

# An Improved Dynamic Clustering Algorithm Based on Uplink Capacity Analysis in Ultra-Dense Network System

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**Abstract.** The Ultra-Dense Network (UDN) system is considered as a promising technology in the future wireless communication. Different from the existing heterogeneous network, UDN has a smaller cell radius and a new network structure. The core concept of UDN is to deploy the Low Power Base Stations (LPBSs). With denser cells, the interference scenario is even severer in UDN than Long Term Evolution (LTE) heterogeneous network. Clustering cooperation should reduce interference among the cells. In this paper, we firstly derive the total uplink capacity of the whole system. Then we present a novel dynamic clustering algorithm. The objective of this algorithm for densely deployed small cell network is to make a better tradeoff between the system performance and complexity, while overcome the inter-Mobile Station (MS) interference. Simulation results show that our approach yields significant capacity gains when compared with some proposed clustering algorithms.

**Keywords:** Ultra-Dense Network · Uplink capacity  
Dynamic clustering algorithm

## 1 Introduction

Fueled by the popularization of smart devices, wireless traffic experienced an exponential growth in recent years. The explosive growth of mobile data traffic these years puts forward high requirements for the bandwidth and performance of coverage and capacity of the 5th generation (5G) networks, such as ultra-high traffic volume density and ultrahigh peak data rate [1]. It is expected [2] that the growth will reach 1000-times by 2020 which is often regarded as the start of the time frame for future generation wireless network. Generally speaking, capacity enhancement can be realized in three ways, i.e. spectrum efficiency improvement, wider bandwidth and cell densification [3]. To deal with this growth rate, the Ultra-Dense Network (UDN) system is considered as a promising technology in the future wireless communication. UDN is viewed as one of the key technologies for 5G [4]. Different from the existing heterogeneous network, UDN has a smaller cell radius and a new network structure. The core concept of UDN is to deploy the Low Power Base Stations (LPBSs). In recent years, UDN attracts many researchers in colleges and workers in industries. Both the industry and academia are

working together, e.g. Mobile and wireless communications Enablers for 2020 Information Society and 5th Generation Non-Orthogonal Waveforms (5GNOW), to meet the capacity demand of the 5G mobile communication systems [2, 5].

With denser cells, the interference scenario is even severer in UDN than Long Term Evolution (LTE) heterogeneous network. This is because the smaller distance between LPBSs. Clustering cooperation should reduce interference among the cells. There have been some researches about cell clustering schemes in UDN. Recently, [6] employs Macro-Diversity-Coordinated Multipoint (MD-CoMP) to deal with the serious inter-Mobile Station (MS) interference and solves the joint optimization problem that is approximated by two sub-problems, i.e. clustering based on load information using game theory and inter-cell resource allocation based graph-coloring algorithms. Thus a Two-Step Joint Clustering and Scheduling (TS-JCS) scheme is proposed in [6]. [7] proposes a graph-based low complexity dynamic clustering algorithm. The key idea in [7] is that dividing the UDN into some clusters under size constraint, the maximum intra-cluster interference and minimum inter-cluster interference. [8] draws attention to the realistic scenario of randomly distributed Femtocell Access Points (FAPs) in heterogeneous networks and proposes a clustering approach combined with an active FAP selection algorithm to boost both spectral and energy efficiency without manual configuration. [9] presents a modified K-means clustering algorithm to maximize the sum throughput and proposes a two stage resource management scheme to solve this problem. Focusing on UDN scenario, [10] gives a definition of cell cluster and designs new synchronization signals. Moreover, a new cell clustering scheme based on the redesigned signals is presented in [10]. [11] proposes a user scheduling algorithm to gauge the performance gain of semi-static clustering and demonstrates the gain of semi-static clustering in the non-asymptotic regime.

