency of different users on the subchannel. For example, there are four users and two subchannels. \( |h_{u,n}|^2 \) represents the gain of user \( u \) on subchannel \( n \). Assume that \( |h_{1,1}|^2 > |h_{1,2}|^2, |h_{2,1}|^2 > |h_{2,2}|^2, |h_{3,1}|^2 > |h_{3,2}|^2, |h_{4,1}|^2 < |h_{4,2}|^2 \), then user 1, 2 and 3 is allocated to subchannel 1 and user 4 is allocated to subchannel 2. However, we set up a subchannel to be occupied by two users at most, so we
need to select two users among user 1, 2 and 3 that can maximize the energy efficiency of the subchannel. And the remaining one will not consider the subchannel 1. Assuming that the combination of user 1 and 2 on subchannel 1 yields higher energy efficiency than user combination 1 and 3, user combination 2 and 3, then user 1 and 2 occupy subchannel 1, user 3 and user 4 occupy subchannel 2. The matching process will terminate until no user needs to match.

At first, all users belong in the set $Z_b$. Then we assign users to subchannels until set $Z_b$ becomes empty. Therefore, when $|Z_b(s)| < 2$, according to the gain between users and subchannels on BS $b$, the user who has the greatest gain is allocated to the corresponding subchannels; when $|Z_b(s)| = 2$, the third user is assigned to the subchannel $s$, and then two of the users with the greatest energy efficiency on the subchannel $s$ are found and removed from set $Z_b$. Then, the subchannel allocation matrix is updated. The steps of the specific subchannel matching are summarized in Algorithm 1.

Algorithm 1 Subchannel Allocation Algorithm

1: Initialize the set of subchannel allocation $M$ and the set of power allocation $P$.
2: for $b = 1$ to $B + 1$ do
3:   Initialize the set of users $Z_b(s)$ which are assigned to subchannel $s$, and the set of users $Z_b(b)$ which are not assigned;
4:   while $Z_b(s) ≠ \phi$ do
5:     for $u = 1$ to $U_b$ do
6:       find $s^*$ satisfies $|h_b,b,u,s^*|^2 ≥ |h_b,b,u,s|^2$;
7:       if $|Z_b(s^*)| < 2$ then
8:         user $u$ is assigned to subchannel $s$, and removed from set $Z_b$,
9:         $m_{b,u,s} = 1$;
10:     end if
11:     if $|Z_b(s^*)| = 2$ then
12:       subchannel $s^*$ selects the two users which can make $EE_{h_b,s^*}$ largest, and rejects the others. This two users are removed from the set $Z_b$, and the subchannel allocation indexes of them are set to one; the user that not be allocated to the subchannels $s^*$ is put in the set $Z_b$, and the subchannel allocation index of this user is set to zero.
13:     end if
14:   end while
15: end for

B. Energy-Efficient Power Optimization

Since the subchannel allocation has already been obtained in the previous section, $m_{b,u,s}$ can be regarded as a constant in the optimization problem, leaving only the variable $p_{b,u,s}$. Then, we can only consider power optimization of NOMA based HetNet system.

Let $\tilde{p}_{b,u,s} = m_{b,u,s}p_{b,u,s}$. Then, the optimization problem in (25) can be written as:

$$\max_{\tilde{P}, P_0 > 0} \tilde{R}(\tilde{P}) - tU(\tilde{P})$$ (27)

s.t. $C1: \sum_{u=1}^{U_b} \sum_{s=1}^{S} \tilde{p}_{b,u,s} \leq P_{b,\text{max}}, \forall b$

$C2: \sum_{u=1}^{U_b} \sum_{s=1}^{S} \tilde{p}_{b,u,s} \geq \tilde{R}_{b,\text{min}}, \forall b$

$C3: \sum_{b=1}^{B} \sum_{u=1}^{U_b} \sum_{s=1}^{S} |\tilde{p}_{b,u,s}|h_{b,B+1,s}^2 \leq I_{\text{max}}$.

