A Cluster-Based Energy-Efficient Resource Management Scheme With QoS Requirement for Ultra-Dense Networks

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ABSTRACT
Ultra-dense networks (UDN) have been considered as one of the best ways to improve the network throughput and energy efficiency (EE). However, massive and unplanned deployment of small cells will cause severe intra-tier interference among small cells and then deteriorate the network EE. For this, a Cluster-based Energy-Efficient Resource Management (CEERM) scheme is proposed to mitigate the interference while guaranteeing the quality of service (QoS) of user equipments (UEs) in this paper. Firstly, we propose a cell clustering algorithm to divide small cells into disjoint cell clusters according to the target of minimizing intra-cluster interference. Finally, a two-step subchannel allocation and non-cooperative game based power allocation scheme is proposed to maximize the network EE. The simulation results show that the proposed scheme CEERM can effectively boost the network EE with low computation complexity.

INDEX TERMS
Ultra-dense networks (UDN), energy efficiency (EE), quality of service (QoS), cluster.

I. INTRODUCTION
Together with the rapid increase of mobile internet devices and applications, wireless traffic has encountered another explosive growth in the past few years, which motivates enhanced mobile broadband (eMBB) scenario in the fifth generation (5G) wireless networks. To meet the challenging design target for the eMBB scenario, spatial densification, including the centralized massive multiple input multiple output (M-MIMO) systems [1] and the distributed ultra dense networks (UDN) [2], [3] have been proposed in recent years. Although M-MIMO systems provide considerable benefits in terms of spectral efficiency (SE) and energy efficiency (EE), the associated deployment costs are usually high. UDN, by integrating a large number of low-power and low-cost small base stations (SBSs) in hot spots or coverage holes, is currently recognized as a promising technique to meet the eMBB throughput requirement and overcome the deployment drawbacks [1]–[3].

In general, with the coexistence of a large number of heterogeneous SBSs, the inter-cell interference is difficult to deal with due to the dynamic interference environment, which may severely degrade the network EE performance [4], [5]. In the latest research, the problem of mitigating interference is investigated to strike a balance between computational complexity and performance improvement [6]–[15]. For example, [6]–[10] focus on the centralized resource allocation to achieve the maximum energy efficiency gain, with the aid of convex optimization-based [6]–[8], graph-based [9], or even game-based [10] approaches. In order to extend the above energy-efficient approaches to UDN scenarios, one of the most challenging tasks is to perform the corresponding algorithms with a sustainable computational load. A straightforward approach often applied to UDN scenarios is grouping geographically-close SBSs into local clusters [11]–[15]. By this way, the resource allocation problems can be re-constructed hierarchically, i.e.
the centralized scheduler allocates resources to SBS clusters and then each SBS cluster coordinates resources usage within its cluster. To be more specific, [11] propose a heuristic semi-dynamic clustering method with low complexity, and for a given cluster, the cluster head manages subchannels and power within the cluster. A distance-based small cell clustering algorithm is investigated in [12], where the two small cells are classified into a cell cluster when the distance between them is smaller than or equals to the threshold. In [13], an affinity propagation power control (APPC) mechanism based clustering is employed to reduce the interference among the cells in the cluster by controlling the transmission power of the cluster center. In [14], the user clustering problem is expressed as correlation clustering and settled by using semidefinite programming method, in which the boolean variable is relaxed. Literature [15] applies a graph coloring algorithm to small cells clustering and resource allocation in UDN. To further improve the network SE, the clustering idea is also extended to the user equipment (UE) side to facilitate the frequency reuse. In [16], a joint user-centric overlapped clustering algorithm is proposed to minimize the total interference within each cluster. To support a more complicated network, particularly dense small-cell network scenarios, a joint UE and SBS clustering method is developed in [17]. In [18], a two-step resource blocks assignment algorithm based on the UE clustering and a power allocation algorithm based on the non-cooperative game are discussed to improve the system EE. [19] proposes a locally distributed scheme suitable for ultra-dense small cellular networks, and divided the initial optimization problem into four steps with reasonable computational complexity, including distributed clustering, subchannel allocation within a cluster, interference resolution between clusters, and power adjustment.

However, the above literature does not consider the fairness or the minimum data rate requirements (i.e., QoS requirements) of UEs. To guarantee the user experience, [20]–[30] further take the QoS requirement of UEs into account. Although QoS-aware algorithms based on convex-optimization are investigated to realize different targets, such as system capacity maximization [20], [21], EE maximization [22], the sum of transmits power for all BSs minimization [23], [24], and SE maximization [25], most of these algorithms are unsuitable for large scale UDN due to the high computational complexity. To better apply to UDN, [26] proposes an interference-separation clustering-based scheme to divide the massive small cells into smaller groups with different priorities, which reduces the network scale. A graph-based QoS-aware resource allocation (RA) scheme [27], [28] and a similarity UE clustering-based interference alignment scheme [29] are proposed to maximize the number of UEs while guaranteeing the QoS requirement of UEs. Moreover, the authors in [30] propose a non-cooperative game based joint base station (BS) association and power allocation (PA) scheme to optimize system throughput with satisfying the signal-to-interference-plus-noise ratio (SINR) requirements of all UEs.