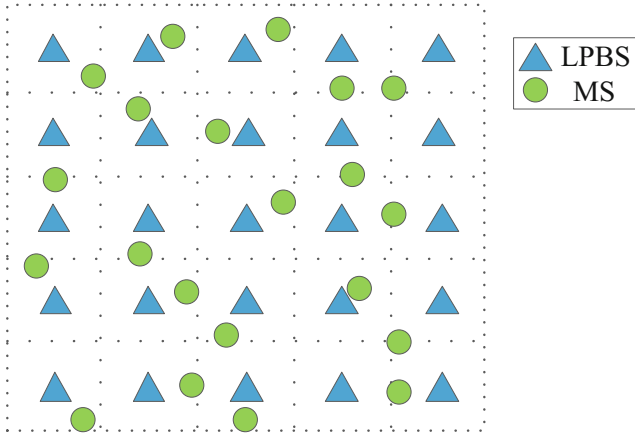
This paper aims to make a better tradeoff between the system performance and complexity for uplink transmission with dynamic clustering approach in UDN. In this paper, the following tasks are completed: we firstly derive the total uplink capacity of the whole system. Then we present a novel dynamic clustering algorithm. The objective of this algorithm for densely deployed small cell network is to improve the total uplink capacity, while overcoming the inter-Mobile Station (MS) interference. Simulation results show that our approach yields significant capacity gains when compared with some proposed clustering algorithms.

The remainder of this paper is organized as follows: In Sect. 2, we present the system model of UDN with multi-user environment and derive the total uplink capacity of the whole system. In Sect. 3, some existing clustering algorithms are described and a novel dynamic clustering algorithm is presented. We provide simulation results in Sect. 4. Finally, conclusions are provided in Sect. 5.

The notation adopted in this paper conforms to the following convention. Column vectors are denoted in lowercase boldface:  $\mathbf{x}$ . Matrices are denoted in uppercase boldface:  $\mathbf{A}$ .  $\mathbf{I}_k$  denotes the identity matrix of size  $k \times k$ .  $(\cdot)^T$  and  $(\cdot)^H$  represent the transpose and conjugate transpose matrix respectively.  $\det(\mathbf{A})$  denotes the determinant of  $\mathbf{A}$ . The operator  $E(\cdot)$  denotes expectation.

## 2 System Model

We consider the uplink transmission in UDN with  $M$  MSs and  $N$  LPBSs. The LPBSs are very dense in UDN, so both MS and LPBS are equipped with a single antenna here. In the UDN system, we assume that LPBS serves the MS which is the nearest to the LPBSs and one MS can be served by several LPBSs. As shown in Fig. 1, MSs uniformly and randomly are distributed in the area and LPBSs are grid-point distribution. Also the number of MSs must be no larger than the number of LPBSs ( $M \leq N$ ). In the following, we will provide the system model of full LPBS cooperation and LPBS clustering scheme.



**Fig. 1.** Structure of UDN with twenty-one MSs and twenty-five LPBSs ( $M = 21, N = 25$ ). The small triangle and the small circle represent LPBS and MS respectively.

### 2.1 System Model of Multi-user with Full Cooperation

In this subsection, we consider the circumstance that all the LPBSs serve all the MSs, i.e. full cooperation. The transmit symbols of each MS are assumed independent complex Gaussian with variance  $P$ . We also assume that the channels from LPBSs to MSs are flat fading and spatial-temporally independent. The uplink channel matrix between the MSs and the LPBSs can be expressed as a  $N \times M$  matrix,

$$\mathbf{H} = [\mathbf{h}_1 \mathbf{h}_2 \cdots \mathbf{h}_M] \tag{1}$$

where  $\mathbf{h}_m \in \mathbb{C}^{N \times 1}$  is the channel vector between the  $m_{th}$  MS and all of the LPBSs. We define that central unit can control and manage the information from different LPBSs. We assume the central unit has full channel state information (CSI), i.e. channel matrix  $\mathbf{H}$  is known by the central unit. Then, the uplink capacity of the MSs can be denoted as

$$C_{uplink-capacity} = \log_2[\det(\mathbf{I}_N + \frac{P}{\sigma^2} \mathbf{H}\mathbf{H}^H)] \tag{2}$$

Full cooperation is restricted by signaling overhead and real-time processing complexity. So all the  $N$  LPBSs need to be divided to some clusters and jointly combine and process the received signals within clusters. In the following, we will give the system model of multi-user with clustering approach.