The objective and SINR functions can be rewritten as:

$$\tilde{R}(\tilde{P}) - tU(\tilde{P}) = \sum_{b=1}^{B+1} \sum_{u=1}^{U_b} \sum_{s=1}^{S} \tilde{r}_{b,u,s} \left(1 - \sum_{r=1}^{B+1} \sum_{b',r \neq b} \lambda_{r,s} h_{b',r,u,s}^2 \tilde{p}_{b',u,s}\right)$$ (29)

$$\tilde{SINR}_{b,u,s} = \frac{|\tilde{p}_{b,u,s}|h_{b,b,u,s}^2}{\sum_{v=1}^{U_b} \sum_{s=1}^{S} \tilde{p}_{v,u,s} + \sum_{r=1}^{B+1} \sum_{b',r \neq b} \tilde{p}_{r,s} |h_{b',r,u,s}|^2 + \sigma^2}$$ (30)

where $\tilde{p}_{r,s} = \sum_{u=1}^{U_b} \tilde{p}_{r,u,v}$.

Through the transformation of the optimization problem mentioned above, we notice that this becomes convex with linear constraints. Therefore, to solve it, we use the Lagrangian dual method.

The Lagrangian function is represented by

$$L(\tilde{P}, \mu, \nu, \xi) = \sum_{b=1}^{B+1} \sum_{s=1}^{S} \left[\tilde{r}_{b,u,s} - t(1 - \sum_{r=1}^{B+1} \sum_{b',r \neq b} \lambda_{r,s} h_{b',r,u,s}^2) \tilde{p}_{b,u,s}\right]$$

$$+ \sum_{b=1}^{B+1} \mu_b \left(P_{b,\text{max}} - \sum_{u=1}^{U_b} \sum_{s=1}^{S} \tilde{p}_{b,u,s}\right)$$

$$+ \sum_{b=1}^{B+1} \nu_b \left(U_b - \sum_{u=1}^{U_b} \sum_{s=1}^{S} \tilde{r}_{b,u,s} - \tilde{R}_{b,\text{min}}\right)$$

$$+ \xi \left(I_{\text{max}} - \sum_{b=1}^{B} \sum_{u=1}^{U_b} \sum_{s=1}^{S} |\tilde{p}_{b,u,s}|h_{b,B+1,s}^2\right),$$ (31)

where $\mu = [\mu_1, \mu_2, \ldots, \mu_{B+1}], \nu = [\nu_1, \nu_2, \ldots, \nu_{B+1}]$ and $\xi$ are the Lagrange multiplier for the function, which correspond to $C1$, $C2$, and $C3$ in constraint (28), respectively.

Therefore, dual function is denoted by

$$D(\mu, \nu, \xi) = \max_{\tilde{P}, P_0 > 0} L(\tilde{P}, \mu, \nu, \xi).$$ (32)

The dual problem is given as:

$$\min_{\mu, \nu, \xi} D(\mu, \nu, \xi).$$ (33)

When the Lagrange multiplier and energy efficiency parameter $t$ are fixed, we can notice that the optimization problem is a standard maximization problem. Thus, the power allocation
can be obtained by partial derivatives of the e.q. (31) for \( \hat{p}_{b,u,s} \).

Therefore, we can have

\[
\frac{\partial L(\hat{p}, \mu, \nu, \xi)}{\partial \hat{p}_{b,u,s}} = \frac{B_w \alpha_{b,u,s}(1 + \nu_b)}{\hat{p}_{b,u,s} \ln 2} - \frac{1}{\sum_{r=1}^{B} \sum_{s \neq b} B_w \alpha_{r,v,s} \ln 2} \left( \sum_{r=1}^{B} \sum_{s \neq b} \frac{B_w \alpha_{r,v,s}}{\hat{p}_{r,v,s} \ln 2} \right) 
\]

\[
\ln 2 \left( - \frac{1}{\sum_{r=1}^{B} \sum_{s \neq b} B_w \alpha_{r,v,s} \ln 2} \right) \left( \sum_{s=1}^{S} f(\hat{p}_{b,u,s}) + \sum_{r=1}^{B} \sum_{s \neq b} \frac{B_w \alpha_{r,v,s}}{\hat{p}_{r,v,s} \ln 2} \right) \right) \right] 
\]

\[
\sum_{s=1}^{S} \left( \frac{B_w \alpha_{b,u,s}}{\hat{p}_{b,u,s} \ln 2} \right) \right) \right] 
\]

where \( f(\hat{p}_{b,u,s}) = \frac{B_w \alpha_{b,u,s}(1 + \nu_b)}{\hat{p}_{b,u,s} \ln 2} \).