In summary, most of the existing work either researches the EE optimization problem without constraining the QoS requirements of users [6]–[10], [18], [19], or tries to meet user’s QoS requirements with optimizing network performance rather than EE [20]–[30]. The following issues inevitably limit the extended application of the above research in complicated UDN scenarios. Firstly, the user fairness and transmission rate are rarely guaranteed during a scheduling period in the EE optimization problem. Secondly, how to achieve an effective balance between improving user quality of experience (QoE) and reducing energy consumption. Finally, the clustering algorithms generally suffer from the implementation complexity, either in terms of network scale or in terms of convergence rate.

To solve the above problems, our main contributions mainly include the following two aspects:

1) We propose a Cluster-based Energy-Efficient Resource Management (CEERM) scheme for Ultra-Dense Networks to maximize the network EE while guaranteeing the QoS requirement of UEs, where all SBSs are clustered into multiple small cell clusters according to the distance among SBSs and UEs are further divided in each small cell cluster into UE clusters with minimal intra-cluster interference to reduce the computational complexity of channel allocation and power allocation.

2) We propose a distributed power allocation algorithm based on the non-cooperative game, which maximizes the energy efficiency of the whole network under the premise of guaranteeing the QoS requirement of all UEs.

The rest of the paper is organized as follows. In Section II, we first introduce the system model and then formulate the cluster-based EE optimization problem. Section III presents the Cluster-based Energy-Efficient Resource Management scheme. Simulation experiments are provided to verify the effectiveness of our proposed scheme in Section IV. Conclude remarks are given in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider a two-tier downlink heterogeneous UDN, where the macro cell base station (MBS) located at the center of the network is responsible for the basic
coverage while dense small base stations (SBSs) are deployed in the hotspots under the coverage of macro cell to enhance network capacity and user experience.

In this paper, we consider the scenario of orthogonal deployments, where there is no inter-tier interference. For clarity, we utilize subscripts \( m \) and \( s \) to distinguish the parameters associated with macro cell and small cells respectively. In this scenario, all available subchannels are divided into two independent fragments: \( N_m \) subchannels set \( \mathcal{M}_m \) used by the macro cell and the remaining \( N_s = N - N_m \) subchannels set \( \mathcal{N}_s \) allocated to small cells. Denote \( \mathcal{M} = \{0\} \) and \( \mathcal{I} = \{1, 2, \cdots , |\mathcal{I}|\} \) to be the sets of MBS and SBSs respectively. Define \( U_m \) and \( U_i \) \( (i \in \mathcal{I}) \) as the sets of macro cell UEs (MUEs) and small cell UEs (SUEs) in small cell \( i \) respectively, where \( |U_m| = U_m \) and \( |U_i| = U_i \). Then the total number of SUEs can be expressed as \( U_s = \sum_{i \in \mathcal{I}} U_i \) and the total number of UEs including MUEs and SUEs can be derived as \( U = U_m + U_s \). The maximum transmit power of MBS and SBSs are given by \( P_m \) and \( P_s \), respectively.

The signal to interference plus noise ratio (SINR) of MUE \( u_m \) \( (u_m \in U_m) \) over subchannel \( n_m \) \( (n_m \in \mathcal{N}_m) \) can be expressed as

\[
\gamma_{u_m, n_m} = \frac{p_{u_m, n_m} h_{u_m, n_m}}{\sigma^2}
\]

where \( p_{u_m, n_m} \) is the transmit power of MBS on subchannel \( n_m \) for MUE \( u_m \), \( h_{u_m, n_m} \) is the channel gain between MBS and MUE \( u_m \) on subchannel \( n_m \) and \( \sigma^2 \) is the thermal noise power on each subchannel. Similarly, the SINR of SUE \( u_i \) in the \( i \)th small cell on subchannel \( n_i \) \( (n_i \in \mathcal{N}_s) \) can be written as

\[
\gamma_{u_i, n_i} = \frac{p_{u_i, n_i} h_{u_i, n_i}}{\sum_{j \in \mathcal{I}, j \neq i} \sum_{n_j \in \mathcal{N}_j} p_{u_j, n_j} h_{u_j, n_j} + \sigma^2}
\]

where \( p_{u_i, n_i} \) is the allocated power for \( u_i \) on subchannel \( n_i \) by the \( i \)th SBS, \( h_{u_i, n_i} \) is the channel gain between the \( i \)th SBS and SUE \( u_i \) on subchannel \( n_i \).

