IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 7, 2016, accepted November 22, 2016, date of publication November 29, 2016, date of current version January 4, 2017.

Digital Object Identifier 10.1109/ACCESS.2016.2633434

Hierarchical Resource Allocation Framework for Hyper-Dense Small Cell Networks

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This work was supported in part by the National Natural Science Foundation of China under Grant 61501510, Grant 61301160, and Grant 61631020, in part by the Natural Science Foundation of Jiangsu Province under Grant BK20150717, in part by the China Postdoctoral Science Foundation Funded Project, and in part by the Jiangsu Planned Projects for Postdoctoral Research Funds.

ABSTRACT This paper considers joint power control and subchannel allocation for co-tier interference mitigation in extremely dense small cell networks, which is formulated as a combinatorial optimization problem. Since it is intractable to obtain the globally optimum assignment policy for existing techniques due to the huge computation and communication overheads in ultra-dense scenario, in this paper, we propose a hierarchical resource allocation framework to achieve a desirable solution. Specifically, the solution is obtained by dividing the original optimization problem into four stages in partially distributed manner. First, we propose a divide-and-conquer strategy by invoking clustering technique to decompose the dense network into smaller disjoint clusters. Then, within each cluster, one of the small cell access points is elected as a cluster head to carry out intra-cluster subchannel allocation with a low-complexity algorithm. To tackle the issue of inter-cluster interference, we further develop a distributed learning-base coordination mechanism. Moreover, a local power adjustment scheme is also presented to improve the system performance. Numerical results verify the efficiency of the proposed hierarchical scheme, and demonstrate that our solution outperforms the state-of-the-art methods, especially for hyper-dense networks.

INDEX TERMS Hyper-dense networks, small cells, hierarchical resource allocation, clustering.

I. INTRODUCTION

The fifth generation (5G) mobile networks are expected to achieve a 1,000-fold capacity increase to meet the ever-increasing penetration of the mobile Internet [1], [2], the Internet-of-things [3], [4], and the industrial service systems [5], etc. The most promising driver for achieving this object is network densification [6]. Deploying low-power and low-cost small cells has been regarded as a key piece of the solution for providing high-quality network efficiency. However, with the dense deployment of small cell access points (SAPs), mutual interference among the cells becomes more and more serious, which makes effective resource allocation be an important but critical issue [7].

Cross-tier interference between small cells and macrocell can be avoided with dedicated-channel deployment (or split-spectrum assignment), while the mitigation of co-layer interference among SAPs requires more efficient coordination schemes. There have been some existing solutions studying the resource allocation for co-tier interference mitigation in small cell networks, e.g., sensing-based distributed approach [8], convex optimization-based method [9] and game-theoretic approach [10]. However, if we extend the traditional system model to a large-scale network scenario with tens and even hundreds of SAPs, most existing methods will be inefficient, due to the critical challenges stemming from the randomness of massive SAP locations and the huge computation and communication overheads. Actually, to meet the increasing requirements of users for high data rate transmission, the *hyper-dense network* probably composed of hundreds of heterogeneous small cells will become an overwhelming trend [11]. Therefore, to fully realize the promised benefits of such extremely dense networks, designing practical solution for efficiently distributing the available radio resources among massive SAPs, while satisfying desired performance criteria, urgently needs to be investigated.

To address the above issue, in this paper, we propose a *hierarchical* resource allocation framework to obtain desirable performance with reasonable computational complexity. Specifically, based on the idea of ''divide and conquer'', we decompose the original optimization problem into four steps with *partially-distributed* management. First, in terms of a large-scale network, we apply the clustering technique to group the massive small cells into different clusters to reduce network complexity, and a simple distributed clustering algorithm is proposed. Secondly, for a given cluster configuration, within each cluster, one of the SAPs is elected as a cluster head (CH) that is responsible for subchannel allocation among the small cells in its associated cluster. To avoid the mutual interference among the SAPs in the same cluster, a low-complexity intra-cluster subchannel assignment algorithm based on graph coloring is introduced. Since each CH resolves the subchannel allocation problem independently from its neighboring clusters, two mutually interfering SAPs attached to different clusters may use the same resource, leading to transmission collision. Therefore, in the third step, cluster-edge SAPs can autonomously select appropriate strategies through learning to achieve inter-cluster interference resolution. Finally, after completing the above three steps, if there still exists interference among some SAPs in the same cluster, the corresponding CH can further adjust these SAPs' transmission powers to improve system performance.

The main contributions of the paper are summarized as follows:

- We formulate the joint subchannel and power allocation in hyper-dense small cell networks as a combinatorial optimization problem, in which the objective is to maximize the system throughput.
- We propose a hierarchical resource allocation framework to obtain an effective solution, which divides the original problem into four steps including clustering, intra-cluster subchannel allocation, inter-cluster interference resolution and power adjustment, reducing the network and computational complexity.
- We design efficient algorithms to perform each stage in a partially-decentralized manner, and analyze the inherent properties of the presented hierarchical scheme and highlight several insights.
- We compare our approach with the state-of-the-art solutions in both small and large network scenarios, and discuss the associated gains. Numerical results show that the proposed method can achieve satisfactory performance while having a faster convergence speed, which is more suitable for dense networks.

The rest of this paper is organized as follows. In Section II, we give a brief review of the related works. Section III describes the system model and formulates the optimization problem. In Section IV, the proposed hierarchical resource allocation framework is outlined, followed by the discussions about the four-step partially-distributed scheme. Then, the complexity, convergence and optimality analysis is provided in Section V. In Section VI, we present the simulation results for different scenarios and topologies to demonstrate the performance gains with our method. Finally, Section VII concludes this paper.

II. RELATED WORK

Extremely dense (hyper/ultra-dense) wireless networks [12]–[14] with small cells have attracted more and more attentions due to their promising driving force for the improvement of cellular system capacity. Several studies have provided some prospects about them from the perspectives of key techniques and challenges [15]–[17]. To fully harvest the gains of such heterogeneous networks, interference management and resource allocation are the most crucial issues.

In the recent studies, there are many *centralized* resource assignment approaches for inter-cell interference mitigation in small cell networks. For example, Liang *et al.* developed a greedy algorithm with a central controller to solve the co-channel and co-tiered interference in [18]. A centralized joint power and subchannel allocation framework was designed in [19] to maximize system capacity for femtocell networks. However, because of the uncertainty in the number and positions of the SAPs, centralized control and human intervention in network management are not viable. In addition, significant signaling overhead and computational complexity also make centralized approaches inefficient.

Instead, *decentralized* resource allocation methods are preferred and a series of distributed solutions have been proposed in existing works, e.g., dual decomposition-based iterative subgradient approach [20], switched-based scheme [21], geometric probability approach [22], and game theory with learning-based schemes [23]–[25]. Nevertheless, the distributed solutions have the advantages of easier implementation and better scalability compared with the centralized methods, but their performance is typically inferior to the centralized schemes. In addition, the convergence speed of the algorithms proposed in conventional decentralized approaches will be very slow in *large-scale* networks with hundreds of small cells, that gives rise to the inherent limitations. In summary, traditional centralized or distributed methods cannot scale easily to the extremely dense networks.