## 2.2 System Model of Multi-user with Clustering Approach of the LPBSs

We can define the set of all the LPBSs of the system as  $\mathcal{A}$ , and the set of all the MSs served by these LPBSs as  $\mathcal{U}$ . Through a clustering algorithm, we could acquire  $\mathcal{R}$ , the set of all disjoint clusters which are subset of  $\mathcal{A}$ . In consideration of signaling overhead and real-time processing complexity, we assume that at most  $K$  LPBSs cooperation is affordable for the system. So the  $\mathcal{R}$  is between  $\frac{N}{K}$  and  $N$ , and  $\mathcal{R}$  needs to be an integer. These clusters are mapped to some groups of MSs. So  $\mathcal{U}$  is correspondingly clustered to  $\mathcal{L}$ , the set of all disjoint groups which are subset of  $\mathcal{U}$ , where  $|\mathcal{R}| = |\mathcal{L}|$ .

Let  $\mathcal{V}(\mathcal{V} \in \mathcal{R})$  be a given LPBS cluster.  $\mathcal{V}$  is mapped to a MS cluster  $\mathcal{T}(\mathcal{T} \in \mathcal{L})$ , i.e.  $\mathcal{V} \rightarrow \mathcal{T}$ . The LPBSs of  $\mathcal{V}$  serve the MSs of  $\mathcal{T}$ . We define the uplink channel matrix as  $\mathbf{H}(\mathcal{V}, \mathcal{T})$ . Transmitted symbols vector by  $\mathcal{T}$  is denoted as  $\mathbf{s}(\mathcal{T})$ . Transmit symbols are assumed independent complex Gaussian random variable with unit variance, i.e.  $E[\mathbf{s}(\mathcal{T})\mathbf{s}(\mathcal{T})^H] = \mathbf{I}_{|\mathcal{T}|}$ . Received signals vector by  $\mathcal{V}$  is denoted as  $\mathbf{y}(\mathcal{V})$ .  $\mathbf{n}(\mathcal{V})$  represents the additive white Gaussian noise, and  $E[\mathbf{n}(\mathcal{V})\mathbf{n}(\mathcal{V})^H] = \sigma^2 \mathbf{I}_{|\mathcal{V}|}$ . In our analysis, the transmit symbols of each MS are assumed independent complex Gaussian with variance  $P$ . So the power allocation matrix of  $\mathcal{T}$  is  $\mathbf{A}(\mathcal{T}) = \sqrt{P} \times \mathbf{I}_{|\mathcal{T}|}$ . Let us denote the received signals of the LPBS cluster  $\mathcal{V}$

$$\mathbf{y}(\mathcal{V}) = \mathbf{H}(\mathcal{V}, \mathcal{T})\mathbf{A}(\mathcal{T})\mathbf{s}(\mathcal{T}) + \sum_{\mathcal{Q} \in \mathcal{L}, \mathcal{Q} \neq \mathcal{T}} \mathbf{H}(\mathcal{V}, \mathcal{Q})\mathbf{A}(\mathcal{Q})\mathbf{s}(\mathcal{Q}) + \mathbf{n}(\mathcal{V}) \quad (3)$$

where  $\sum_{\mathcal{Q} \in \mathcal{L}, \mathcal{Q} \neq \mathcal{T}} \mathbf{H}(\mathcal{V}, \mathcal{Q})\mathbf{A}(\mathcal{Q})\mathbf{s}(\mathcal{Q})$  represents the inter-cluster interference from MSs which are not included in  $\mathcal{T}$ .