Accordingly, the rate of MUE \( u_m \) on subchannel \( n_m \) and the rate of SUE \( u_i \) on subchannel \( n_i \) can be written respectively as

\[
R_{u_m, n_m} = B \log_2 (1 + \gamma_{u_m, n_m})
\]

\[
R_{u_i, n_i} = B \log_2 (1 + \gamma_{u_i, n_i})
\]

where \( B \) denotes the bandwidth of one subchannel. Hence, the throughput of macro cell and \( i \)th small cell can be expressed as \( R_m = \sum_{u_m \in U_m} \sum_{n_m \in \mathcal{N}_m} x_{u_m, n_m} R_{u_m, n_m} \) and \( R_i = \sum_{u_i \in U_i} \sum_{n_i \in \mathcal{N}_s} x_{u_i, n_i} R_{u_i, n_i} \), respectively. The binary indicator variable \( x_{u_i, n_i} \) indicates whether subchannel \( n_i \) is assigned to SUE \( u_i \) by the \( i \)th SBS.

Generally, the power consumption of BSs includes basic power consumption and transmit power consumption [10]. Thus, the total energy consumption of macro cell and small cell can be given by

\[
p_{m}^{\text{total}} = \sum_{u_m \in U_m} \sum_{n_m \in \mathcal{N}_m} \xi_m p_{u_m, n_m} + p^b_m
\]

\[
p_{s}^{\text{total}} = \sum_{u_i \in U_i} \sum_{n_i \in \mathcal{N}_s} \xi_s p_{u_i, n_i} + p^b_s
\]

where \( \xi_m \geq 1 \) and \( \xi_s \geq 1 \) denote the reciprocal of drain efficiency of the power amplifier of MBS and SBS, respectively. \( p^b_m \) and \( p^b_s \) represent the basic power consumption of MBS and the \( i \)th SBS. In orthogonal deployments, we can treat the macro cell and small cells independently since they do not share spectrum resources. To further mitigate the intra-tier interference, we focus on the RA scheme for small cells while MBS can also utilize the same scheme to realize RA. For small cells, the EE optimization problem for joint subchannel assignment and power allocation can be formulated as follows:

\[
\arg \max_{\mathcal{x}, \mathcal{p}} \sum_{u_i \in U_i} \sum_{n_i \in \mathcal{N}_s} \xi_i x_{u_i, n_i} R_{u_i, n_i} + P^b_s
\]

s.t. \( C1: \ x_{u_i, n_i} \in \{0, 1\}, \ \forall i \in \mathcal{I}, \ \forall u_i \in U_i, \ \forall n_i \in \mathcal{N}_s \)

\( C2: \ \sum_{u_i \in U_i} x_{u_i, n_i} = 1, \ \forall i \in \mathcal{I}, \ \forall n_i \in \mathcal{N}_s \)

\( C3: \ p_{u_i, n_i} \geq 0, \ \forall i \in \mathcal{I}, \ \forall u_i \in U_i, \ \forall n_i \in \mathcal{N}_s \)

\( C4: \ \sum_{n_i \in \mathcal{N}_s} p_{u_i, n_i} \leq P_s, \ \forall i \in \mathcal{I} \)

\( C5: \ \sum_{n_i \in \mathcal{N}_s} x_{u_i, n_i} R_{u_i, n_i} \geq R_{th}, \ \forall i \in \mathcal{I}, \ \forall u_i \in U_i \)

where \( R_{th} \) denotes the minimum rate requirement of each SUE. Constraints \( C1 \) and \( C2 \) represent that each subchannel can only be assigned to one SUE in each SBS. \( C3 \) and \( C4 \) are the linear constrains for power allocation. Constraint \( C5 \) guarantees the QoS requirements of users.

### III. THE CLUSTER-BASED ENERGY-EFFICIENT RESOURCE MANAGEMENT SCHEME

The optimization problem (7) is a mixed-integer nonlinear fractional program (MINLFP) problem, which is NP-hard. Convex-optimization based centralized schemes [7], [8] are too complex to solve problem (7) effectively in a real-time scenario. For this, we propose a Cluster-based Energy-Efficient Resource Management (CEERM) scheme and then transform the original optimization problem into a new clustering-based optimization problem as problem (8).

Where \( C \) is defined as the set of generated cell clusters and \( |C| \) is the number of cell clusters. \( \forall k \in \{1, 2, \cdots , |C|\} \) denotes the index of cell cluster. Constraint \( C6 \) and \( C7 \) indicate that the union set of all cell clusters \( C \) form the set of small cells \( \mathcal{I} \) and the set of any two cell clusters are disjoint.

