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A Hierarchical Clustering Algorithm for Interference Management in Ultra-Dense Small Cell Networks

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ABSTRACT Ultra-dense small cell networks (UD-SCNs) will be an integral part of next generation network (NGN). How to deal with serious interference is one of the important challenges in a UD-SCN. In this paper, the cooperative interference management problem for a UD-SCN is explored by allowing small cell base stations (SBSs) to collaborate with their neighbors. The proposed coalitional structure generation among SBSs can mitigate the co-tier interference within a coalition, thus improving the network capacity. Specifically, a cooperative scheme among the neighboring SBSs is formulated as a coalitional structure generation with characteristic forms. Furthermore, the relative sub-channel resources are allocated in the process of cluster generation. Compared with the existing SBS cooperative schemes, the novelty of the proposed SBS cooperation method, which uses a hierarchical clustering algorithm (SC-HCA) to compute the pairs of members, is demonstrated. The computation can enhance the efficiency of the proposed algorithm and is especially suitable for UD-SCN scenarios with tens and even hundreds of cells. The simulation results show that the proposed SC-HCA achieves a 422.13% system data rate improvement relative to that of the non-cooperative scheme in a UD-SCN scenario.

INDEX TERMS Coalitional structure generation, hierarchical clustering, interference management, ultra-dense small cell networks.

I. INTRODUCTION

To achieve the many promises of next generation network (NGN), researchers in this area of communication are facing numerous challenges. For instance, accommodating 1000-time increase in the volume of data traffic has been suggested by many organizations and standard bodies. To this end, in order to obtain the extra transmission bandwidth, millimeter-wave communication technology was proposed in [1]; additionally, to enhance the spectral efficiency, a massive multiple-input multiple-output (MMIMO) method was proposed in [2]. However, since the extra spectrum will not be sufficient to support the fast-growing data traffic, in the long term, the number of small cells will grow rapidly. In this way, data rates will increase, coverage will improve, and more efficient energy consumption and network performance will be achieved. Therefore, ultra-dense small cell networks (UD-SCNs) are considered potential candidates for future cellular networks and have drawn significant attention from the research community and industry in recent years [3]–[6].

Although the research on UD-SCNs is in an immature stage, the deployment of small cells in cellular networks adds many new challenges, ranging from interference mitigation to resource optimization, site scheme issues and low-cost products [7], [8]. One of the most important challenges is determining how to deal with interference management, which has recently been investigated in the literature. In [9], the authors formulated a resource allocation optimization–based interference management problem in a combined network with centralized and distributed small cell networks (SCNs).

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In [10], the authors presented a centralized scheduling and interference coordination scheme to enhance dense network performance. In [11], the authors investigated the co-tier interference problem for SCNs using a non-cooperative interference minimization game approach. In [12], a reinforcement learning-based power control method was used to restrain the downlink co-tier interfere for UD-SCNs. In [13], the authors presented an information theory framework and exploited some implementable schemes for interference management. These studies mainly focused on decentralized interference management approaches, in which small cell base stations (SBSs) act in a non-cooperative way, i.e., every SBS considers only its own quality of service (QoS), while neglecting the impact of co-tier interference. Hence, the co-tier interference reduces the system data rate, especially for picocells that are deployed outdoors.

To better address and improve these issues, one promising solution is to enable SBSs to coordinate transmissions. To that end, the idea of cooperation or clustering in SCNs has been discussed in the literature. In [14], the authors proposed a cluster-based dynamic mechanism to locally integrate coupled SBSs into clusters and maximize the energy efficiency of SCNs. In [15], the authors presented a coalition game-based resource allocation approach to enable self-healing and cell outage compensation in SCNs. In [16], the authors formulated SBS cooperation as a coalition formation game with overlapping coalitions; each SBS could simultaneously join one or more coalitions to mitigate co-tier interference. In [17], the authors proposed a cluster-based resource allocation scheme considering sub-channel and power assignment problems for downlink transmission in UD-SCNs. In [18], the authors introduced the bargaining cooperative game algorithm to investigate the potential cooperative gains and improve the spectral efficiency of UD-SCNs. In [19], the authors presented a classical cooperative model with transferable utility in partition form to solve the femtocell spectrum sharing problem. In [20], the authors proposed a user-centric small cell clustering scheme to enhance the signal-to-interference ratio (SIR) and suppress interference. Although these studies are based on cooperation or clustering concepts, they have several drawbacks: (i) they have a slow convergence speed or no guaranteed convergence speed in massive small-cell deployment scenarios with tens and even hundreds of cells; (ii) they have high complexity and are thus not highly suitable for large-scale network scenarios; and (iii) they only consider the simplest scenario, i.e., each SBS only serves a single small cell user equipment (SUE). Hence, it is critical to perform further research on more effective interference mitigation strategies for UD-SCNs.

To alleviate the limitations of the existing schemes, in this paper, we propose a novel and easy-to-operate interference mitigation strategy based on hierarchical clustering or coalitions among SBSs for the downlink transmission of UD-SCNs. To mitigate interference stemming from UD-SCNs, we consider the idea of coalitional structure generation with characteristic forms and a hierarchical clustering technique. This technique can decompose the original sub-channel allocation problem into a smaller sub-problem for each cluster to mitigate the interference and reduce the large-scale network complexity. Specifically, a new cooperative interference management model for UD-SCNs is proposed, in which an SBS can coordinate with other SBSs and enter other clusters based on a correlative utility. The generation of clustering or coalitional structures is largely based on the suitability function, which is described by the gain in the data rates of two clusters. Additionally, in the course of generating clusters, the correlation frequency resources within the same coalition are assigned in accordance with a local scheduler. Notably, our SC-HCA is particularly appropriate for hyper and dense deployment networks of SBSs.

The main contributions of this paper are as follows.

- To evaluate the formation conditions of clustering, we designed a new function called the suitability function and two new matrices called connection matrix and clustering suitability matrix. Whether the two clusters or two members are appropriate or not depends on the suitability function.
- The co-tier interference mitigation problem for an HD-SCN (considering coalitional structure generation with characteristic forms) is modeled in a hierarchical clustering form with the goal of maximizing the system data rate. Cluster or coalitional structure formation is contingent upon the suitability function.
- The effectiveness of the proposed SC-HCA was verified via a series of system level simulations. These simulations show that the proposed approach largely improves the system throughput in comparison with other schemes.