Unlike previous studies, in this work, we present a partially-distributed framework based on clustering which decomposes the original optimization problem into several sub-problems for resolution in a hierarchical mechanism, i.e., ''divide and conquer''. Note that, although clustering has been used as a technique to coordinate the co-tier interference in small cells in the literature [26], how to mitigate inter-cluster interference is a thorny issue, which is often neglected in most existing works [27]. As a result, the gains of cluster-edge SAPs will be heavily watered-down. Furthermore, the proposed methods of applying a central controller such as gateway to group the small cells into disjoint clusters and perform resource allocation, e.g., in [7] and [28], are also not appropriate in large-scale small cell networks due to the random and massive deployment of SAPs. Different from the aforementioned existing works with clustering, we utilize a distributed cluster formulation scheme which only requires local information exchange. Moreover, the inter-cluster interference is also addressed by an effective coordination mechanism with autonomous learning to improve the system efficiency. These properties make the proposed hierarchical solution particularly suitable for extremely dense heterogeneous small cell networks.

III. NETWORK AND INTERFERENCE MODELS AND PROBLEM FORMULATION

Consider the downlink transmission for a dense small cell network where K randomly deployed SAPs are overlaid on a macrocell. It is assumed that the small cell and macrocell networks operate on split spectrum, in which the cross-tier interference can be avoided. There are N orthogonal subchannels with the bandwidth of Δf available for the SAPs in the network. For presentation, denote the SAP set as $\mathbf{K}$ and subchannel set as $\mathbf{N}$, i.e., $\mathbf{K} = \{1, 2 \ldots K\}$ ($|\mathbf{K}| = K$) and $\mathbf{N} = \{1, 2, \ldots, N\}$ ($|\mathbf{N}| = N$). Similar to the previous studies [29], [30], we consider that there is only one active user equipment (UE) communicating with the SAP in each time slot, and the SAPs and the users are all equipped with single antennas. The UE belonging to SAP k is denoted by χ_k. A closed-access scheme is assumed for all small cells, where access to a SAP is restricted only to the registered UEs.

Let $\boldsymbol{\eta} = \left[\eta_i^n\right]$ with size of $N \times K$ be the subchannel allocation matrix, and η_i^n is equal to 1 if subchannel n is allocated to SAP i; otherwise, it is equal to 0. Moreover, we denote the transmit power assigned to the link between SAP k and UE χ_k on subchannel n by p_{k,χ_k}^n, $p_{k,\chi_k}^n \in \left\{\lambda_1 P_{k,\max}, \ldots, \lambda_M P_{k,\max}\right\}$, where $P_{k,\max}$ is the power limit and $0 = \lambda_1 < \lambda_2 < \ldots < \lambda_M = 1$. We indicate with $\left|h_{i,\chi_i}^{(n)}\right|^2$ the channel power gains and denote N_0 as the additive white Gaussian noise power. Therefore, for SAP k with subchannel $n \in \mathbf{N}$, the signal-to-interference-plus-noise ratio (SINR) can be given by:

$$\gamma_{k,\chi_k}^n = \frac{p_{k,\chi_k}^n \left|h_{k,\chi_k}^n\right|^2}{\sum\limits_{j \in \mathbf{K}, j \neq k} p_{j,\chi_j}^n \left|h_{j,\chi_j}^{(n)}\right|^2 + N_0}. \tag{1}$$

Then, based on Shannons capacity formula, the achievable rate of UE χ_k on subchannel n in small cell k can be defined as:

$$R_{k,\chi_k}^n = \Delta f \log_2(1 + \gamma_{k,\chi_k}^n). \tag{2}$$

In this paper, our target is to maximize the system throughput, jointly considering the subchannel assignment and power control. Therefore, the corresponding problem for downlink transmission in a small cell network can be mathematically formulated as follows:

$$\begin{aligned} &\max_{\eta_k^n, p_{k,\chi_k}^n} \sum_{k=1}^{K} \sum_{n=1}^{N} \eta_i^n \Delta f \log_2(1 + \gamma_{k,\chi_k}^n) \\ &s.t.\ (a): p_{k,\chi_k}^n \in \left\{\lambda_1 P_{k,\max}, \ldots, \lambda_M P_{k,\max}\right\}, \quad \forall k, n \\ &\qquad (b): \eta_k^n \in \{0, 1\}, \quad \forall k, n. \end{aligned} \tag{3}$$

Constraint (a) represents the transmit power limits of each SAP. Constraint (b) restricts that each element of the allocation matrix is a binary variable.

Remark 1: The problem (3) is a binary combinatorial optimization problem, in which the objective is to find the optimal subchannel assignment $\left\{\eta_k^n\right\}_{k=1}^K$ *and power control* $\left\{p_{k,\chi_k}^n\right\}_{k=1}^K$ *determining which subchannel should transmit data for which SAP on which power level, whose solution is intractable. What's more, in a dense network scenario, the computational complexity will increase greatly such that a centralized mode of operation or conventional decentralized optimization techniques cannot be applied directly for a practical solution. For example, consider a network with 50 small cells, four power levels and five subchannels, in which each small cell choosing one pair of subchannel and power for transmission, the number of all possible strategy selection profiles is* $4^{50} \times 5^{50} \approx 1.13 \times 10^{65}$ *, for which it is hard to achieve the effective solutions using conventional optimization approaches. To address this challenge, a more efficient resource allocation method with acceptable computational threshold and desirable system performance is in urgent need.*

IV. PROPOSED HIERARCHICAL RESOURCE ALLOCATION SCHEME

In response to the infeasibility of applying existing centralized/distributed methods, in this section, we develop a partially-distributed resource allocation scheme with hierarchical framework, which is proved to be suitable for large-scale networks. Specifically, the proposed hierarchical solution decomposes the original optimization problem into the following four steps, as described in Fig. 1.