From the above, we can derive the uplink capacity of the LPBS cluster  $\mathcal{V}$  as

$$C(\mathcal{V}) = \log_2 \left[ \frac{\det\left(\frac{P}{\sigma^2} \mathbf{H}(\mathcal{V}, \mathcal{T})\mathbf{H}(\mathcal{V}, \mathcal{T})^H + \frac{P}{\sigma^2} \sum_{\mathcal{Q} \in \mathcal{L}, \mathcal{Q} \neq \mathcal{T}} \mathbf{H}(\mathcal{V}, \mathcal{Q})\mathbf{H}(\mathcal{V}, \mathcal{Q})^H + \mathbf{I}_{|\mathcal{V}|}\right)}{\det\left(\frac{P}{\sigma^2} \sum_{\mathcal{Q} \in \mathcal{L}, \mathcal{Q} \neq \mathcal{T}} \mathbf{H}(\mathcal{V}, \mathcal{Q})\mathbf{H}(\mathcal{V}, \mathcal{Q})^H + \mathbf{I}_{|\mathcal{V}|}\right)} \right] \quad (4)$$

The total uplink capacity of the whole system is represented by

$$C_{total} = \sum_{\mathcal{V} \in \mathcal{R}} C(\mathcal{V}) \quad (5)$$

### 3 Clustering Algorithm

In this section, we provide three kinds of LPBS clustering algorithms which we divide many LPBSs into small group in order to reduce the complexity and the energy consumption of signal processing in UDN systems. Our objective is to design a methodology to avoid severe inter-MS interference and improve the total capacity of the system.

In the uplink of UDN system, system performance is mainly limited by the inter-MS interference, especially when some MSs are near to each other. Cooperation of LPBSs could benefit from inter-MS interference cancellation. By clustering, a better tradeoff between the cooperation benefit and joint processing complexity can be obtained. It is reasonable especially when the number of LPBS is large.

#### 3.1 Static Clustering Algorithm

In this algorithm, the cluster size and the cluster scheme are fixed. The idea of the static clustering algorithm is that usually the interference between the MSs served by the neighbor LPBSs is severe. Then the LPBSs are clustered according to their locations and never changed in time. This algorithm is very simple but short of flexibility. But not all of the MSs served by the neighbor LPBSs cause severe interference. So static cooperation brings little benefit with some clusters. On the other hand, since cooperation clusters are static, this algorithm can ignore the interference between the MSs served by the nonadjacent LPBSs, and this will introduce severe inter-cluster interference.

#### 3.2 Semi-dynamic Clustering Algorithm

This algorithm specifies the size of the cluster, however, the cluster scheme changes dynamically. For any one of these LPBSs, we use order searching scheme to find the cooperation partner based on interference to signal power ratio and form a cluster. This algorithm is more flexible than static clustering algorithm. However, the fixed cluster size may block some better cluster schemes and degrade the system performance.

#### 3.3 Dynamic Clustering Algorithm

In this subsection, we propose a novel dynamic clustering algorithm which can improve the total system capacity. In this algorithm, the size of the cluster and the cluster scheme are changing. But considering the signaling overhead and real-time processing complexity, we assume that the size of the cluster keeps less than  $K$ , i.e. at most  $K$  LPBSs cooperation is affordable for the system. Every LPBS serves its nearest MS. So, in one LPBS cluster  $\mathcal{V}$ , the LPBSs' nearest MSs are regarded as the MS cluster  $\mathcal{T}$ , i.e.  $\mathcal{V}$  is mapped to the MS cluster  $\mathcal{T}$ . This cluster scheme is formed based on a

pre-defined Signal-Interference Matrix (SIM). The dynamic clustering algorithm is summarized as follows:

- (1) Map the each LPBS to their nearest MS. The LPBSs which serve the same MS forms a cluster. If one LPBS only serve one MS, the LPBS is a single cluster. Then the initial cluster set  $\mathcal{R}_0$  is obtained.  $M$  MSs are correspondingly clustered to  $\mathcal{L}_0$ . We can know the initial size of the cluster, i.e.  $|\mathcal{R}_0| = |\mathcal{L}_0| = M$ .
- (2) Define a SIM as

$$SIM = \begin{bmatrix} I_{11} & I_{12} & \cdots & I_{1M} \\ I_{21} & I_{22} & \cdots & I_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ I_{N1} & I_{N2} & \cdots & I_{NM} \end{bmatrix} \quad (6)$$