The structure of the paper is as follows. Section 2 presents the UD-SCN system model. Section 3 describes the proposed SC-HCA in detail. Section 4 includes the simulation results and analysis. Section 5 concludes the paper and suggests further work.

II. SYSTEM AND CHANNEL MODEL

A. SYSTEM MODEL

In this work, we consider downlink transmission for orthogonal frequency division multiple access (OFDMA) in a two-tier heterogeneous UDN that consists of a high-power microcell base station (MBS) and dense low-power SBSs deployed within the range of the MBS, as illustrated in Fig.1. In the cellular network, each SBS is linked with a core network by an Internet Protocol backhaul and gateway [21]. Each SUE gives access to the corresponding SBS. Additionally, the gateway acts as a coordinator of SBSs, and high-density SBSs are deployed in the UDNs. In this scenario, since the number of available sub-channels is limited, it is not realistic if each SUE has an orthogonal sub-channel [22]. Therefore, any sub-channel is likely assigned to more than one SUE, which causes serious co-channel interference (CCI), i.e., cross-tier interference and co-tier interference, as also illustrated in Fig.1.

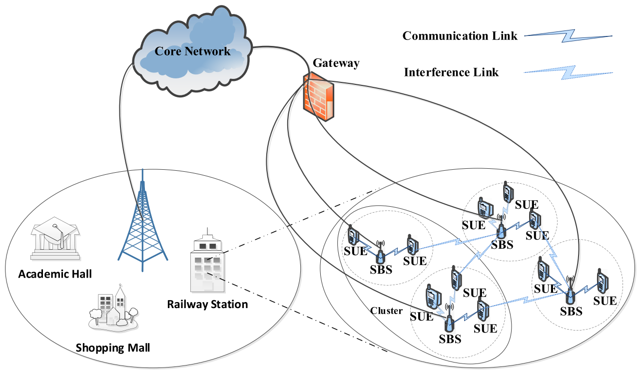

FIGURE 1. System model of an ultra-dense small cell network.

Let us assume that an SCN with F small cell base stations (SBSs) exists. $\mathbf{F} = \{1, \ldots, f, \ldots, F\}$ represents the number of SBSs in the SCN and collects all SBS indices. All SBSs are deployed indoors, e.g., inside an office building in closed-access mode. Every SBS $f \in \mathbf{F}$ serves U_f SUEs, and $\mathbf{U} = \{1, \ldots, U\}$ denotes all the SUEs that are served by the corresponding SBS $f \in \mathbf{F}$. $\mathbf{N} = \{1, \ldots, n, \ldots, N\}$ represents all the available orthogonal frequency sub-channel indices, and N is the number of sub-channels in the SCN. Every SBS $f \in \mathbf{F}$ chooses N_f orthogonal frequency sub-channels at random, which are the corresponding initial frequency resources of SBS f and provide services to U_f SUEs. Moreover, the total transmission power of each SBS P_f is fixed.

B. CHANNEL MODEL

In this work, the practical fading effects, which include path loss, penetration loss and Rayleigh fading, are considered [23]. In this case, for a random sub-channel $n \in N_f$, the channel gain experienced through the links of SUEs $u_f \in U_f$ associated with SBS $f \in \mathbf{F}$ is given by:

$$G_{f,u_f}^{(n)} = D_{f,u_f}^{-\alpha} RF_{f,u_f}^{(n)} \tag{1}$$

where D_{f,u_f} is the distance from SBS f to one of the corresponding SUEs u_f. α is the path loss exponent. $RF_{f,u_f}^{(n)}$ is the Rayleigh fading value from SBS f to one of its SUDs u_f for the sub-channel n.

For a random sub-channel $n \in N_f$, the interfering sub-channel gain through the links of SUEs $u_f \in U_f$ associated with SBS $f \in \mathbf{F}$ is given by:

$$G_{d,u_f}^{(n)} = D_{d,u_f}^{-\alpha} W_{d,u_f}^{-1} RF_{d,u_f}^{(n)} \tag{2}$$

where W_{d,u_f}^{-1} is the internal wall penetration loss.

Accordingly, the downlink data rate obtained by the SUE u_f served by SBS f for sub-channel n in the non-cooperative case is given by:

$$R_{f,u_f}^{(n)} = \sum_{n \in N_f} \sum_{u_f \in U_f} \log_2 \left(1 + \frac{P_{f,u_f}^{(n)} G_{f,u_f}^{(n)}}{\delta^2 + I_{co-tier}} \right) \tag{3}$$

where δ^2 is the variance of the Gaussian noise. $P_{f,u_f}^{(n)}$ is the downlink transmission power between SBS f and its SUDs u_f for the sub-channel n. $I_{co-tier}$ is the total co-tier interference received by the SUDs u_f from other SBSs for the sub-channel n, and $I_{co-tier}$ is formulated as:

$$I_{co-tier} = \sum_{d \in \mathbf{F}, d \neq f} P_{d,u_f}^{(n)} G_{d,u_f}^{(n)} \tag{4}$$

It should be noted that in a UD-SCN, the co-tier interference is one of the most important issues that can seriously affect network performance [16], [24]. However, in this work, we assume that all SBSs are located in large indoor hotspot areas where there are no walls between each SBS and the corresponding SUEs and there are walls between all SBSs. Moreover, since the MBS is deployed outdoors, there are walls between the MBS and SBSs or its SUEs. Additionally, the wall loss and the long distance between the MBS and SUEs are considered. Considering the wall loss and the long distance between the macrocell and SUEs, the cross-tier interference is much weaker than the co-tier interference caused by transmission from one SBS to another [16]. Nevertheless, in this work, the co-tier interference problem is effectively solved.

III. HIERARCHICAL CLUSTERING FOR INTERFERENCE MANAGEMENT IN A UD-SCN

In this section, a new cooperative framework for a UD-SCN is proposed, which contributes to developing a reasonable and efficient resource allocation scheme. We first consider some basic definitions.