1) *Distributed clustering:* massive SAPs are firstly divided into several disjoint groups through local information exchange, where now a cluster becomes a resource assignment unit, dramatically reducing the network complexity.
2) *Intra-cluster subchannel allocation:* in each cluster, one of the SAPs is elected to be a cluster head to perform subchannel allocation within its attached cluster based on coloring an interference graph. Note that this step is carried out *in parallel*.
3) *Inter-cluster collision resolution:* those SAPs located at the edge of two neighboring clusters need to change their subchannel occupancy strategies through autonomous learning, for resolving the possible

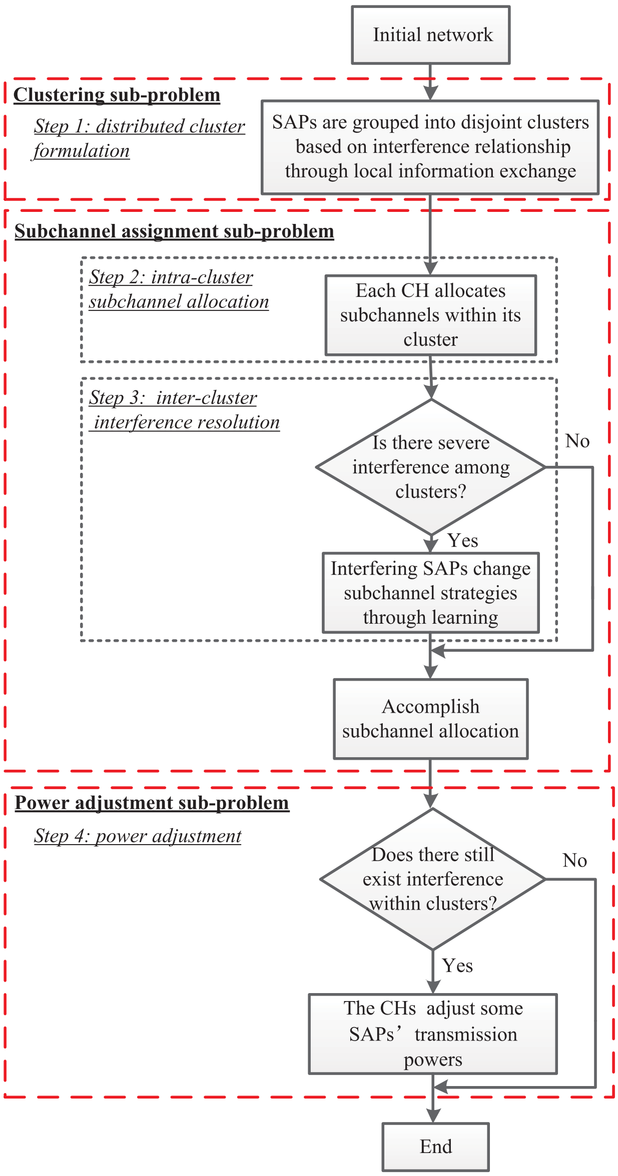

FIGURE 1. **Flowchart of the proposed clustering-based hierarchical framework.**

inter-cluster interference when they operate on the same resources.

4) *Power adjustment:* after accomplishing subchannel allocation according to the above mentioned rules, the CHs can further coordinate the transmission powers of some SAPs which still cannot avoid subchannel access collisions within clusters to improve the system efficiency.

For each step, we provide effective algorithms and analyze their properties, which are described as follows.

A. STEP 1: DISTRIBUTED CLUSTERING

In a dense deployment of small cells with tight interference constraints, clustering is a very efficient technique which can divide the large-scale network into smaller modules, dramatically reducing the complexity of network. The optimal clustering yields the cluster configuration achieving the highest sum-rate, which can be obtained by an exhaustive search. For K SAPs, the number of possible cluster formulation ways is given by [7]:

$$\sum_{k=1}^{K} \frac{1}{k!} \sum_{i=0}^{k} (-1)^{k-i} \binom{k}{i} i^K \approx \mathcal{O}\left(K^K\right). \tag{4}$$

It is clear that the number of possible clustering ways grows exponentially with the number of SAPs. Therefore, applying exhaustive search to seek the optimal cluster configuration is prohibitive. In essence, clustering methods can be categorized into two subgroups: centralized and decentralized clustering. Although the centralized clustering scheme with a coordinator can obtain better cluster configuration, it requires the global information of the entire network [7], which is not suitable for the considered large-scale network scenario. Instead, decentralized clustering methods with a self-organized manner are more preferred. Motivated by the idea of clustering rule proposed in [31], here, we present a simple distributed cluster formulation scheme as shown in Algorithm 1.[1]

Algorithm 1 Distributed Cluster Formulation Algorithm

1: Initially, indicating with s_i the ith small cell, i.e., $\cup_i s_i = \mathbf{K}$; set $|c_l| = 0$ and $l = 1$.
2: **for** $i = 1$ to K
3: s_i establishes a list of interfering neighbor SAPs by sensing the environment, and then transmits and shares the associated interfering list with its corresponding neighbors.
4: **end**
5: **for** $i = 1$ to K
6: **if** s_i has the highest degree of interfering neighbors, **then**
7: s_i elects itself as a cluster head and informs its neighbors, $|c_i| = |c_i| + 1$
8: its j associated interfering neighbors will be grouped into cluster members and send attachment request to the CH s_i, and $|c_i| = |c_i| + j$
9: Remove the SAPs in the cluster c_i from $\mathbf{K}$
10: **while** $|\mathbf{K}| > 0$
11: Sort the list of remainder SAPs decreasingly according to their interference degree; repeat 6 to 9
12: **end**
13: **else**
14: $i + 1$, go back to 5
15: **end if**
16: **end**

At first, a list of interference neighbors can be obtained by each SAP by exploiting its attached users' measurement

[1] Our main objective is to apply the idea of clustering to decompose the large-scale network. Since there would be little variation in the following steps with different cluster constructions, the discussions about the optimal cluster formulation are omitted, and are also not the focuses of this paper.

reports. Due to the lower coverage of SAPs, the signal transmitted by a given SAP causes interference only to the UEs located in a few neighboring cells. Thus, such local interference relationship among the small cells can be characterized by an interference graph. Here, we use a distance-determined model [32] for presentation . The interference graph can be denoted as $G = (\mathbf{V}, \mathbf{E})$, where $\mathbf{V}$ is the set of vertices denoting SAPs and $\mathbf{E}$ is the edge set, i.e., $\mathbf{V} = \{v_1, v_2 \ldots v_K\}$ and $\mathbf{E} = \left\{(i,j) | \, i,j \in \mathbf{K}, d_{ij} < d_0\right\}$ where d_{ij} is the distance between SAP i and j, and d_0 is the threshold. Afterwards, the list is transmitted and shared amongst the corresponding neighboring SAPs. Therefore, every SAP can compute the number of interfering neighbors. According to this information, a SAP will elect itself as CH if it has the highest interference degree, while its associated neighbors act as cluster members. Specifically, an example of the cluster formation stage is given in Fig. 2. A dense network consisting of 10 SAPs is considered in Fig. 2-(a), and it is divided into three clusters as shown in Fig. 2-(b).