After getting the power allocation scheme, we can use the subgradient method to update the multiplier. The updated Lagrange multiplier can be written as

\[
\mu_b (l + 1) = \mu_b (l) - \delta_1 (l) \left( \frac{B_w \alpha_{b,u,s}}{\sum_{s=1}^{S} \sum_{u=1}^{U} \hat{p}_{b,u,s} (l)} \right), \tag{36}
\]

\[
\nu_b (l + 1) = \nu_b (l) - \delta_2 (l) \left( \sum_{s=1}^{S} \sum_{u=1}^{U} \hat{p}_{b,u,s} (l) - \frac{B_w \alpha_{b,u,s}}{\sum_{s=1}^{S} \sum_{u=1}^{U} \hat{p}_{b,u,s} (l)} \right), \tag{37}
\]

\[
\xi (l + 1) = \xi (l) - \delta_3 (l) \left( I_{\text{max}} - \frac{B_w \alpha_{b,u,s}}{\sum_{s=1}^{S} \sum_{u=1}^{U} \hat{p}_{b,u,s} (l)} \right) \right) 
\]

\[
\xi (l) - \delta_3 (l) \left( I_{\text{max}} - \frac{B_w \alpha_{b,u,s}}{\sum_{s=1}^{S} \sum_{u=1}^{U} \hat{p}_{b,u,s} (l)} \right) \right) 
\]

where \( I_{\text{max}} \) denotes the number of iterations and \( \delta_1 (l) \), \( \delta_2 (l) \) and \( \delta_3 (l) \) represent the step size of the \( l \)-th iteration. The process of power optimization is summed in Algorithm 2.

### IV. ALGORITHM DESIGN

Based on the transformation of the energy efficiency expression of the objective function and the solution of the power distribution matrix in the previous section, in this section we propose an iterative power optimization algorithm.

#### A. Iterative Power Optimization Algorithm

In objective function (25), we transform the optimization problem into an equivalent subtractive form by means of energy efficiency parameter \( t \). The optimal value of \( t \) is also equivalent to the optimal value of energy efficiency. The Lagrange dual method in the previous section is also based on the fixed parameter \( t \). Therefore, an iterative algorithm is proposed to solve \( t \).

**Algorithm 2 Iterative Power Optimization Algorithm**

1. Initialize the maximum number of iterations \( E_{\text{max}} \), set the number of iterations \( e = 0 \), energy efficiency \( l(0) \), and maximum tolerance \( \varepsilon \);
2. while \( |\hat{R}(P(e)) - tU(P(e))| > \varepsilon \) or \( e < E_{\text{max}} \) do
3. Initialize \( L_{\text{max}} \), set the number of iterations \( l = 0 \), and Lagrange multipliers \( \mu_b \), \( \nu_b \) and \( \xi \);
4. repeat
5. for \( b = 1 \) to \( B + 1 \) do
6. for \( u = 1 \) to \( U_b \) do
7. for \( s = 1 \) to \( S \) do
8. a) update \( \hat{p}_{b,u,s} \) using (35);
9. b) update \( \mu_b \) from (36);
10. c) update \( \nu_b \) from (37);
11. d) update \( \xi \) from (38);
12. end for
13. end for
14. end for
15. \( l = l + 1 \);
16. until Convergence or \( l = l_{\text{max}} \);
17. \( e = e + 1 \), \( l(e) = \frac{R(E(e))}{U(P(e))} \);
18. end while

Firstly, the maximum error tolerance and maximum iteration number are set up, and the energy efficiency parameter \( t \) is initialized. In each iteration, the Lagrangian dual theory is applied for solving the primary power allocation problem, and the total EE, i.e., the parameter \( t \), is calculated according to the updated power allocation matrix. The system EE gradually converges as the number of iterations increases. The specific steps of the iterative power optimization algorithm is summarized in Algorithm 2.