A. COALITIONAL STRUCTURE GENERATION WITH SBS COOPERATION

All members are denoted by a set of all SBSs $\mathbf{F} = \{1, \ldots, f, \ldots, F\}$. A coalition is denoted by a set $CS = (C_1, \ldots, C_l, \ldots, C_L)$, where C_l represents a cluster. One member is not joined to more than one cluster so that $f \in C_l$ and $C_l \cap C_m = \phi$ are maintained; one member has to join one of the clusters so that $U_{C_l \in CS} C_l = \mathbf{F}$ is reinforced. The relative definitions of coalitional structure generation are introduced from references [25]–[27].

Definition 1: A coalitional structure generation over $\mathbf{F}$ is represented by a set CSG, which is a set of all partitions from F members. We have $CS_j \subseteq CSG$ and $j \in \{1, \ldots, J\}$, where J denotes the total number of coalitions.

Definition 2: The optimal solution CSG^* of a CSG problem is mathematically represented by:

$$CSG^* = \arg \max_{CS \in CSG} \sum_{l=1}^{L} v(C_l | C_l \in CS) \tag{5}$$

where $v(C_l | C_l \in CS)$ represents the utility of cluster C_l. For simplicity, in the remainder of this paper, we replace $v(C_l | C_l \in CS)$ with $v(C_l)$.

According to Definition 2, when the utility $v(C_l)$ reaches a maximum, the component of the cluster C_l needs to be given.

For $v(C_l)$, the value of cluster C_l does not depend on the members of other clusters in the same coalitional structure. In other words, externalities in the model do not need to be considered. This characteristic treats every cluster as isolated. Hence, it is worth mentioning that the model is formulated as a coalitional structure generation with characteristic forms (CSG-CF) rather than partition forms (PF) [15].

Therefore, to obtain the value $v(C_l)$ of cluster $C_l \in CS$, (3) is re-written as (6), i.e., the data rate can be expressed by CS:

$$v(C_l) = \sum_{f \in C_l} \sum_{n \in N_f} \sum_{u_f \in U_f} \tau_{f,u_f}^{(n)} \log_2 \left(1 + \frac{P_{f,u_f}^{(n)} G_{f,u_f}^{(n)}}{\delta^2 + I_{co-tier}} \right) \quad (6)$$

where $\tau_{f,u_f}^{(n)}$ is the fraction of the time duration of transmission between SBS f and an SUE u_f via the sub-channel n. The associated co-tier interference $I_{co-tier}$ in (6) is re-written as:

$$I_{co-tier} = \sum_{\overline{C_l} \in CS \setminus C_l} \sum_{d \in C_l, d \neq f} P_{d,u_f}^{(n)} G_{d,u_f}^{(n)} \quad (7)$$

In our model, when SUEs occupy the same sub-channels, a cluster will form to overcome the co-tier interference, not vice versa, as shown in Fig. 2. The two dotted lines denote the same sub-channel being occupied, and each solid line denotes a different sub-channel. Next, SC-HCA is proposed to manage co-tier interference and enhance the throughput in our network model.

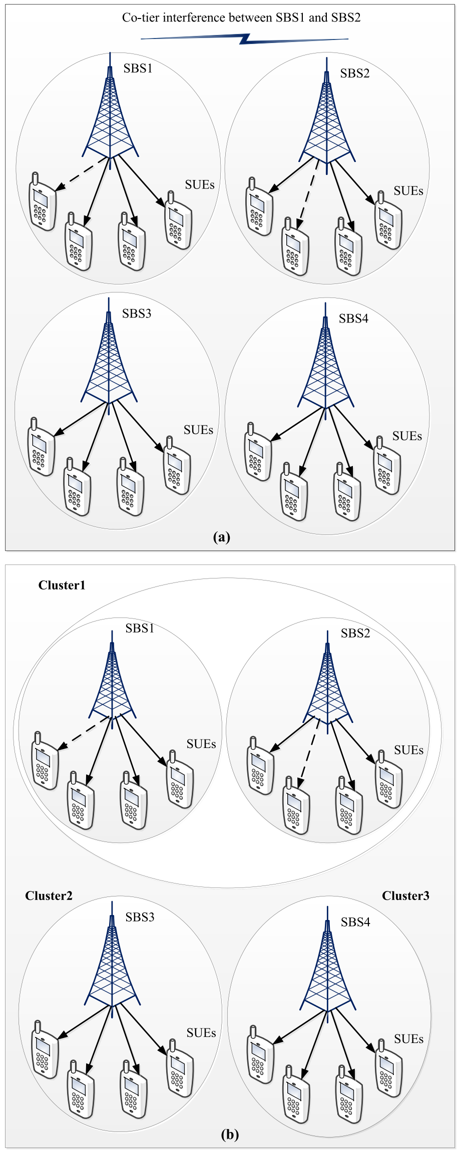

FIGURE 2. **A simple example with $F = 4$ SBSs for determining how to form a cluster: (a) Non-cooperative SBS deployment, (b) Cooperative SBS deployment.**

B. OPTIMIZATION PROBLEM FORMULATION

The aim of the paper is to maximize the system data rate by jointly designing SBS clusters with mutually orthogonal sub-channels under the limited conditions of sub-channels for the considered UD-SCN. Therefore, an optimization problem will be formulated. In advance of formulation, two matrices are defined.

Let $\boldsymbol{X} = [x_{f,u}]$ with $(F \times U)$ elements represent the association matrix, which is given by:

$$x_{f,u} = \begin{cases} 1, & \text{if SUE } u \text{ is served by SBS } f \text{ in the cluser } C_l \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Let $\boldsymbol{Y} = [y_u^{(n)}]$ with $(U \times N)$ elements represent the sub-channel allocation matrix, which is given by:

$$y_u^{(n)} = \begin{cases} 1, & \text{if sub-channel } n \text{ is allocated to the cluser } C_l, \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