We define $\mathbf{C}$ as the set of clusters of small cells. Each SAP must be a member of only one cluster and the resulting clusters should cover all SAPs in the network. A cluster $c_l \in \mathbf{C}$ is the lth set of SAPs such that $c_l \in \mathbf{K}, \forall l \in \{1, 2, \ldots, |\mathbf{C}|\}$, $\cup_{l=1}^{|\mathbf{C}|} c_l = \mathbf{K}$, and $\cap_{l=1}^{|\mathbf{C}|} c_l = \phi$. Once the initial network with hyper-dense deployment of small cells is partitioned into disjoint clusters, *the resource assignment problem for overall network can be transformed into a situation in which cluster is a resource allocation unit*. Hence, the formulated problem based on clustering is given by:

$$\begin{aligned} &\max_{\eta_k^n, p_{k,\chi_k}^n} \sum_{l=1}^{|\mathbf{C}|} \sum_{k \in c_l} \sum_{n=1}^{N} \eta_i^n \Delta f \log_2(1 + \gamma_{k,\chi_k}^n) \\ &s.t. \ (a) : p_{k,\chi_k}^n \in \left\{\lambda_1 P_{k,\max}, \ldots, \lambda_M P_{k,\max}\right\}, \quad \forall k, n \\ &\qquad (b) : \eta_k^n \in \{0, 1\}, \quad \forall k, n \\ &\qquad (c) : \cup_{l=1}^{|\mathbf{C}|} c_l = \mathbf{K} \\ &\qquad (d) : \cap_{l=1}^{|\mathbf{C}|} c_l = \phi. \end{aligned} \tag{5}$$

Remark 2: It is noted that original system utility is $U_0 = \sum_{i \in \mathbf{K}} u_i$, *after clustering, which can be re-written as* $U_0 = \sum_{l=1}^{|\mathbf{C}|} \sum_{i \in c_l} u_i$, *where* u_i *denotes the achievable payoffs of SAP i, i.e., throughput here. From the possible strategy selection profile perspective, for the initial network, we can have* $(N \times M)^K$, *while that is* $\sum_{l=1}^{|\mathbf{C}|} (N \times M)^{|c_l|}$ *in terms of the clustering configuration, where N and M indicate the number of subchannels and power levels, respectively. Since in a large-scale network,* $|c_l| < K$ *and* $|\mathbf{C}| < K$ *hold,* $\sum_{l=1}^{|\mathbf{C}|} (N \times M)^{|c_l|} \ll (N \times M)^K$ *follows. That is to say, the proposed clustering scheme dramatically decreases the network complexity and computational overhead.*

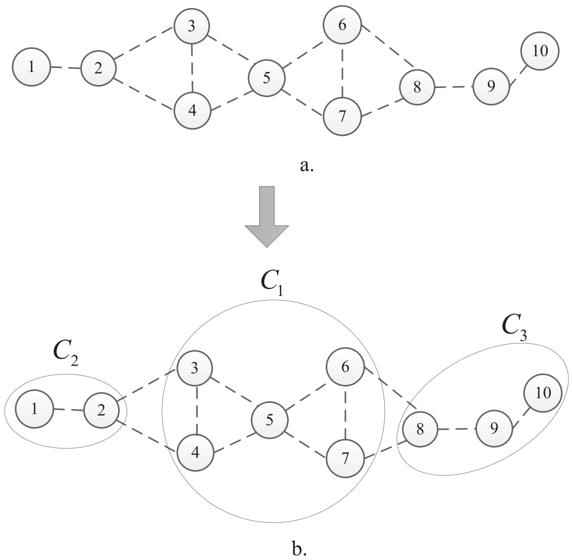

FIGURE 2. Distributed cluster formulation procedure. (a) Original network topology. (b) Distributed cluster formulation.

B. STEP 2: INTRA-CLUSTER SUBCHANNEL ALLOCATION

Applying the clustering scheme presented in the first step, we have partitioned the large-scale network into smaller disjoint groups. Now a cluster becomes a resource allocation unit in which an associated cluster head can achieve resource management in a centralized manner via exchanging simple messages within the cluster. For each cluster c_l, since the object is to maximize the sum-rate of all small cells within the cluster, co-tier interference needs to be avoided, if possible. To do so, we present a low-complexity intra-cluster subchannel allocation algorithm based on the sequential coloring scheme [33].

Assuming each color denotes a subchannel, graph coloring facilitates subchannel assignment, where two SAPs connected by an edge in the interference graph should not use the same subchannel simultaneously, for mitigating co-channel interference, i.e., the following constraint should be satisfied, if possible:

$$\left(\eta_i^n + \eta_j^n\right) b_{ij} \leq 1, \quad \forall i, j \in c_l, c_l \in \mathbf{C}, n \in \mathbf{N}, \tag{6}$$

where b_{ij} is a binary index that takes the value of 1 if there exists an interference edge between the SAP i and j, and 0 otherwise. Let $\beta \in \{1, 2 \ldots N\}$ be the color number of vertices in G, and N is the total number of sub-channels. The corresponding CH of the cluster c_l is CH_l, which is elected to be responsible for the resource management within the cluster. The details of the intra-cluster subchanel allocation algorithm are listed in Algorithm 2. It is worth pointing out that, in this step, intra-cluster subchannel assignment is performed *in parallel*, which greatly speed up the procedure achievement.

However, due to the fact that each CH performs the subchannel allocation independently from its neighboring clusters, two mutually interfering SAPs attached to different

Algorithm 2 Intra-Cluster Subchannel Allocation Algorithm

1: **Initialization:** Set the iteration $l = 1$ and the color number $\beta = 1$.
2: **for** $i = 1$ to $|c_l|$, $c_l \in \mathbf{C}$
3:   **while** $\beta < N$
4:     **if** none of the adjacent vertices of v_i in cluster c_l are assigned color β, **then**
5:       CH_l assigns color β to the vertex v_i
6:     **else**
7:       $\beta = \beta + 1$, go to 4
8:     **end if**
9:   **end**
10:   CH_l assigns a sub-channel from $\mathbf{N}$ to v_i randomly
11: **end**

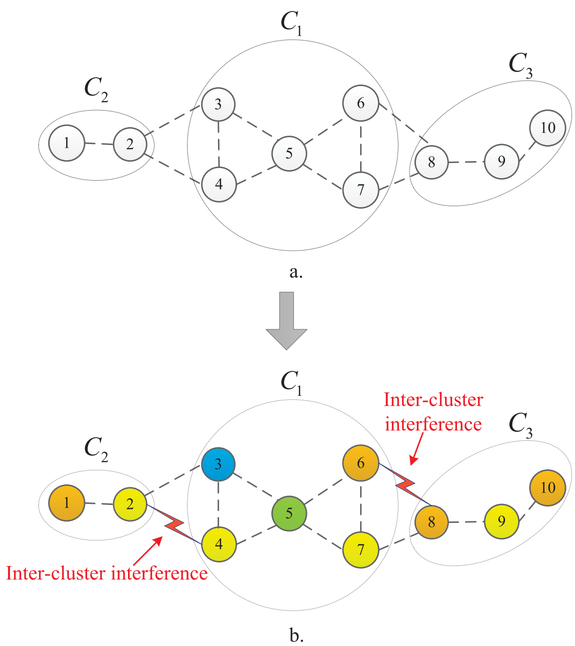

FIGURE 3. **Subchannel allocation within clusters based on graph coloring. (a) Cluster configuration. (b) Intra-cluster subchannel allocation.**

clusters might operate on the same resources. Consequently, although achieving intra-cluster subchannel allocation, the interference between two neighboring clusters may still exist. For example, given the cluster configuration as Fig. 3-(a), after accomplishing the subchannel assignment within the clusters C_1, C_2 and C_3, it may engender transmission collisions between SAPs 2 and 4, 6 and 8, since they utilize the same resources. As a result, the performances of some cluster-edge users (i.e., the users attached to the SAPs 2, 4, 6 and 8) are relatively bad because of the existence of inter-cluster interference. Nevertheless, this issue was not addressed in most existing works [7], [28], which will be solved at the stage of inter-cluster interference resolution.