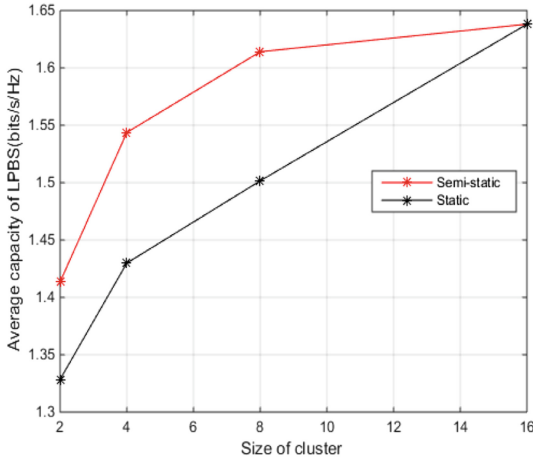
where  $I_{im} = P \times |\hat{h}_{im}|^2$ .  $\hat{h}_{im}$  is a parameter of the channel from the  $i_{th}$  LPBS to the  $m_{th}$  MS.  $\hat{h}_{im}$  could be the instantaneous CSI, large-scale CSI, or path loss. For each row, taking the maximum of  $I_{im}(1 \leq m \leq M)$  as the signal, we use  $S_{ik^i}(1 \leq k^i \leq M)$  to represent the maximum of  $I_{im}(1 \leq m \leq M)$ . So we know the  $k_{th}^i$  MS is served by the  $i_{th}$  LPBS, i.e. the  $k_{th}^i$  MS is the nearest MS to the  $i_{th}$  LPBS.

- (3) Each LPBS updates the cluster scheme based on the order of its signal component  $S_{ik^i}(1 \leq k^i \leq M)$ , from large to small. The update order based on the signal component is more benefit for the MSs with better channel condition. That is because they have more potential of achieving higher channel capacity. After the  $g_{th}$ ,  $\mathcal{R}_{g-1}$  becomes  $\mathcal{R}_g$ ,  $g \in \{1, 2, \dots, N\}$ . And the final cluster scheme will be  $\mathcal{R}_N$ , correspondingly  $\mathcal{L}_0$  becomes  $\mathcal{L}_N$ . The update obeys the follow rules:
  - (a) Find out the biggest interference component  $I_{im}$  of current LPBS  $i$ ,  $m \in \{1, 2, \dots, (k^i - 1), (k^i + 1), \dots, M\}$ .
  - (b) Define a parameter  $\delta$  called threshold. If  $\frac{I_{im}}{S_{ik^i}} < \delta$  or  $\frac{I_{im}}{\sigma^2} < \delta$ , consider the interference to current LPBS is small enough to ignore, and keep the current cluster scheme. If  $\frac{I_{im}}{S_{ik^i}} \geq \delta$  and  $\frac{I_{im}}{\sigma^2} \geq \delta$ , combine the cluster of  $i_{th}$  LPBS and the LPBS cluster serving the  $m_{th}$  MS. In this algorithm, we try to put the MSs which cause the strongest interference to each other in one cluster, to take more advantages of cooperation. And the parameter of threshold provides the possibility of simple non-cooperation processing for some MSs which are unnecessary to cooperate with others. These characteristics make this algorithm could realize dynamic adjusting according to the channel condition of the MSs.
  - (c) If the number of LPBSs in the new cluster after the combing does not exceed the maximum  $K$ , then go to the next updating step. Otherwise, the cluster scheme does not change, then also go to the next updating step.

## 4 Simulation Results and Analysis

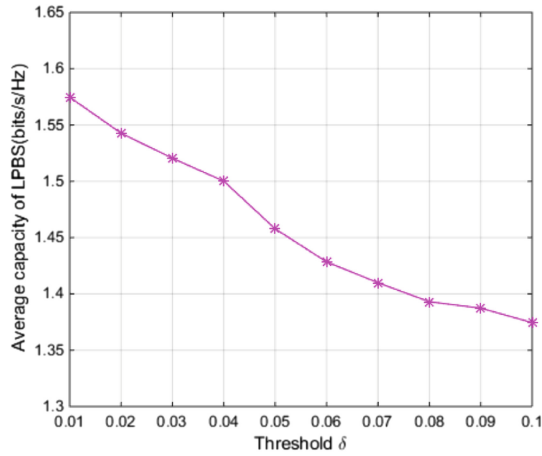
For simplicity, as show in Fig. 1 a grid-point model is considered in our paper. The LPBSs are deployed in grid, and each of them is equipped with one omnidirectional antenna. The location of MSs follow random distribution in the cell. The length of the cell is 35 m, and the minimum distance between MS and LPBS is 10 m. The channel vector between the  $m_{th}$  MS and  $i_{th}$  LPBS is  $\hat{h}_{im} = \sqrt{\beta_{im}}\gamma_{im}$ , where  $\sqrt{\beta_{im}}$  represents the large-scale fading which consist of path-loss and shadow fading.  $\gamma_{im}$  represents the small fading and  $\gamma_{im} \in CN(0, 1)$ .