Accordingly, the optimization value of the data rate from a cluster C_l can be formulated as follows:

$$\max_{X,Y} \sum_{f \in C_l} \sum_{n \in N_f} \sum_{u_f \in U_f} \tau_{f,u_f}^{(n)} \log_2 \left(1 + \frac{\frac{P_f}{\sum_{u \in \mathbf{U}} x_{f,u}} G_{f,u_f}^{(n)}}{\delta^2 + I^*_{co-tier}} \right)$$

$$\text{s.t. } C1 : I^*_{co-tier} = \sum_{\overline{C_l} \in CS \setminus C_l} \sum_{d \in C_l, d \neq f} \frac{P_d}{\sum_{u \in \mathbf{U}} x_{d,u}} G_{d,u_f}^{(n)}$$

$$C2 : x_{f,u} = \{0, 1\}, \quad \forall f, \ \forall u,$$

$$C3 : \sum_{u=1}^{U} x_{f,u} \leq A_f, \quad \forall f,$$

$$C4 : y_u^{(n)} = \{0, 1\}, \quad \forall n, \ \forall u,$$

$$C5 : \sum_{n=1}^{N} y_u^{(n)} = 1, \quad \forall u. \quad (10)$$

The descriptions for the above optimization problem are given below. In this work, we assume that P_f is the total transmission power of SBS f, and it is equally allocated among all of the served SUDs. Therefore, the transmission power of each SBS f for each served SUE is expressed as $P_f / \sum_{u \in \mathbf{U}} x_{f,u}$. $C2$ and $C3$ indicate that any SBS f can supply service to no more than one A_f. $C4$ and $C5$ indicate that each SUE can only be allocated to a single sub-channel.

Unfortunately, the above optimization problem is a non-linear binary integer programming problem, and the exact solution in polynomial time cannot be obtained. Furthermore, the exhaustive search algorithm is unrealistic because of its extremely huge computational complexity, especially for the ultra-dense deployment scenario of SBSs and SUEs. Additionally, the above joint optimization problem includes coalitional structure generation with independent SBS cooperation and sub-channel resource allocation, which will cause an excessively high computation load, particularly in the UDN scenario. Therefore, a low-complexity hierarchical clustering algorithm is proposed for SBS cooperation-based coalitional structure generation. Moreover, in the process of forming clusters, sub-channels can be effectively assigned. In the following section, we will assess the proposed SC-HCA with the aid of a hierarchical clustering algorithm and coalitional formation theory.

C. HIERARCHICAL CLUSTERING ALGORITHM TO ACHIEVE SBS COOPERATION

Before the SC-HCA is proposed, three relative definitions should be established: a suitability function, a connection matrix and a coalition suitability matrix.

Definition 3: In view of CSG, considering two clusters $C_f, C_{f''}$ and their union set cluster $C_{ff''}$, it is evident that $C_{ff''}$, $CS \in CSG$ and $CS' \in CSG$. Then, the gain among the above three clusters is considered. Hence, a suitability function $S(C_f, C_{f'})$ is given by:

$$S(C_f, C_{f'}) = v(C_{ff'}|C_{ff'} \in CS') \\ -v(C_f|C_f \in CS) - v(C_{f'}|C_{f'} \in CS) \quad (11)$$

To assess the appropriateness when the two clusters C_f, $C_{f''}$ are merged with respect to their suitability before merging, the suitability function $S(C_f, C_{f'})$ is defined. In other words, if merging is beneficial to the value of the cluster, i.e., it increases the network utility, then the value of the suitability function is greater than 0. In this case, the union set cluster $C_{ff''}$ is applied to replace the two clusters C_f and $C_{f'}$. Notably, the value of the formed cluster should be computed using (6) and (7).

Definition 4: When two clusters $C_f, C_{f''}$ are integrated into one cluster $C_{ff''}$, a cluster suitability matrix $SM^{(h)}_{|CS|\times|CS|}$ is applied to reduce the value of the suitability function $S(C_f, C_{f'})$. h represents the current iteration hierarchy or level of the cluster suitability matrix. In addition, the values of the cluster suitability matrix are iteratively updated on the basis of the suitability function $S(C_f, C_{f'})$.

This definition helps to improve the algorithm efficiency since it only has to compute the suitability function for pairs of players. Considering a cluster suitability matrix, successful player merging occurs no more than once at each iteration. Only when the suitability function is positive will successful merging occur. Therefore, the sum of the cluster values in each coalition is never reduced.

	f_1	f_2	f_3	f_4	f_5	f_6
f_1	-Inf	-Inf	15.04	-Inf	-Inf	2.13
f_2	-Inf	-Inf	-Inf	-6.91	-6.90	-3.56
f_3	-Inf	-Inf	-Inf	-5.66	0.42	-Inf
f_4	-Inf	-Inf	-Inf	-Inf	6.06	-2.44
f_5	-Inf	-Inf	-Inf	-Inf	-Inf	-4.86
f_6	-Inf	-Inf	-Inf	-Inf	-Inf	-Inf

(a) $SM^{(0)}_{6\times6}$

	f_2	f_4	f_5	f_6	f_1, f_3
f_2	-Inf	-6.91	-6.90	-3.58	-Inf
f_4	-Inf	-Inf	6.06	-2.44	77.28
f_5	-Inf	-Inf	-Inf	-4.86	70.27
f_6	-Inf	-Inf	-Inf	-Inf	82.55
f_1, f_3	-Inf	77.28	70.27	82.55	-Inf

(b) $SM^{(1)}_{5\times5}$

	f_2	f_4	f_5	f_1, f_3, f_6
f_2	-Inf	-6.91	-6.90	19.24
f_4	-Inf	-Inf	6.06	-5.74
f_5	-Inf	-Inf	-Inf	1.61
f_1, f_3, f_6	19.24	-5.74	1.61	-Inf

(c) $SM^{(2)}_{4\times4}$

	f_4	f_5	f_1, f_3, f_6, f_2
f_4	-Inf	-6.06	-12.34
f_5	-Inf	-Inf	-4.78
f_1, f_3, f_6, f_2	-12.34	-4.78	-Inf

(d) $SM^{(3)}_{3\times3}$

FIGURE 3. An example showing the evolutional process of suitability matrix $SM^{(h)}_{|CS|\times|CS|}$: (a) $SM^{(0)}_{6\times6}$, (b) $SM^{(1)}_{5\times5}$, (c) $SM^{(2)}_{4\times4}$ and (d) $SM^{(3)}_{3\times3}$.