C. STEP 3: INTER-CLUSTER COLLISION RESOLUTION

Since the prior subchannel access collisions between two neighboring clusters are unknown for respective CH, it is

Algorithm 3 Decentralized Inter-Cluster Interference Resolution Algorithm

1: **Initialization:** Set the iteration $t = 0$, and the initial evaluation value $\mathrm{Q}(a) = 0$, for $\forall i \in \{1, 2, \ldots N_f\}$, $\forall m \in \{1, 2, \ldots M\}$.
2: **Loop for** $i = 1$ to $|\mathcal{N}_f|$, $t = 0, 1, \ldots$
3:   **if** exploration probability is less than ε **then**
4:     select action randomly
5:   **else**
6:     choose action $a_t^{i,m} = \arg\max_{a \in A} \mathrm{Q}(a)$
7:   **end if**
8:   receive immediate reward for SAP i at time $t+1$: $r_{t+1}^{i,m} = \Delta f \log_2 \left(1 + \gamma_i^{(n)}\right)$
9:   update Q (a) according to the rules as:

$$\mathrm{Q}_{t+1}(a) = (1-\alpha)\mathrm{Q}_t(a) + \alpha(r_t(a) + \lambda \max_{a' \in A} \mathrm{Q}_t(a')) \quad (7)$$

10: **End loop**

intractable to eliminate inter-cluster interference by the coordination from CHs with a centralized scheme. To tackle this challenge, we resort to the distributed learning scheme, in which those SAPs located at the edge of clusters interfered by other neighboring SAPs from different clusters can adopt the suitable subchannel selection strategies through autonomously learning. Based on the reinforcement learning scheme [34], we propose a distributed inter-cluster collision resolution algorithm only relying on the interaction with the environment, which is described in Algorithm 3.

The main idea of the algorithm can be summarized as follows: we indicate with $\mathcal{N}_f$ the set of SAPs located at the edge of clusters, which need to adjust their subchannel occupations through learning. It is clear that $|\mathcal{N}_f|$ is less than K. For an arbitrary SAP i ($i \in \mathcal{N}_f$), the object is to find an appropriate policy that maximizes the expected cumulative reward during the learning period:

$$\arg\max_{i \in \mathcal{N}_f} \left(E \left(\sum_t \lambda r_t^i \right) \right), \quad (8)$$

where λ is the discount factor ($0 \leq \lambda < 1$) and r_t^i is the received reward at time t. The action set for SAP i is denoted as $\mathbf{A} = \left(a^{i,1}, a^{i,2}, \ldots\right)$, which can potentially enable SAP i to mitigate inter-cluster interference while not interfering its neighboring SAPs in the same cluster. We define $\mathrm{Q}(a)$ as an evaluation value for the expected cumulative reward over a long time for the agents with taking action a. In this algorithm, a SAP performs the exploration step with probability ε, and α_t denotes the learning rate that is used to control the speed of adjustment of $\mathrm{Q}(a)$. A new value of $\mathrm{Q}(a)$ is obtained based on the previous value along with the new observed reward. Here, the new observed payoff is biased by the outcome of choosing the best action based on the available knowledge. The stop criterion of the algorithm is to content that the predefined maximum iteration number is reached.

Theorem 1: Given learning rates $0 \le \alpha_t < 1$, and $\sum_{t=0}^{\infty} \alpha_t = \infty$, $\sum_{t=0}^{\infty} {\alpha_t}^2 < \infty$, then the proposed decentralized inter-cluster interference resolution algorithm can converges to a stationary point as $t \to \infty$, with probability 1.

Proof: According to the convergence proof for the action-play process proposed in [35], we can get that if given the bounded rewards with the conditional learning rates as described in the theorem, $\forall a$, as $t \to \infty$, $Q_t(a) \to Q_t^*(a)$ holds with probability 1, where $Q_t^*(a)$ denotes the optimal stationary value. In the algorithm, it is noted that the obtained reward for each player is the data rate receiving from the strategy selection, which is bounded, i.e., $|r_t| \le R$. Thus, following the similar analysis in [35], Theorem 1 can be achieved. ■

D. STEP 4: POWER ADJUSTMENT

After accomplishing the above three steps, if there still exists co-tier interference among the SAPs in an arbitrary cluster c_l ($c_l \in \mathbf{C}$), the corresponding CH can further perform local power adjustment to improve the system performance. The optimization problem can be formulated as:

$$\max_{p_{k,\chi_k}^n} \sum_{k \in c_l} \sum_{n=1}^{N} \eta_i^n \Delta f \log_2(1+\gamma_{k,\chi_k}^n)$$
$$s.t.\ (a): p_{k,\chi_k}^n \in \left\{\lambda_1 P_{k,\max}, \ldots, \lambda_M P_{k,\max}\right\}, \quad \forall k, n. \quad (9)$$

Since the considered power levels are discrete, for given subchannel allocation, the local power adjustment will become relatively simple, which can be efficiently solved by using the exhaustive search scheme in an optimal manner. Notably, since the power value is discrete and power set is finite, it is expected that the complexity of applying exhaustive search is low and reasonable in practice. Actually, in terms of the local power adjustment, an even simpler alternative is to use the equal power transmission, which can remove all computations of the exhaustive search method. The reason is that, during the period of subchannel allocation, the worst-case initial interference has been considered, where all SAPs are assumed to be transmitting on all subchannels with uniform maximum power. In other words, we have tried to minimize the subchannel access collision through the previous three steps with coordination, so using maximum power allocation is feasible. What's more, we found that utilizing uniform maximum power could yield almost the same performance as applying exhaustive search through simulations. Notably, this kind of strategy has been also applied in some existing related works [7], [36].

V. COMPLEXITY, CONVERGENCE AND OPTIMALITY ANALYSIS

A. COMPUTATIONAL COMPLEXITY AND COMMUNICATION OVERHEAD

1) STEP 1 - DISTRIBUTED CLUSTERING

This step mainly relys on local information exchange for constructing neighbor list to achieve clustering. For each SAP, it needs calculate the distance between each other and $K-1$ comparisons to determine the neighbor relationship. Hence, the complexity of distributed clustering is $\mathcal{O}\left(K^2\right)$ for a dense network with K SAPs.