![Fig. 2. The flow chart of the proposed algorithm.](image-url)
problem is a complex non-convex non-linear optimization problem, we adopt approximate convex transformation and introduce energy efficiency parameters which transform the objective function into equivalent subtraction form. Then the subchannel allocation and power allocation are decoupled, and the sub-channel matching and power allocation are optimized respectively to reduce the computational complexity. Firstly, the subchannel allocation problem is solved by Algorithm 1. Secondly, in Algorithm 2, according to the subchannel allocation scheme, given the number of iterations and tolerance, the Lagrangian dual decomposition method is used to update the power in each iteration until the energy efficiency converges.

B. Complexity Analysis

In this section, we discuss the complexity of the subchannel matching and power optimization algorithm. Table 1 summarizes computational complexity and explains each symbol in computational complexity.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Terms</th>
<th>Computational Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm 1</td>
<td>Each BS performs subchannel allocation, where the number of BSs is $B+1$. Each user finds $s^*$ satisfying $</td>
<td>h_{b,b,u,s}</td>
</tr>
<tr>
<td>Algorithm 2</td>
<td>Calculating the power of each BS user on each subchannel requires $(B + 1)U_bS$ operations. $\Delta_1$ is the number of iterations when the EE converges. $\Delta_2$ is the number of iterations when Lagrange multipliers in each iteration of EE converges.</td>
<td>$O((B + 1)(U_bS \times \Delta_1\Delta_2))$.</td>
</tr>
</tbody>
</table>

V. SIMULATION RESULTS

We verify the proposed subchannel matching and power optimization algorithm in terms of EE by simulations. The MBS is located at the center of the macro cell. In the simulations, the macro cell radius is 500 meters. The total system bandwidth is 1 MHz, the carrier frequency is 2 GHz, and the number of subchannels is 10. The small cell is randomly allocated within the range of macro cell and the radius of small cell is 10 meters.

Fig. 3 shows the system EE when the iteration number for Algorithm 2 is from 0 to 20 with SWIPT and without SWIPT. In the Fig. 2, the maximum power of each SBS is 30 dBm, the number of SBSs is set to 10, and each small BS has 6 users. As shown in this figure, the system EE can converge in 8 iterations. The EE of the system with SWIPT is about $2.4 \times 10^7$ bps/Joule, while the EE of system without SWIPT is around $1.6 \times 10^7$ bps/Joule. The system with energy harvesting units can collect energy at the time of transmission, thus it can drastically reduce energy consumption. Compared to the case without SWIPT, the performance of the system can be improved by more than 1.5 times.

Fig. 4 illustrates the system EE when the users number per small cell is from 2 to 6 with different schemes. The maximum power of each SBS is 23 dBm and the number of SBSs is 10. From this figure, we can obtain that as the users number in small cell increases, the energy efficiency of system with SWIPT increases more pronounced, while the increasing in the energy efficiency of systems without SWIPT is relatively gradual. The reason for this phenomenon is that as
Fig. 4. Energy efficiency versus the number of users per small cell with different schemes.

As the number of users increases, SBSs will provide services to more users, and the energy harvesting unit on each user equipment greatly relieves the pressure of energy supply, which leads to the gap between the two system getting more and more obvious. In fact, the proposed subchannel allocation algorithm is a suboptimal scheme. The subchannel allocation and power control are solved separately. Therefore, the proposed resource allocation method in this paper is suboptimal. The optimal resource allocation method is greedy search (exhaustive search). In Fig. 4, we also compare the proposed algorithm with the greedy search based scheme. As can be seen from the figure, the performance of the greedy search based scheme is higher than that of the proposed scheme. But the gap is small. Although greedy search based scheme can achieve better energy efficiency, in fact, as the number of users increases, the time complexity is also growing rapidly. The proposed algorithm has lower complexity than the greedy search scheme.