To better understand the definition of the suitability matrix, we provide an example of the evolutional process of the suitability matrix $SM^{(h)}_{|CS|\times|CS|}$, as shown in Fig. 3. Assuming that there are 6 SBSs in an SCN, we use (6) and (7) to obtain the corresponding values of the formed cluster. Then, we can obtain the first hierarchical cluster, i.e., each SBS is in a non-cooperative state, where $|CS| = 6$ and $h = 0$. The specific suitability matrix $SM^{(0)}_{6\times6}$ is shown in Fig. 3(a). Next, the maximum value is selected, and the corresponding SBSs form a cluster. Finally, we use the $SM^{(0)}_{6\times6}$ model to find $SM^{(1)}_{5\times5}$, as shown in Fig. 3(b). $SM^{(2)}_{4\times4}$ and $SM^{(3)}_{3\times3}$ are obtained in the same manner, as shown in Fig. 3(c) and Fig. 3(d) respectively. The hierarchical clustering continues until all values are negative, as shown in Fig. 3(d).

Definition 5: A member connection matrix is a 0-1 symmetric matrix, which is represented as $CM^{(h)}_{|CS|\times|CS|}$. Considered any two members $f, f' \in F$, the connection matrix is given by:

$$CM^{(h)}_{|CS|\times|CS|} = \begin{cases} 1, & if\ N_f \cap N_{f'} \neq \emptyset, f, \quad f' \in \mathbf{F},\ |\mathbf{F}| = F \\ 0, & otherwise \end{cases} \quad (12)$$

For any two members $f, f' \in F$, the value of $CM^{(h)}_{|CS|\times|CS|}$ is set to 1 if the initial sub-channel resources $N_f \cap N_{f''}$ are maintained; otherwise, the value of $CM^{(h)}_{|CS|\times|CS|}$ is set to 0.

D. SC-HCA ANALYSIS AND PROPERTIES

1) ALGORITHM ANALYSIS

On the basis of the suitability function, connection matrix and suitability matrix, a novel SC-HCA scheme is proposed. Algorithm 1 shows the pseudocode, which contains three stages: (i) Initialization occurs in the non-cooperative case. The whole network system is partitioned for F single clusters. In this case, every cluster contains a member, i.e., an SBS. (ii) In neighbor seeking, all members are able to form possible member couples, which are mirrored by the connection matrix $CM^{(h)}_{|CS|\times|CS|}$ of the member couples. Then, considering every possible member couple f and f', the values of the suitability function $S(f, f')$ are obtained by (6) and saved in the suitability matrix $SM^{(h)}_{|CS|\times|CS|}(f, f')$. (iii) Coalitional

Algorithm 1 SBSs Cooperation Using Hierarchical Clustering Algorithm (SC-HCA)

1. Input: relative parameters, the set of members $\mathbf{F}$, suitability function $S(\bullet)$, i.e., zero matrix $\mathbf{0}_{\mathbf{F}\times\mathbf{F}}$.
2. Output: the optimal coalition set of all members CS, the value of system utility $U(CS)$.
* **Stage 1: Initialization**
3. The original coalition formation of all members is represented as $CS = \{\{1\},\ldots,\{f\},\ldots,\{F\}\}\ldots$, i.e., all members $\{1,\ldots,F\}$ are non-cooperative state in the considered network; Then we their data rate is obtained by using (3) and (4) under the non-cooperative state.
* **Stage 2: Neighbor seeking**
4. Acquire $CM^{(h)}_{|CS|\times|CS|}$. according to Definition 5.
5. Acquire $SM^{(h)}_{|CS|\times|CS|}$ for every member couples according to $CM^{(h)}_{|CS|\times|CS|}$.
6. **for** $f, f' = 1 : F, f \neq f'$.
    if $CM^{(h)}_{|CS|\times|CS|}(f,f') = 1.(.)$
        $SM^{(h)}_{|CS|\times|CS|}(f,f') = S(C_f, C_{f'})$
        % by (6) for computing and saving.
    end if
 end for
7. $SM^* =$ *infinity*.
8. $h = 0$ % iteration hierarchy.
* **Stage 3: One iteration process for obtaining cluster generation**
9. **while** $(SM^* \geq 0\& \& |CS| \sim= 1)(.)$ do
    $h = h + 1;$
10. $[SM^{(h)}_{|CS|\times|CS|}\_Colu, index] = \max(SM^{(h)}_{|CS|\times|CS|})$
    % seek out maximum of each column in
    $SM^{(h)}_{|CS|\times|CS|}(f,f')$..
11. $[SM^*, index2] = \max(SM^{(h)}_{|CS|\times|CS|}\_Colu)$
    % seek out maximum in $SM^{(h)}_{F\times F}(f,f')$.
12.   Combined = [$index\ (index2)$, $index2$].
13.   The present coalitional structure CS is updated: deleting the clusters or members that have been combined, and supplement a row and a column for the combined clusters;
14.   The present members' connection matrix $CM^{(h)}_{|CS|\times|CS|}$ is updated.: deleting the row and column of $CM^{(h)}_{|CS|\times|CS|}$ that associates with the clusters or members which have been combined and supplement a row and a column for the combined cluster;
15.   coali_size = $|CS|$
16.   **for** $i = 1$: coali_size -1
17.   **if** $CM^{(h)}_{|CS|\times|CS|}(i, end) = 1.()$
18. $CM^{(h)}_{|CS|\times|CS|}$ for the newly formed CS is computed by (6) and (7).
19.   **end if**
20.   **end for**
21. **end while**

structure generation occurs at each iteration, and the optimal value of the suitability matrix $SM^{(h)}_{|CS|\times|CS|}(f,f')$ is obtained from (6) and (7) so that a suitable cluster can be generated (Lines 10, 11 and 18). If the optimal suitability value is not less than 0 and $|CS| > 1$ is maintained, i.e., the grand cluster is not generated (Line 9), the merging of a member or the clustering of pairs is beneficial to system performance. Therefore, a single member or a clustering couple is replaced by the union set of the member or clustering couples and is then removed from the present coalitional structure (Line 13 and 14). If not, the appropriate coalitional structure is generated, and the SC-HCA ends.

2) ALGORITHM PROPERTIES

The main properties of the proposed SC-HCA are analyzed and discussed from the following aspects: stability, convergence, communication and computational overhead.

Property 1: The proposed SC-HCA can converge to a steady state with a finite number of steps.