Problem (8) decomposes the original problem into two subproblems: the clustering sub-problem and RA sub-problem. Firstly, the small cells and SUEs are divided into disjoint
clusters one after another to reduce the complexity of RA. Thereafter, the RA sub-problem in each cell cluster is divided into smaller sub-problems like subchannel allocation and power allocation. In this section, we concretely describe the implementation process of cell clustering, UE clustering, subchannel assignment and power allocation in our proposed scheme.

$$\arg \max_{X,P} \sum_{k=1}^{C} \sum_{i \in C_k} \sum_{i' \in \mathcal{U}_k} \sum_{n_j \in N_i} x_{i,j} R_{i,j,n_j}$$

subject to:

1. $x_{i,j,n_j} \in \{0,1\}$, $\forall i \in \mathcal{I}$, $\forall u_i' \in \mathcal{U}_i$, $\forall n_j \in N_i$

2. $\sum x_{i,j,n_j} = 1$, $\forall i \in \mathcal{I}$, $\forall n_j \in N_i$

3. $p_{i,j,n_j} \geq 0$, $\forall i \in \mathcal{I}$, $\forall u_i' \in \mathcal{U}_i$, $\forall n_j \in N_i$

4. $\sum_{n_j \in N_i} p_{i,j,n_j} \leq P_s$, $\forall i \in \mathcal{I}$

5. $\sum_{n_j \in N_i} R_{i,j,n_j} \geq R_{th}$, $\forall i \in \mathcal{I}$, $\forall u_i' \in \mathcal{U}_i$

6. $\bigcup_{k=1}^{C} C_k = \mathcal{I}$, $\bigcap_{k=1}^{C} C_k = \phi$ (8)

A. CELL CLUSTERING AND UE CLUSTERING

For the reason that small cells are deployed densely in UDN, the intra-tier interference and energy consumption problem are intractable to tackle by centralized mode. An intuitive way is to group SBSs into local clusters by such as conflict-graph [12], k-means [18] algorithms. The previous clustering researches are most dependent on a self-defined interference threshold and a preset number of clusters while not considering the interference topology of the network. Assuming that all the cell clusters are sufficiently far away from each other, we can ignore inter-cluster interference. To reduce intra-cluster interference and maintain better SE, UEs in each cell cluster are further divided into UE clusters.

1) MAX-DEGREE BASED CELL CLUSTERING

To better reflect the proximity relationship between BSs, we propose a max-degree based cell clustering algorithm, which is flexible to group SBSs based on network topology without a predetermined number of clusters. We first determine whether there are neighboring relationships $\mathcal{D}(i,j)$ between SBS $i$ and SBS $j$ in UDN according to the distance $d_{ij}$ between them, which is given as

$$\mathcal{D}(i,j) = \begin{cases} 1, & \text{if } d_{ij} \leq d_{th} \text{ and } i \neq j \\ 0, & \text{otherwise} \end{cases}$$

where $d_{th}$ represents the threshold of interference distance. $\mathcal{D}(i,j)=1$ denotes that there is an interference relationship between SBS $i$ and SBS $j$, otherwise, the interference relationship does not exist. A matrix $\mathcal{D}$ with an element $\mathcal{D}(i,j)$ describes the neighboring relationships of small cells waiting for clustering in the whole network. Then, we can further derive $\mathcal{D}_l$ to denote the set of neighboring SBSs of SBS $i$ according to $\mathcal{D}$. The size of $\mathcal{D}_l$ is the degree of SBS $i$ representing the number of neighboring SBSs of SBS $i$. Considering that the closer the small cells are, the higher the interference will be. The purpose of the cell clustering algorithm is to cluster the SBSs close to each other into the same cell cluster as much as possible.

The main idea is to firstly select SBS $i^*$ with the largest degree as a cluster center and then take turns choosing SBSs which are closest to SBS $i^*$ in $\mathcal{D}$ as the members of this cluster. Then, cell clusters composed of only one SBS are further merged into the existing cell cluster nearest to them. Finally, we further merge all generated candidate cell clusters according to the neighboring relationship of corresponding cluster centers to avoid strong interference between cell clusters.

The algorithm of cell clustering is summarized in Algorithm 1. $\mathcal{S}$ represents the set of SBSs waiting for clustering. $\mathcal{S}^0$ is the set of SBSs whose cell cluster has only one small cell. $\zeta$ denotes the current candidate cell cluster. $\mathcal{C}^0$ is the set of cluster centers. Fig. 2 shows the clustering results with different $d_{th}$.

2) MAX-CUT BASED UE CLUSTERING

In each cell cluster, we develop a UE clustering algorithm to further mitigate the intra-cluster interference. Because the process of UE clustering in each cell cluster is similar, we take UE clustering in the $k$th cell cluster as an example. At first, we set up an interference graph $G(V, \mathcal{E})$ in the $k$th cell cluster, where the vertex set $V$ consists of all UEs and the edge set $\mathcal{E}$ consists of edges between vertexes. The element $E(u_i', u_j')$ is the weight of the edge between UE $u_i'$ and UE $u_j'$ in the $k$th cell cluster, i.e. $\forall i,j \in \mathcal{C}_k$. It is defined as

$$E(u_i', u_j') = E(u_i', u_j') = \begin{cases} e_{u_i', u_j'} & \text{if } i \neq j \\ E_{th} & \text{otherwise} \end{cases}$$

(10)

where $e_{u_i', u_j'} = L_{u_i', u_j'} + L_{u_i', u_j'} + \sum_{d_{th}}$ is utilized to describe the interference degree between UE $u_i'$ and $u_j'$, where $L_{u_i', u_j'}$ indicates the path loss between SU $u_i'$ and $u_j$, and $E_{th}$ is the upper bound of the weight, which limits the number of UE in one UE cluster and is set large enough to effectively reuse spectrum resources. From the formula (10), we can see that