2) STEP 2 - INTRA-CLUSTER SUBCHANNEL ALLOCATION

Subchannel assignment within clusters is based on sequential coloring (or greedy coloring) scheme, whose complexity depends on the density of graph. It is known that, in general, if a graph G with n vertices has maximum degree Δ, then it can be colored with no more than $\Delta + 1$ colors with greedy coloring algorithms. In algorithm 2, we assume that if $\Delta > N$ (N is the subchannel number), the color will be assigned randomly. Hence, for a given cluster c_l with $|c_l|$ SAPs, the complexity of completing the subchannel allocation is of the order $\mathcal{O}\left(|c_l|^2\right)$ in worst case.

3) STEP 3 - INTER-CLUSTER COLLISION RESOLUTION

To mitigate the interference among the neighboring clusters, cluster-edge users need to change the strategy selections through autonomous learning. Assume the available subchannel set for an cluster-edge user is $\mathbf{A}$, the predefined maximum iteration number for the learning scheme is $I_{\max}$, then the proposed inter-cluster collision resolution has complexity of $\mathcal{O}(|\mathbf{A}|\, I_{\max})$.

4) STEP 4 - POWER ADJUSTMENT

The complexity of this problem depends on the utilized solution method, e.g., using the exhaustive search scheme with a computational complexity of $\mathcal{O}(M)$, where M is the number of power levels. Since the transmission interference on subchannels has been reduced as much as possible in the above three steps, a special case is considered in this paper. That's equal transmit power is used on all the subchannels, which can yield almost the optimum performance when the power adjustment procedure benefits from using exhaustive search. The step of equal transmit power with given subchannel allocation has complexity of $\mathcal{O}(1)$.

Achieving hierarchical resource allocation also requires some communication cost, which mainly includes the overhead of information exchange between the neighboring SAPs in the phases of the distributed clustering and the subsequent algorithms execution. Since each SAP only needs to communicate with its neighbors via backhaul channels in a local area, the communication overhead among SAPs will be tolerable.

B. CONVERGENCE AND OPTIMALITY ANALYSIS

In terms of the proposed hierarchical resource allocation framework with four-step partially-distributed manner, the convergence can be analyzed as follows. It is expected that only if the number of SAPs in the system is finite, an arbitrary large network could be divided into smaller groups by using clustering technique with easy operation. Since intra-cluster subchannel allocation is carried out by CHs at the central unit, the convergence is predictable, and this stage can be quickly completed. The convergence proof for the step of inter-cluster collision resolution based on autonomous learning has been provided in Subsection IV-C. Regarding power adjustment, it is obvious that the process will converge to a stable state by using the interior point method or equal transmit power.

As for optimality, as we are solving a non-deterministic polynomial hard (NP-hard) problem, optimality cannot be guaranteed. However, the system performance of the proposed scheme is empirically shown to approach optimality with a very small gap in small-scale networks, and to be very desirable in large-scale scenarios with relatively low complexity. The detailed simulation results can be found in the next part.

To sum up, the results of the hierarchical scheme operating with a partially-distributed manner can be proved to converge to the exact status, thereby efficiently solving the resource allocation problem with suboptimal performance for ultra-dense networks.

Remark 3: The proposed hierarchical resource allocation scheme possesses the benefits of easy implementation and good scalability, in which the corresponding algorithm for each step is not limited to the methods given in this article. That is, the aforementioned four stages can also be performed by applying other existing feasible algorithms owing to the universality of the framework. The superiority of our scheme is that it imposes limited complexity and only requires local information, while achieving desirable system performance with faster convergence speed, which are validated in the section of simulation results. All these advantages render the hierarchical scheme a strong candidate for resource assignment in the hyper-dense heterogeneous small cell networks.

VI. SIMULATION RESULTS

In this section, the numerical simulation and analysis are conducted to estimate the performance of the proposed hierarchical resource allocation scheme. Here, we consider a small cell network with random deployment of femtocell access points (FAPs) in a square area, and each FAP can cover a circular cell region of radius 10 meters. The available spectrum in the network is divided into multiple subchannels each with a bandwidth of 180 kHz. We set the discount factor $\lambda = 0.3$ and the learning rate $\alpha = 0.3$ for the inter-cluster interference resolution stage. The channel gains include path-loss and shadowing. The following path-loss equation is used to estimate path-loss between femtocells and UEs. For path-loss between a femtocell and its UE, $PL = 38.46 + 20\log d$ and for path-loss between a femtocell and a general UE $PL = 38.46 + 20\log d + qL$, where d is the distance between a FAP and the UE and qL accounts for loss due to walls [7]. Table 1 lists the parameters used for obtaining the numerical results.

The simulation results mainly include the following three parts. In the first part, we present the convergence behavior of the proposed scheme and compare the convergence speeds of our solution and a traditional learning algorithm. In the second part, we show the throughput performance comparison of the proposed hierarchical scheme with some other existing methods both in small scenarios and big scenarios.

TABLE 1. Simulation parameters.

Parameters	Value
Carrier frequency (f_c)	2 GHz
Subchannel bandwidth, Δf	180 kHz
Distance between UE and FAP	1m
Transmission power (p_T)	20dBm
Noise power density, N_0	-174 dBm/Hz
Standard deviation of shadowing between femtocell and its UE	4dB
Standard deviation of shadowing between femtocell and another UE	8dB

Finally, the fairness performance comparison is illustrated in the third part.

A. CONVERGENCE BEHAVIOR

We consider a large-scale small cell network with random deployment of 50 FAPs in a $100m \times 100m$ square area. The inner wall loss is set to 10 dB and 5 subchannels are available in the network. To show the convergence of the proposed algorithms, Fig. 4 depicts the evolution of the number of FAPs on each subchannel. It is noted that the system converges to a stable state in about 210 iterations. This result validates the convergence of the proposed hierarchical scheme in dense network scenario.

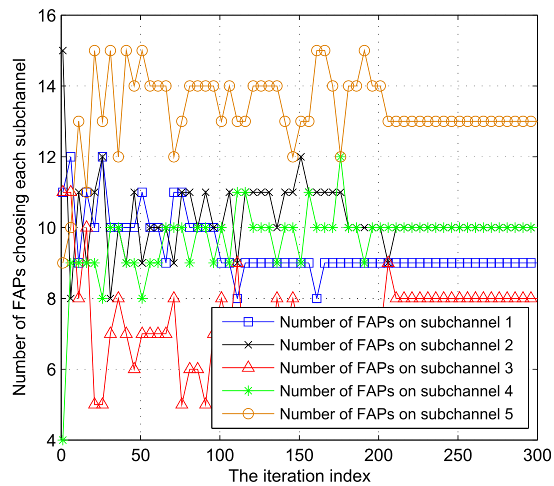

FIGURE 4. The evolution of the number of FAPs on each subchannel.