Proof: First, since the total number of players (SBSs) in the proposed SC-HCA is finite, the potential number of clusters that can be formed is also finite. Second, the proposed SC-HCA changes a single player per iteration and then stops when the grand cluster is generated or the suitability function value is non-positive. Hence, the formation process of clusters must be able to converge to a steady state with a finite number of steps, i.e., F steps at most.

Property 2: The communication overhead of the proposed SC-HCA is approximately $(U_f F)^h$.

Proof: The communication overhead of the proposed algorithm focuses mostly on the step of cluster formation, namely, the transmission from each SBS $f \in F$ to one of the corresponding SUEs $u_f \in U_f$ for sub-channel $n \in N_f$. The iteration hierarchy level is h to achieve coalitional structure generation. Therefore, the communication overhead of the proposed SC-HCA is approximately $(U_f F)^h$.

Property 3: The computational overhead of the proposed SC-HCA is $O(F^3)$ in the worst-case scenario.

Proof: The computational overhead of the proposed SC-HCA is directly related to the number of merge operations required by each independent player. As explained in Section III.A, a cluster can possibly be formed if and only if SUEs occupy the same sub-channels. Hence, at each iteration level h, there are $F - h$ clusters. In addition, to make sure that a pair of clusters will be merged at the $h + 1$ level, at most $\binom{\text{F-h}}{2} = \frac{(F-h)(F-h-1)}{2}$ pairs of clusters are considered. Therefore, the total number of cluster pairs that can potentially be formed is:

$$\sum_{h=0}^{F-1} \binom{\text{F-h}}{2} = \sum_{k=1}^{F} \binom{k}{2} = \frac{(F-1)F(F+1)}{6} \tag{13}$$

Equation (13) shows that the total number of merge operations in terms of the proposed SC-HCA is proportional to F^3. Hence, the computational overhead of the proposed SC-HCA is $O(F^3)$ in the worst-case scenario.

IV. SIMULATION AND ANALYSIS

In this section, we evaluate the proposed SC-HCA by developing a comprehensive MATLAB system-level simulation platform. The environment of the platform is described as follows.

To evaluate the proposed SC-HCA, we conduct a series of MATLAB simulations. We consider an indoor square area of A m $\times$ A m to accommodate a maximum of F SBSs that are randomly deployed. In the square area considered here, there are N available frequency sub-channels, and it is assumed that F SBSs have a random uniform distribution. The actual positions or coordinates (x_f, y_f) of the f-th SBS are thus given by $x_f = Aa_f$, $y_f = Ab_f$, $f = 1, \ldots, F$, where a_f and $b_f \sim$ U(0, 1) are the uniform distribution between 0 and 1.

We assume that each SBS has a circular coverage area with a radius of 50 m and has 4 sub-channels to separately serve 4 SUEs, which is a typical assumption for small cell networks, as indicated in reference [24]. We further assume that the transmission power of each SBS is set to 20 dBm and the noise variance is -104 dBm.

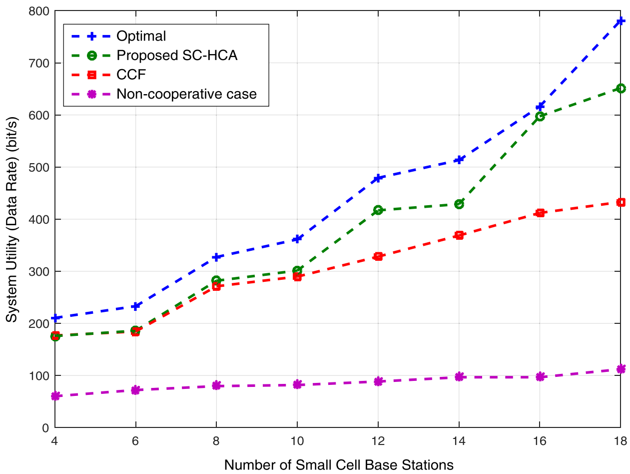

FIGURE 4. Proposed algorithm versus the number of SBSs for small-size SCNs.

For comparison, we simulate a non-cooperative scheme in which cells are independent and are only concerned with the quality of service of individual cells. To the best of our knowledge, there are no other comparable methods that can easily switch SBSs among clusters. Other cooperative algorithms [14]–[19] are difficult to implement in practical SCNs with hundreds of SBSs, as discussed in Section 1. Additionally, since the formation of the optimal coalitional structure through the exhaustive search algorithm under ultra-dense SBS deployment is time consuming, we do not compare the proposed algorithm with the optimal solution. However, for a more comprehensive evaluation, the following two comparison experiments are considered: (i) we compare the proposed algorithm with the classical coalitional formation (CCF) method presented in [19] and use the optimal coalitional structure through an exhaustive search algorithm for small-size SCNs, as shown in Fig. 4; (ii) we compare the proposed SC-HCA with the modularity-based user-centric (MUC) clustering method [28] which has high SBS density. Without loss of generality, considering the relevant literature [28] and the effectiveness of this practical simulation, a 200 m $\times$ 200 m network plane is simulated, as shown in Fig. 6.

Fig. 4 presents the overall system utility with regards to the data rate achieved by the proposed SC-HCA model as a function of the network size F compared with that of three other models, including a model with an optimal coalitional structure, a CCF and a non-cooperative case. The number of available frequency sub-channels N is 20, and the square area A is 500 m. Fig. 4 shows that as F increases, the proposed method displays improved system utility compared to that of CCF in a non-cooperative scenario. The performance improvement reaches up to 16.33% and 343.58% for $F = 14$ SBSs relative to that in the CCF and non-cooperative cases, respectively. Based on the results for the proposed method and the optimal coalitional structure, we can see that the proposed method achieves better performance at approximately 80% of the optimal level.