![FIGURE 2. The cell clustering results with different $d_{th}$, the number of small cells is 12. (a)$d_{th} = 80m$. (b)$d_{th} = 120m$. Small cells with the same color are constituted as one cluster.](image-url)
Algorithm 1 Max-Degree Based Cell Clustering

1: **Initialization**: \( S = \emptyset, C = \emptyset, \zeta = \emptyset, \) and \( \rho = \emptyset \).
2: For each SBS \( i \in S \), create the neighboring SBSs set \( D_i \) according to \( D \) and calculate its interference degrees.
3: **while** \( S \) is not empty **do**
4: \( SBSs \) \( i^* \) = \( \arg \max_{i \in S} |D_i| \) as cluster center.
5: \( \zeta = \{i^*\}, C^c = \{i^*\} \).
6: **while** \( D_{i^*} \) is not empty **do**
7: \( SBS s \) \( j^* \) from \( D_{i^*} \), where \( d_{j^*i^*} \leq d_{j'i} \), \( \forall i' \in D_{i^*}, i' \neq i \).
8: Add the selected SBSs \( j^* \) into \( \zeta \) as \( \zeta = \zeta \cup \{j^*\} \).
9: Remove the SBSs \( j^* \) from \( D_{i^*} \) as \( D_{i^*} = D_{i^*} \setminus \{j^*\} \).
10: **end while**
11: Remove all SBSs in \( \zeta \) from \( S \) as \( S = S \setminus \zeta \), and extract SBSs of \( \zeta \) as a new cell cluster and save it in \( C \).
12: Reset \( \zeta = \emptyset \).
13: **end while**
14: for all \( i \in S^c \) **do**
15: if \( D_i \) is not empty **then**
16: Select the cell cluster \( C_k \) having SBS \( j^* \) = \( \arg \min_{j \in D_i} d_{j,i} \).
17: Add the SBSs \( i \) into \( C_k \) as \( C_k = C_k \cup \{i\} \).
18: Remove the SBSs \( i \) from \( C^c \) as \( C^c = C^c \setminus \{i\} \).
19: **end if**
20: **end for**
21: Set \( S = C^c \), once again execute step 2-20 to merge the cell cluster. Then, we get the final cell clusters by the result of \( C \).

UEs in the same small cell cannot be assigned to the same UE cluster. In addition, we give a metric to represent the priority of UE \( u^*_i \) in the \( k \)th cell cluster [17], which is given as

\[
\rho_{d_j} = \frac{\sum_{j \neq i} P_j L_{d_j,i}}{P_j L_{d_j,i}} \quad \forall i, j \in C_k \tag{11}
\]

We develop a UE clustering algorithm to group vertices of the graph into UE clusters with minimum intra-cluster interference. The objective of the UE clustering scheme is to minimize the sum weights of all UE clusters. Therefore, if we assign the same subchannels to UEs in the same UE cluster, the total interference is expected to be mitigated. We select a vertex with maximum priority as the starting point in \( G(V, E) \). Iteratively, we traverse \( G(V, E) \) to add vertices that minimize the weight of the current UE cluster. Once the sum weight of all edges in the current UE cluster reaches the upper bound \( E_{th} \), the UE cluster is extracted and a new UE cluster starts to generate from the remaining vertices. Fig. 3 shows the UE clustering results with different number of UEs per cell, where UE vertices with the same color belong to the same UE cluster, and UE1 represents a user that forms a user cluster together with other users, while UE2 represents a user that forms a user cluster alone.

The details of UE clustering algorithm in the \( k \)th cell cluster are described in Algorithm 2. \( \zeta \) is the current candidate UE cluster, \( v \) is the set of candidate vertexes to expand the current UE cluster. \( UC \) denotes the set of generated UE clusters in the \( k \)th cell cluster and each element of \( UC \) indicates a UE cluster in the \( k \)th cell cluster.

Algorithm 2 Max-Cut Based UE Clustering

1: **Initialization**: \( \zeta \) is empty and \( V = \bigcup_{i \in C_k} U_i \).
2: **while** \( V \) is not empty **do**
3: Select the vertex \( v^* \) = \( \arg \max_{v \in V} \rho_v \) as the start point and let \( \zeta = \{v^*\} \).
4: Create a candidate list, \( v = V \setminus \zeta \).
5: **while** the sum weight of \( \zeta \) is less than \( E_{th} \) **do**
6: Select the vertex \( v' \) from \( v \), where \( v' = \arg \min_{v' \in V} (\sum_{v \in \zeta} E(u, v')) \).
7: Add the selected vertex \( v' \) into \( \zeta \) as \( \zeta = \zeta \cup \{v'\} \).
8: **end while**
9: Remove the last vertex \( v' \) as \( v = v \setminus \{v'\} \).
10: Remove all the UEs of \( \zeta \) from set \( V \) as \( V = V \setminus \zeta \), extract the UEs of \( \zeta \) as a new UE cluster and save it in \( UC \).
11: Reset \( \zeta = \emptyset \).
12: **end while**

B. SUBCHANNEL ALLOCATION AND POWER ALLOCATION

Since the EE problem is a MINLFP problem, the joint subchannel and power allocation of each cell cluster is computationally intractable. Hence, we solve the problem by subchannel allocation and power allocation iteratively. This scheme has been proved to be effective to achieve good performance with much lower complexity [7].