In general, the achievable system performance of traditional distributed resource allocation algorithms often relys on the number of iterations so that these methods will require very long time to guarantee the convergence in large-scale networks. However, in this work, the proposed hierarchical scheme is partially-distributed. In order to investigate the superiority of our method in terms of convergence speed, from a statistical perspective, we compare its convergence speed with that of conventional decentralized learning algorithm proposed in [37]. In this policy, the process of dynamic resource allocation for each small cell is carried out concurrently based on Q-Learning. That is to say, all the players (i.e., the FAPs) will participate in the resource competition simultaneously through self-organizing learning without information exchange.

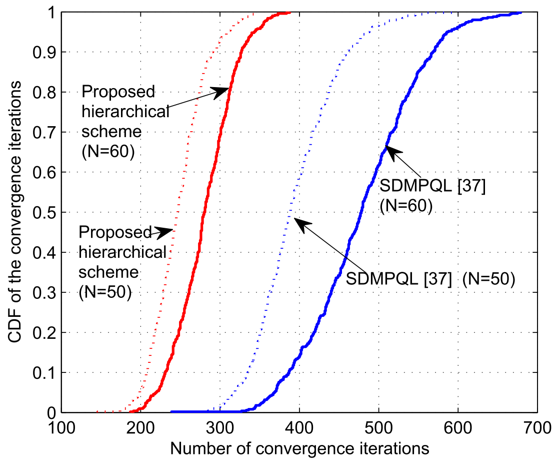

FIGURE 5. Convergence speed comparison for different network scales.

For simplicity, we term the "Synchronous Decision-Making Process Based on Q-Learning" presented in [37] as "SDMPQL" scheme. Specifically, the cumulative distribution function (CDF) of the iterations needed to converge to the stable state is shown in Fig. 5. It is noted from the figure that for a given network scale (e.g., $N = 50$), the convergence speed of our proposed hierarchical scheme is faster than that of the distributed global learning algorithm as expected. Moreover, when the network scales up from $N = 50$ to $N = 60$, the convergence speed of the hierarchical scheme slightly decreases, whereas that of global Q-learning algorithm decreases significantly. The reason is that, in this work, the original resource allocation for the large-scale network is transformed into a simpler situation, where each disjoint cluster becomes a resource assignment unit with centralized management by the CHs within each cluster. Furthermore, resource allocation for the respective cluster is performed in parallel. Therefore, it is expected that the proposed hierarchical resource allocation framework with partially-distributed scheme has faster convergence speed than traditional distributed global learning algorithm. The result shows the advantage of our method in dense networks in terms of convergence speed.

B. THROUGHPUT PERFORMANCE

In this subsection, we compare the throughput performances of different resource allocation methods for both small and big networks. In the small scenario, we apply the exhaustive search as a benchmark to show the near-optimal system throughput of our solution. Then, to validate the scalability and performance gains of the proposed hierarchical scheme for large-scale networks, the performance comparison between the proposed approach and some other existing methods in big scenarios is also provided.

1) SMALL-SCALE NETWORKS

Since finding the global optimum is intractable for traditional computing techniques in large-scale networks with tens and even hundreds of nodes, firstly, a small scenario is considered in which several FAPs varied from 10 to 15 are randomly deployed in $50m \times 50m$ area. The inner wall loss is set to 10 dB and 3 subchannels are available in the network. In this context, we compare the achievable system throughput of the following three schemes: (i) the proposed hierarchical scheme, (ii) exhaustive search and (iii) random allocation (RA) scheme. Specifically, the exhaustive search is assumed to be implemented by an omnipotent controller in a centralized manner, whose performance is global optimum, serving as an upper bound. On the other hand, in the random allocation scheme, each FAP selects an arbitrary subchannel to transmit data with equal probability in each time slot.

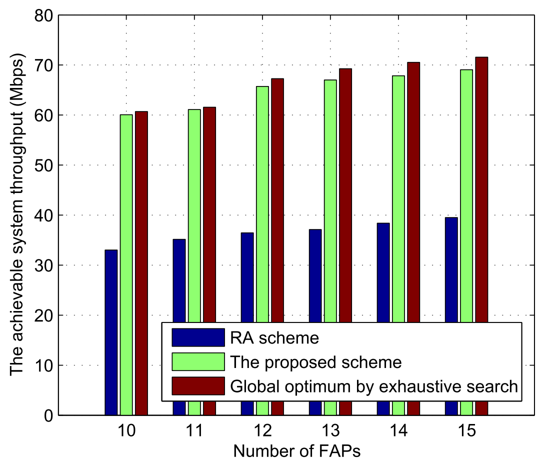

FIGURE 6. Comparison of the achievable system throughput of three schemes.

The comparison results about the achievable system throughput for the above-mentioned three methods are described in Fig. 6. For the proposed scheme and random allocation approach, the simulation results are obtained by independently simulating 10^4 trials and then taking the average results. We can observe that our hierarchical scheme has a performance that is close to the optimal solution with exhaustive search and much better than the random allocation approach. The results demonstrate the near-optimal performance of the proposed scheme in small scenarios.

2) LARGE-SCALE NETWORKS

In order to investigate the advantages of our method over some existing resource allocation solutions in large-scale scenarios, in this subsection, we consider ultra-dense networks where three other approaches are applied to be as benchmarks for comparison. Specifically, these solutions include:

- *Distributed interference graph coloring (DIGC) scheme* [38]: in this policy, each player chooses a color (i.e., denoting the subchannel) from a given set (subchannel set) uniformly randomly at the beginning of each time slot, and informs its neighbors of the tentative choice. If the selection does not conflict with any of its neighbors, then the player will perform data transmission on that subchannel; otherwise, it gives up the color and repeats the above procedure in next time slot, until completing the color assignment.
- *Synchronous decision-making process based on Q-learning (SDMPQL) scheme* [37]: all the players compete for the resources based on autonomous learning.
- *Random allocation (RA) approach*: each player elects a strategy randomly regardless of other players' choices.

With parameter variation, the comparisons of system throughput of the proposed hierarchical resource allocation scheme with that of the aforementioned three existing solutions for large-scale networks are described as follows.

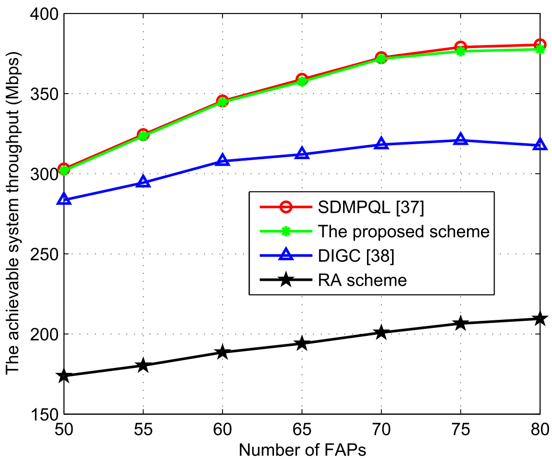

FIGURE 7. Total throughput of the system versus the number of FAPs.