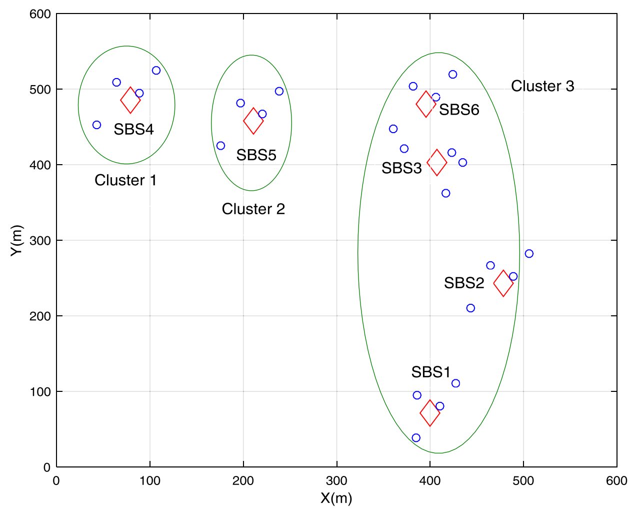

FIGURE 5. A snapshot of a CSG created by the proposed algorithm in an SCN.

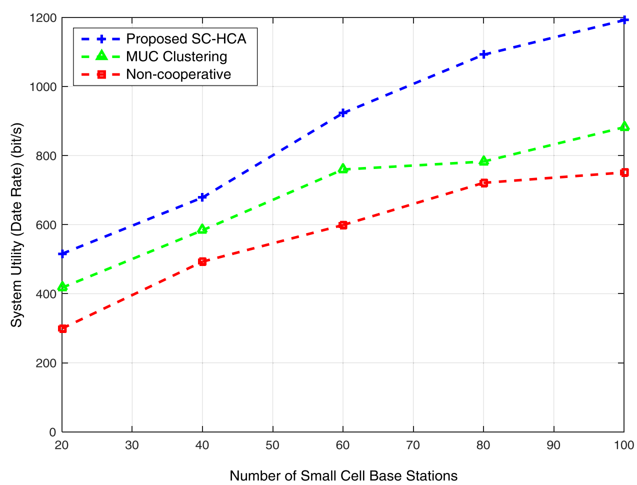

FIGURE 6. Different algorithms versus the number of SBSs for UD-SCNs.

In Fig. 5, we present a snapshot of an SCN resulting from the proposed SC-HCA with $F = 6$ SBSs and $A = 500$ m.

The blue circles represent the four corresponding SUEs of SBSs. The cooperative network shown in Fig. 5 is the final coalitional structure. Initially, all the SBSs non-cooperatively act on their transmissions, as shown in Fig. 3(a). After using the proposed algorithm, they cooperate in the coalitional structure in Fig. 5. This coalitional structure consists of three clusters: Cluster 1, Cluster 2, and Cluster 3. The members of Cluster 1 and Cluster 2 are SBS4 and SBS5, respectively. The members of Cluster 3 include SBS1, SBS3, SBS6, and SBS2. SBS4 and SBS5 have no incentive to cooperate with other SBSs, as their suitability matrices are negative for all other SBSs or clusters, as shown in Fig. 3(b) and Fig. 3(c).

Let us now compare the proposed SC-HCA to the MUC clustering approach and the non-cooperative scheme. Fig. 6 illustrates the system utility as a function of the SBS density for the abovementioned solutions. In this simulation, the number of available frequency sub-channels N is 20, and the square area A is 200 m. First, we observe that there is an increase in system utility as the SBS density increases for all schemes. Second, it can be seen that the proposed SC-HCA outperforms the MUC clustering method and non-cooperative scheme because the cooperation among SBSs instead of SUEs in the proposed algorithm can effectively mitigate co-tier interference. As the network scale increases, the advantage of the proposed algorithm becomes more obvious. For instance, the proposed algorithm achieves 28.33% and 35.15% improvements relative to the results of MUC clustering when $F = 80$ and $F = 100$, respectively.

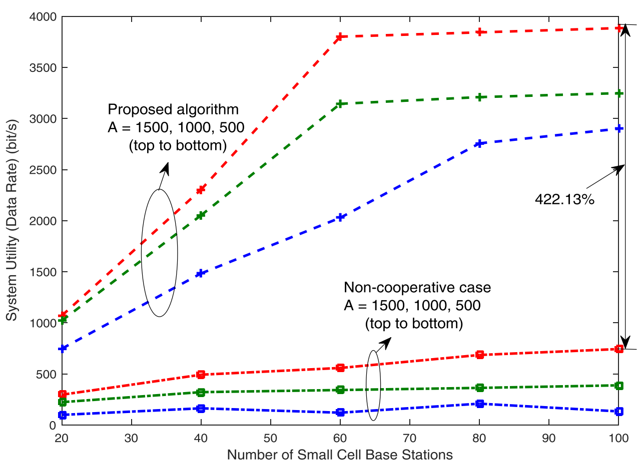

FIGURE 7. Proposed algorithm versus the number of SBSs for UD-SCNs.

Fig. 7 shows the overall system data rate for the network created with the proposed SC-HCA and the non-cooperative scenario as a function of the network size F, where the number of available frequency sub-channels N is 20 and the respective square areas for A are 500 m, 1000 m, and 1500 m. Fig. 7 demonstrates that the proposed SC-HCA yields a significant system performance advantage over the non-cooperative scheme. The gain in the proposed algorithm increases with increasing values of F and A. When the network size F and the admissible distributive area A are gradually increased, the system utility growth rate is most evident. Notably, cooperation and the formation of coalitions aid in the suppression of co-tier interference. The larger the network size is, the greater each SBS's potential for cooperation, and the more effective the proposed algorithm becomes. For instance, the proposed scheme reaches up to a 422.13% improvement relative to the performance of the non-cooperative scheme when $F = 100$ and $A = 1500$ m.

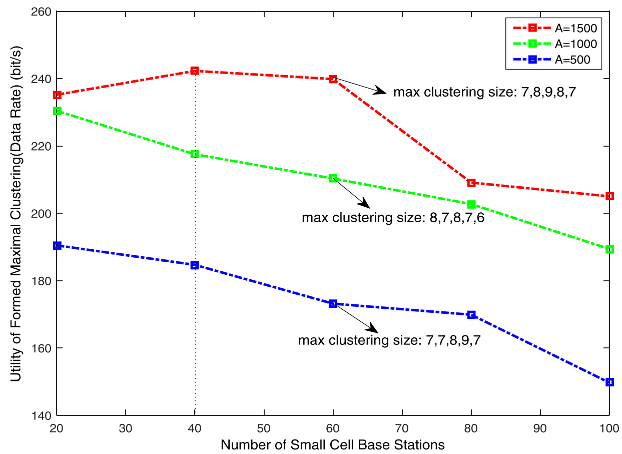

FIGURE 8. Utility of the formed maximal clusters versus the number of SBSs.