1) TWO-STEP SUBCHANNEL ALLOCATION

For given PA, we propose a two-step subchannel allocation algorithm for each cell cluster. In the first step, we iteratively assign subchannels to UE clusters with the largest rate requirement according to channel gains. In the second step, the remaining subchannels of each SBS are firstly allocated to SUEs without meeting the rate requirement, and then to SUES.
Algorithm 3 Two-Step Subchannel Allocation
1: Initialization: \( R_a = 0 \), \( \forall u \in \cup_{i \in C_k} \mathcal{U}_i \).
2: while \( N_s \) is not empty do
3: if \( R_a \geq R_h \), \( \forall u \in \cup_{i \in C_k} \mathcal{U}_i^* \) then
4: Select UE group \( \mathcal{U}_{C_i}^* = \arg \max_{u \in \cup_{i \in C_k} \mathcal{U}_i^*} (R_{ih} - R_a) \).
5: else
6: Select UE group \( \mathcal{U}_{C_i}^* = \arg \max_{u \in \cup_{i \in C_k} \mathcal{U}_i^*} |R_{ih} - R_a|^+ \).
7: end if
8: Assign \( n^* \) to \( \mathcal{U}_{C_i}^* \), where \( n^* = \arg \max_{u \in N_s \cup \cup_{i \in C_k} \mathcal{U}_{C_i}^*} h_{u,n_s} \).
9: Update \( R_{ah} \), \( \forall u \in \cup_{i \in C_k} \mathcal{U}_i^* \) and the situation of subchannel allocation \( \psi \).
10: Remove \( n^* \) from \( N_s \) as \( N_s = N_s \setminus \{n^*\} \).
11: end while
12: for all \( i \in C_k \) do
13: while \( N_s^i \) is not empty do
14: if \( \mathcal{U}_i^* \) is not empty then
15: Select the UE \( u^* = \arg \min_{u \in \mathcal{U}_i^*} R_{ah} \).
16: else
17: Select the UE \( u^* = \arg \max_{u \in N_s \setminus \mathcal{U}_{C_i}^*} h_{i,u,n_s} \).
18: end if
19: Assign \( n^* \) to UE \( u^* \) where \( n^* = \arg \max_{u \in N_s \setminus \mathcal{U}_{C_i}^*} h_{i,u,n_s} \).
20: Remove \( n^* \) from \( N_s^i \) as \( N_s^i = N_s^i \setminus \{n^*\} \).
21: Update \( R_{ah} \) and the situation of subchannel allocation \( \psi \).
22: if \( \mathcal{U}_i^* \) is not empty and \( R_{ah} \geq R_h \) then
23: \( \mathcal{U}_i^* = \{u^*\} \).
24: end if
25: end while
26: end for

Algorithm 4 Non-Cooperative Game Based Power Allocation
1: Initialization: \( t = 0 \) and \( \eta_{C_i, EE}(t) = 0 \).
2: \( p_{i,n_s} = \frac{P_s}{I_{C_i}} \), \( \forall i \in C_k \), \( \forall n_s \in N_s \) and \( \lambda_i = R_i \left( \mathcal{P}_{C_i} \right) \setminus \Pi_{\mathcal{C}_i} \), \( i \in C_k \).
3: while \( t \neq T \) or \( f_{C_k}(t) - f_0(t) > \Delta \) do
4: \( t = t + 1 \).
5: Update power strategies of each SBS in \( k \)th cluster based on (12), (13) and (14).
6: Calculate \( \lambda_i(t), \forall i \in C_k \) and \( \eta_{C_i, EE}(t) \).
7: end while