Fig. 7 shows the variation in system throughput with the number of FAPs. We change the FAP number from 50 to 80, corresponding to the increasing of femtocell density. We have five subchannels and the inner wall loss $qL = 10dB$. It is noted that our proposed hierarchical scheme offers a higher system throughput in comparison with the DIGC and RA schemes. What's more, with the increasing of femtocell number, the achievable system throughput using our scheme increases more quickly than the above-mentioned two schemes. This is because the co-tier interference will be severer when the femtocell density becomes higher. However, the DIGC and RA schemes lack more effective coordination. Also, from the Fig. 7, we can notice that the proposed scheme can achieve the performance which is close to that of the SDMPQL scheme.

Fig. 8 shows the variation in system throughput with the subchannel number. We change the number of subchannels from 5 to 10 with 80 FAPs and $qL = 10dB$. In Fig. 8, it is noted that as the subchannel number increases, the subchannel selection collisions decrease, hence, the achieved throughput increases. We can also see that the gaps for the proposed hierarchical scheme, SDMPQL and DIGC are gradually becoming smaller with the increase of subchannel number. This is because the achievable system throughput of the three methods is all close to the maximum value when the spectrum resource is so adequate that the subchannel selection collisions appear rarely.

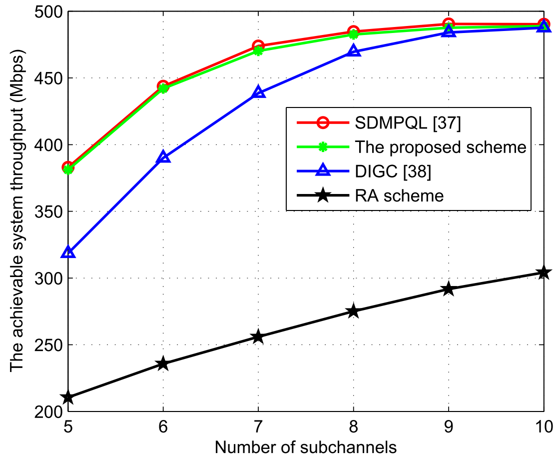

FIGURE 8. Total throughput of the system versus the number of subchannels.

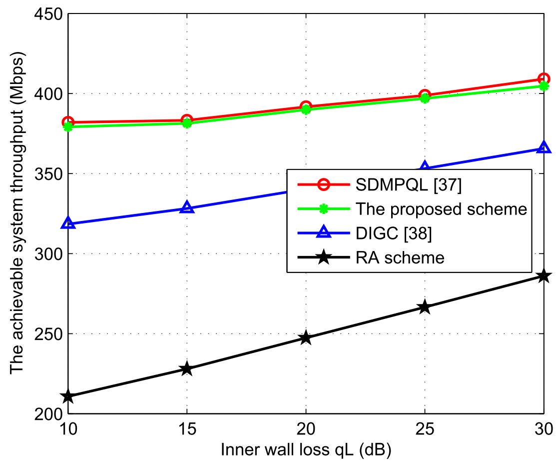

FIGURE 9. Total throughput of the system versus inner wall losses.

Fig. 9 shows the variation in system throughput with the inner wall losses. We have 80 FAPs and 5 subchannels with changing of inner wall losses from 10 dB to 30 dB. It is obvious from the figure that increasing the inner wall losses has a positive impact on the achieved throughput for the system. As the inner wall loss increases, mutual interference among FAPs will decrease, hence, stimulating the increasing of the system throughput.

C. FAIRNESS PERFORMANCE

Fairness is evaluated in terms of the fairness index [39], which determines how fairly the resources are distributed among

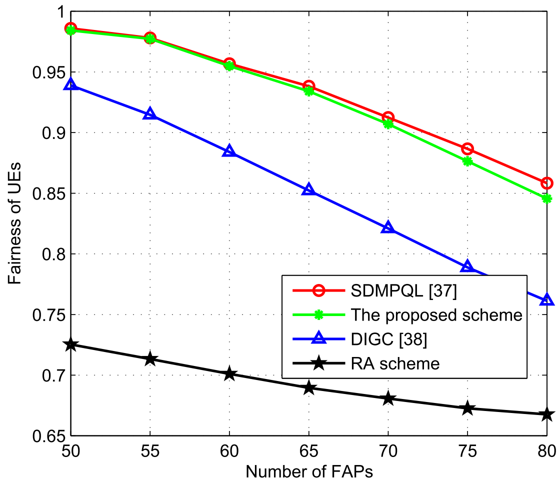

FIGURE 10. Fairness comparison.

existing UEs. It is expressed as follow:

$$\lambda = \frac{(\sum_{i=1}^{K} R_i)^2}{K \sum_{i=1}^{K} {R_i}^2}, \tag{10}$$

where K is the sum of UEs, and R_i is the throughput of UE i. Fig. 10 shows fairness index calculated with the four different schemes. We can learn from the figure that our proposed hierarchical resource allocation scheme can get very good fairness, even though in large-scale high-density network scenarios, it can still achieve 0.85.

D. DISCUSSIONS

We summarize the above simulation results as follows:

- Fig. 4 validates the convergence of the proposed scheme for a large-scale network.
- Fig. 6 shows the near-optimum performance of our method for small networks.
- From Fig. 7 to Fig. 10, it is clear that our scheme outperforms several existing resource allocation methods, i.e., distributed interference graph coloring and random allocation schemes, for dense networks in terms of throughput and fairness performance.
- Associated with Fig. 5, we can notice that the hierarchical allocation scheme yields almost the same performance as the synchronous decision-making scheme, with a faster convergence speed.

These results demonstrate our method is more suitable for extremely dense small cell networks.

VII. CONCLUSION

In this work, we have proposed a novel hierarchical resource allocation framework to address the downlink co-tier interference problem in hyper-dense small cell networks. Large scale poses several challenges that could not be effectively addressed by the previous centralized or distributed solutions. To tackle this issue, we provided a partially-distributed scheme to divide the initial optimization problem into four steps with reasonable computational complexity, including distributed clustering, intra-cluster subchannel allocation, inter-cluster interference resolution and power adjustment. Simulation results confirmed that our proposed scheme could achieve satisfactory system performance with a faster convergence speed, and were more suitable for ultra-dense small cell networks.

ACKNOWLEDGMENT

This paper was presented at the International Conference on Information Technology and Management Innovation 2015, Shenzhen, China.

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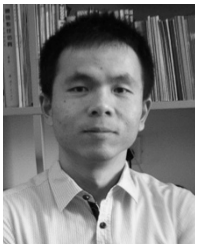

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