Fig. 8 shows the utility of the formed maximal clusters resulting from the SC-HCA with respect to an increasing number of SBSs, where the number of available frequency sub-channels N is 20 and the respective square areas for A are 500 m, 1000 m, and 1500 m. In Fig. 8, we also show the sizes of the formed maximal clusters, namely, $\{7,7,8,9,7\}$, $\{8,7,8,7,6\}$ and $\{7,8,9,8,7\}$, with regard to the corresponding F and A values. Fig. 8 shows that as the number of SBSs increases, the resultant maximal clustering data rate decreases. This result occurs for three reasons. First, regardless of F, the size of the formed maximal clusters is generally maintained in the range of 6$\sim$9. This large size provides adequate public sub-channels, and, on the contrary, a small size makes it impossible to prevent co-tier interference. It is clear that the above two cases are not beneficial to system performance. The empirical results from the simulation experiments show that the most suitable range of the maximal cluster size is 6$\sim$9. Second, as F grows, a clustering utility reduction is observed. The reason for this phenomenon is to avoid co-tier interference. Moreover, the number of public sub-channels among SBSs gradually increases; this is not related to the improvements observed in overall system performance, as shown in Fig. 7. Third, when F stays constant, the larger A becomes, the higher the utility the SBSs can reach, as illustrated by the black dashed lines in Fig. 8. The reasoning for this result is the influence of the co-tier interference reductions with increasing A.

Fig. 9 shows the SC-HCA in the non-cooperative scenario in terms of system utility as the total number of available sub-channels (N) varies. In this simulation, we considered

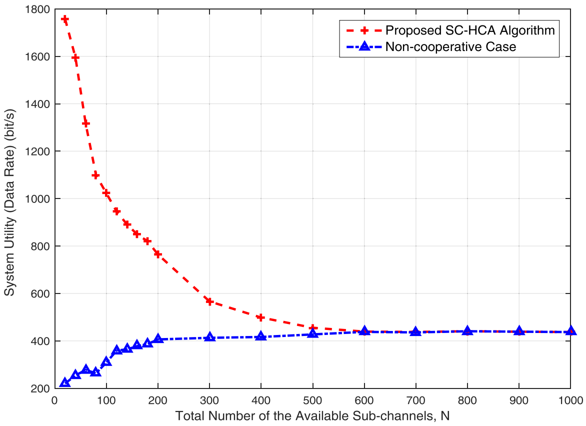

FIGURE 9. System utility versus total number of available sub-channels.

a square area of 1500 m × 1500 m and $F = 30$ SBSs deployed in a small cell network. Although Fig. 8 shows that the system utility for the SC-HCA is superior to that for the non-cooperative scenario, the system utility of the proposed algorithm decreases as the total number of available sub-channels (N) increases. Finally, as in the non-cooperative scenario, the system utility of the SC-HCA reaches a stable data rate as N increases because when the number of available sub-channels considerably increases, the probability of conflicts on the same sub-channel diminishes. Hence, according to the principle of the proposed algorithm, the incentive of cooperation among SBSs is also considerably reduced. Therefore, the advantage of the proposed algorithm is gradually suppressed, and the system utility decreases and slowly approaches that in the non-cooperative case. There is no difference between the proposed algorithm and the non-cooperative case in terms of system utility until N increases to approximately 600, where the two scenarios appear to overlap.

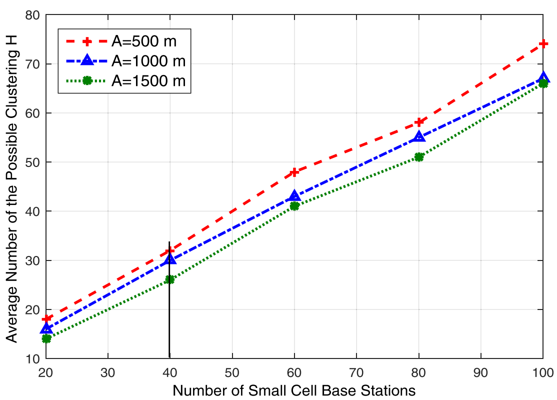

FIGURE 10. Average number of the possible clusters versus the number of SBSs.

Fig. 10 shows that the average number of possible clusters H (the number required to allow the cluster suitability matrix to approach steady state) under different area scenarios using the proposed SC-HCA. It is observed that as F increases, the average number of possible clusters also increases. The reason for this behavior is that the larger the scale of the network is, the greater the number of potential clusters. Additionally, when F is constant, the larger A is, the smaller the required H, as shown by the black solid line in Fig. 10 when $F = 40$. Notably, the larger the scenario is, the more discrete the SBSs are and the smaller H becomes.

V. CONCLUSION

In this paper, cooperative interference management in a UD-SCN was researched. To find a more reasonable assignment scheme for downlink sub-channel resources, the proposed SC-HCA introduces coalition structure generation and a hierarchical clustering algorithm. An SBS cooperative problem was formulated as a coalitional structure generation scenario with characteristic forms. Then, co-tier interference was mitigated, and the network capacity was improved. Since the SC-HCA mainly considers the value of a pair of member utilities, it is effective in the hyper and dense deployment of SBSs. The simulation results show that the proposed algorithm is able to increase the network data rate by 422.13% for a network of 100 cells compared to the traditional method. In the future, we will study the practicality of allocating transmission power based on the SC-HCA.

APPENDIX

See Table 1.

TABLE 1. Mathematics symbols used frequently in this paper.

Symbol	Quantity
$R^{(n)}_{f,u_f}$	downlink data rate obtained by the SUE u_f served by SBS f over the sub-channel n
$I_{co\text{-}tier}$	co-tier interference
CS	a set of a coalition
C_l, C_m	a cluster from a coaltion
CSG	coalitional structure generation
argmax	return the indices of the maximum values
$v(\bullet)$	utility of a cluster
$[\bullet]$	elements from a matrix
$S(\bullet)$	suitability function
h	the current iteration hierarchy
SM	suitability matrix
CM	connection matrix

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