each SBS. According to the QoS constraints, the lower bound of the transmit power of SBS i on subchannel \( n_s \) is
\[
p_{i,n_s}^{\min} = \frac{\eta_{C_i, EE}(t)}{h_{i,n_s}} \left( \frac{\eta_{C_i, EE}(t)}{h_{i,n_s}} - 1 \right)
\]
where \( N_{u_{C_i}} \) is the number of remaining subchannels of UE \( u_{C_i} \).
\[
p_{i,n_s}^{\max} = P_s + p_{i,n_s}
\]
If \( p_{i,n_s}^{\min} > p_{i,n_s}^{\max} \), then \( p_{i,n_s} = p_{i,n_s}^{\max} \). Hence, the optimal transmit power of SBS i on subchannel \( n_s \) can be obtained as
\[
p_{i,n_s}(t + 1) = \left[ \frac{B p_{i,n_s}(t) g_{i,n_s}(t)}{\lambda_{C_i} \xi \ln(2) + \frac{\sum_{i \in C_k} p_{i,n_s}^{\max} g_{i,n_s}(t)}{\lambda_{C_i} \xi \ln(2) + \sum_{i \in C_k} P_s \sum_{n_s} \eta_{C_i} h_{i,n_s} h_{i,n_s}^{n_s}}} \right] p_{i,n_s}^{\max}
\]
where
\[
g_{i,n_s} = \left( \frac{1}{h_{i,n_s}} + \alpha^2 \right)
\]
\[
i_{C_k} = \sum_{j \in C_k} p_{j,n_s} h_{j,n_s} h_{j,n_s}^{n_s} + \sum_{e \in E \setminus \mathcal{C}_k} \sum_{j \in C_k} P_s \sum_{n_s} \eta_{C_i} h_{e,n_s} h_{i,n_s}^{n_s}
\]
The algorithm 4 describes the non-cooperative game based PA algorithm. The matrix \( \mathcal{P}_{C_k} \) denotes the PA result in the \( k \)th cell cluster. \( \lambda(t) \) is the EE of SBS \( i(i \in C_k) \) in \( th \) iteration, which can be obtained by \( R_i \left( \mathcal{P}_{C_i}(t) \right) / \Pi_{\mathcal{C}_i} \), \( \eta_{C_i, EE}(t) \) denotes the EE of \( k \)th cell cluster in \( th \) iteration, which can be obtained by \( \sum_{i \in C_k} R_i \left( \mathcal{P}_{C_i}(t) \right) / \sum_{i \in C_k} \Pi_{\mathcal{C}_i} \). \( T \) is the iteration index. \( T \) and \( \Delta \) represent the maximum number of iteration and the maximum tolerance value, respectively.

C. COMPUTATIONAL COMPLEXITY
In this part, we analyze the complexity of CEERM scheme by four processes. The complexity of cell clustering process can be calculated as \((I - 1) + (I - 2) + (I - 3) + \ldots + 1\), which is \(O(I^2)\). We define the average number of SBSs...
and UEs in each cluster as $\bar{I}_c$ and $\bar{U}_c$, respectively. $\bar{U}_c$ represents the average number of UEs associated to each small cell. Then, the complexity of UE clustering process is $O\left(|C| (\bar{I}_c - 1) [\bar{U}_s + (\bar{U}_s - 1) + \ldots + 1]\right)$, which can be rewritten as $O(\bar{I}_c^2 \bar{U}_s^2)$ in the worst case. The complexity of SA process and PA process is $O(|C| N_s^2 + U_s (N_s - N_c \bar{U}_s)/|UC| - 1)^2 + IN_s (\bar{I}_c - 1) \bar{T}$ and $O (IN_s (\bar{I}_c - 1) \bar{T})$, respectively, where $|UC|$ and $\bar{T}$ are average number of UE clusters and iterations of PA in each cell cluster.

Generally, the computational complexity of cluster-based energy-efficient resource management scheme is $O(I^2 + I^2 U_s^2 + |C| N_s^2 + U_s (N_s - N_c \bar{U}_s)/|UC| - 1)^2 + IN_s (\bar{I}_c - 1) \bar{T}$, which can be rewritten as $O(I^2 U_s^2 + IN_s^2 + I^2 N_s \bar{T})$ in the worst case. In each iteration, the complexity of power allocation can be reduced from $O(IN_s (I - 1))$ to $O(IN_s (\bar{I}_c - 1))$ by using cell clustering algorithm, where $I \gg \bar{I}_c$. Although cell clustering algorithm and UE clustering algorithm increase the computational complexity, they are still effective to mitigate the intra-cluster interference in SA process and reduce the computational complexity in PA process.

### IV. SIMULATION RESULTS

In this section, simulation results are provided to demonstrate the effectiveness of our proposed CEERM scheme. We consider a two-tier UDN, where massive small cells are randomly deployed in the coverage of macro cell. The values of simulation parameters are chosen following the guidelines of 3GPP [31], and the primary system parameters are summarized in Table 1. We use Rayleigh fading to model the channel between BS and UE. We take average results from 100 times Monte Carlo simulations trials. In each trial, we generate the locations of SBS and UE randomly.

First, the convergence of the CEERM scheme in terms of network EE versus the iteration times is analyzed in Fig. 4. It can be seen from Fig. 4(a) that the curves of network EE in different cell clusters can converge in less than 15 iterations. In other words, the Nash equilibrium is obtained within 15 iterations through the PA algorithm based on non-cooperative games. Moreover, since the size and topological structure of each cell cluster are different, the final convergence EE of different cell clusters is also different. Fig. 4(b) shows the relationship between average EE of all cell clusters and iteration times. The average EE of all cell clusters can converge in about 12 iterations. Hence, simulation results illustrate the convergence of CEERM scheme.