Fig. 5 shows the system EE when the users number per small cell is from 4 to 20, for the number of small cells is 20, 30 and 50, respectively. The maximum power of each SBS is set to 23 dBm. When the number of SBSs and users on the SBSs goes up, the EE of the system increases correspondingly. When the number of SBS is 50, the EE is obviously higher than the case when the number of SBS is 20 and 30. The EE of 50 SBSs is about twice that of 30 SBSs and 2.5 times that of 20 SBSs. We can find that the more the number of SBSs and users, the better the performance of the system. That is, the proposed algorithm is more effective when the number of BSs and users is larger.

Fig. 6 shows the sum rate of the system when the users’ number per small cell is from 4 to 20, for the number of small cells is 20, 30 and 50, respectively. The maximum power of each SBS is set to 23 dBm. When the number of SBSs and users on the SBSs increases, the total system rate increases correspondingly, and the performance of the proposed EE optimization algorithm is better. When the number of SBSs is 50, the system sum rate is significantly higher than the case when the number of SBSs is 20 and 30. The total sum rate of 50 SBSs is 36% higher than that of 30 SBSs and 73% higher than that of 20 SBSs.

Fig. 7 shows the system EE when the number small cells is from 4 to 12 with different schemes.

Fig. 7 shows the system EE when the number small cells is from 4 to 12 with different schemes. The maximum power
of each SBS is 23 dBm, and the number of users on each SBS is 10. We compare our EE optimization scheme with random subchannel allocation scheme and OMA scheme. Random subchannel allocation refers to the user occupying the subchannel randomly without considering the channel state and other conditions. From Fig. 7, it is clear that the energy efficiency of the proposed subchannel matching scheme is significantly superior to that of the random subchannel allocation scheme and OMA scheme.

Fig. 8 demonstrates the EE of the proposed scheme and the fixed power scheme when the maximum power of each SBS is from 5 dBm to 30 dBm. In this figure, the number of SBSs is set to 10, and each small BS has 6 users. From Fig. 8, when the maximum power value of BS increases, the EE of the proposed scheme increases correspondingly, while the EE of the fixed power scheme decreases. The proposed scheme optimizes the power consumption, and the increase of energy consumption is not obvious as that of the fixed power scheme, so the effectiveness of the proposed scheme is more pronounced.

Fig. 9 describes the EE of the proposed scheme and the fixed power scheme when the number of users per small cell is from 2 to 10 with the maximum power of each SBS is 15 dBm and 25 dBm, respectively. In this figure, the number of SBSs is set to 10. And when there are only two or four users per small BS, the difference between the EE of our optimization scheme and that of the fixed power scheme is not large. When the number of BS users increases to 10, the system EE of the proposed scheme increases more obviously, and the gap with the fixed power scheme is widened. Therefore, the proposed scheme can achieve better EE when the number of BS users is large enough.

Fig. 10 describes the EE of the proposed scheme and the fixed power scheme when number of small cells is from 20 to 50 and the maximum power of each SBS is 15 dBm and 25 dBm, respectively. The users’ number of the small BS is set to 6. With the number of SBSs goes up, system EE improves more slowly. In the proposed scheme, the slope of the EE curve is larger, and larger, and the improvement of energy efficiency is more obvious. Even when the number of small base maximum BS power is 25 dBm, the EE of the proposed scheme is about $6.5 \times 10^8$ bps/Joule, while the EE of the fixed power scheme is about $1 \times 10^8$ bps/Joule.

VI. Conclusion

In this paper, the subchannel allocation and power optimization were investigated in NOMA based HetNets with the consideration of energy harvesting and cross-tier interference mitigation. Since the limited energy supply, an energy efficiency optimization problem with energy harvesting was proposed. Since the original objective function was non-convex with fractional form, we transformed it into an equivalent subtractive form. An efficient subchannel matching scheme based on the merits of channel conditions was proposed. Then, given the determined subchannel allocation, the power allocation was obtained through Algorithm 2 based on Lagrange dual method. The energy efficiency can be converged in several iterations. Finally, simulations results demonstrated the convergence and
effectiveness of the proposed algorithms in terms of energy efficiency. In future work, we will study more realistic energy harvesting model, i.e. non-linear energy harvesting model, and we will also consider more cases and techniques, such as Massive MIMO for multi-antenna situations.

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