In Fig. 2, the average uplink capacity per LPBS versus the size of cluster in static cluster cooperation and semi-static and is given. With the increasing of the size of the cluster, the average uplink capacity per LPBS is increasing. But the big and constant size of the cluster will cause the signaling overhead and real-time processing complexity.

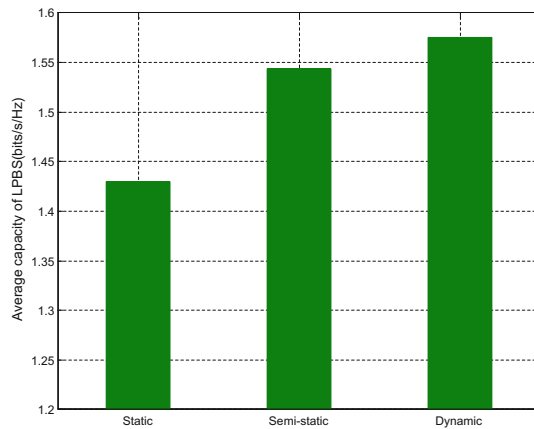


**Fig. 2.** Average uplink capacity per LPBS versus the number of cooperate LPBSs in static cluster and semi-static cluster cooperation.

In Fig. 3, the average uplink capacity per LPBS versus the threshold in dynamic cluster cooperation is given. With the increasing of the threshold  $\delta$ , the average uplink capacity per LPBS is decreasing. With the threshold increasing, the users which originally belongs to a certain LPBS became an interfere user of other LPBS. Thus the useful signals turn into interference. In UDN, the density and mobility of UE is very high, it is important to adjust the threshold of each LPBS dynamically. The dynamic clustering method can change the threshold according to the real-time SINR or the quality of UE, it can ensure the high quality of service (QoS) of UE and keep the computational complexity in an acceptable level.



**Fig. 3.** Average uplink capacity per LPBS versus the threshold  $\delta$  in dynamic cluster cooperation.



**Fig. 4.** The comparison of these three kinds of schemes

Figure 4 is the comparison of these three kinds of schemes, in order to a better comparison between the three methods, we choose the appropriate parameters based on the simulation parameters in three cases. We set the cluster size is 4 in the static way and choose 4 LPBS for cooperation in semi-dynamic way. In the dynamic clustering method, we select threshold as 0.02. It can be seen that under the static way, the average uplink capacity is much smaller than other two ways. This is because that the static way just removes the strong interference, but it cannot manage the interference effectively to all users. As to the semi-dynamic way, because of the use of direct collaboration between LPBSs, the interference within the cluster can be completely eliminated. However, the collaboration between LPBSs will cause an extra cost to ensure the information interaction. By using dynamic clustering method, the threshold



can be decreased when the number of UE become large and vice versa. It can get a better balance between the interference and computational complexity.

## 5 Conclusions

In the uplink of UDN, there exists severe interference among LPBSs because of the densely deployed small cell. Cluster cooperation is a promising solution. However, the challenge is the additional signaling overhead and real-time processing complexity. In this paper, we derive the total uplink capacity of the whole system, and we present a novel dynamic clustering algorithm to make a better tradeoff between the system performance and complexity. This algorithm also provides flexibility to use the CSI according to capability of the system. We compare this algorithm with proposed static clustering algorithm and semi-dynamic clustering algorithm. The simulation results prove this algorithm leads to significant capacity gains.

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