Here, we examine the network performance under different $d_{th}$ for the proposed CEERM scheme. We set it in the range of 40m-120m, with 20m as the step length. Fig. 5 describes the cumulative distribution function (CDF) of network throughput under different $d_{th}$. The figure shows that the network throughput increases as $d_{th}$ increases. This is because higher $d_{th}$ can introduce more cooperation among SBSs, so that the proposed CEERM approach can better coordinate interference. At the same time, the computational complexity of the proposed scheme will increase. Thus, we can make a trade-off between performance and complexity by tuning $d_{th}$.

Next, we compare the network performance under different $N_m$, where $N_m \in \{16; 24; 32; 40; 48\}$. The CDFs of non-cooperative games. Moreover, since the size and topological structure of each cell cluster are different, the final convergence EE of different cell clusters is also different. Fig. 4(b) shows the relationship between average EE of all cell clusters and iteration times. The average EE of all cell clusters can converge in about 12 iterations. Hence, simulation results illustrate the convergence of CEERM scheme.

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### TABLE 1. Simulation parameters.

| Parameters                  | Value       |
|-----------------------------|-------------|
| Carrier frequency           | 2GHz        |
| Total Bandwidth             | 12MHz       |
| Bandwidth per subchannel    | 180/KHz     |
| Number of subchannels       | 4/4         |
| Number of Small Cells       | 4, 8, 12, 16, 20, 24, 28, 32 |
| Number of UE per Cell       | 4           |
| Path Loss Model for Macro Cell | 128.1 + 37.6 log(10d)dB |
| Path Loss Model for Small Cell | 140.7 + 37.6 log(10d)dB |
| Minimum Distance between UE and MBS | 35m |
| Minimum Distance between UE and SBS | 10m |
| Maximum Transmitted Power of MBS | 46dBm |
| Maximum Transmitted Power of SBS | 30dBm |
| Typical Cell Radius of Macro Cell | 289m |
| Static Power of MBS         | 800w        |
| Static Power of SBS         | 130w        |
| Typical Cell Radius of Small Cell | 40m |
| Thermal Noise               | $-174$dBm/Hz|
network EE for these scenarios are presented in Fig. 6. The results show that a higher \( N_m \) has a lower network EE. Since the central MBS uses more spectrum resources to serve a small number of MUEs instead of a large number of SUEs, the SBS consumes more energy to ensure the QoS of the SUEs, leading to the deterioration of EE.

Moreover, we analyze the network performance of the proposed CEERM scheme by changing \( R_{th} \). Fig. 7 illustrates that the network EE decreases when \( R_{th} \) increases. Since the transmit power of SBSs are increased to satisfy the higher \( R_{th} \), more energy consumption and interference will deteriorate the network EE.

Finally, we compare the proposed CEERM approach with the round robin approach, the existing approach [18], and the distributed without interference coordination (DWIC) approach. For the sake of effective comparison, we adopt the same PA method for different schemes. In the round robin approach, subchannels are allocated to UE clusters by round robin. In the DWIC approach, each cell as a cell cluster adopts the proposed CEERM method. In the existing approach [18], a cell clustering algorithm based on improved K-means algorithm and a UE grouping algorithm with minimal intra-cluster interference are proposed. However, compared with CRREM, [18] does not guarantee the QoS requirement of UEs. The relationship between the network throughput and the number of SBSs with different schemes is described in Fig. 8. We find that for all solutions, the growth rate of network throughput decreases as the number of SBS increases. This is because more SBSs incur more serious intra-tier interference, thereby effectively improving network performance. This also indicates that the proposed CEERM approach can mitigate interference more effectively than the DWIC approach which does not consider inter-tier interference and intra-tier interference. Fig. 9 plots the relationship curves of network EE and the number of SBS for the four schemes. It can be seen that the network EE first increases at the initial stage, and then declines as the number of small cells increases. Because when the number of small cell reaches a certain level, the increase in energy consumption is faster than the increase in network throughput, which ultimately deteriorates the network EE. In addition,
the network EE of the proposed CEERM approach is superior to other schemes.

**V. CONCLUSION**

In this paper, we design a CEERM scheme consisting of a clustering phase and a RA phase to maximize network EE while ensuring QoS of UEs. In the clustering stage, the small cells are divided into disjoint clusters by the algorithm based on max-degree, and then SUEs in each cell cluster are further grouped into UE clusters by the algorithm based on max-cut, so as to minimize the interference within the cluster. The clustering process not only mitigates the intra-interference, but also reduces the computational complexity of subsequent RA. For the RA stage, each cell cluster executes the two-step SA algorithm and PA algorithm based on non-cooperative game in sequence. The simulation results show that compared with the DWIC approach without interference coordination, the CEERM scheme can significantly enhance network throughput and EE, and as the number of SBSs in UDN increases, its superiority become more and more obvious. In this work, we meet the communication requirements of users by satisfying the user rate requirement. However, with the diversified development of wireless communication services, the service requirements of different users in future network will also vary greatly. We will further consider classifying users according to variety user QoS requirements, and study energy-efficient resource allocation schemes based on user types.

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