A Practical Semi-dynamic Clustering Scheme Using Affinity Propagation in Cooperative Picocells

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Abstract

Coordinated multi-point (CoMP) is corroborated to be an effective technology to mitigate co-channel interference (CCI) and enhance system performance in picocell systems which consist of a large number of pico base stations. In picocell systems, effective CoMP clustering schemes could provide significant gains of system performance such as cellular throughput and cell-edge spectrum efficiency (SE). Moreover, an intrinsic problem of densely deployed networks is the cost of signaling overhead and data exchanging between BSs in clusters. In this paper, a novel semi-dynamic clustering scheme based on affinity propagation for CoMP-Pico is presented to maximize user SE and throughput under the constraint of backhaul cost. Our proposed scheme consists of online and offline stages which can balance the trade-off between performance and complexity. Simulation results show that the proposed

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scheme yields significant gains of SE and throughput compared with existing clustering schemes. In addition, with consideration of backhaul overhead and complexity, our scheme is more suitable for implementation in practical systems.

Index Terms

Picocell, Small Cell, CoMP, Clustering, Affinity Propagation.

I. Introduction

In heterogeneous small cell networks (HetSNets), the massive deployment of small base stations (SBSs, such as pico BS, femto BS) will cause serious co-channel interference (CCI) problem [1]. Coordinated Multi-Point transmission/reception (CoMP) technique is proposed as a key approach to resolve it efficiently. Moreover, CoMP together with HetSNets can improve the system coverage and user spectral efficiency (SE) in LTE-Advanced [2]. There are four different scenarios are considered for the CoMP including joint transmission, dynamic point selection, dynamic point blanking, and coordinated scheduling/beamforming [3]. In this paper, we will focus on joint transmission, where several BSs form a coordination BS cluster (CBC) to jointly serve the users where proper scheduling scheme could mitigate CCI.

The BSs in a CBC are connected via high capacity backhaul links on which complex signaling and user data are exchanged. To reduce the backhaul overhead, some clustering schemes for CBC have been proposed in the literature. The existing clustering strategies could be classified into three categories: static clustering, fully-dynamic clustering and semi-dynamic clustering. In [4], Marsch proposed a static clustering algorithm wherein major portions of CoMP gains can be obtained with minimal signalling overhead between clusters. Although the static scheme is simple, the fixed size of clusters might cause unnecessary joint processing. Moreover, the static scheme is simple to operate but is feeble to handle the different degrees of interferences and can only provide limited throughput gain. In this sense, dynamic clustering algorithms are more flexible and practical [5]–[7]. In [7], a full-dynamic clustering algorithm was presented for a multi-user distributed antenna system to maximize system capacity with low implementation complexity assuming perfect channel state information (CSI). In [8], the author utilized another dynamic greedy algorithm in the formation of CBCs for multi-cell cooperative processing. The proposed dynamic greedy algorithm can achieve significant sum rate gains, while enhancing the fairness of the system. Even though full-dynamic clustering schemes can mitigate CCI dynamically, the large signaling flow and time consumption in dense HetSNets could not be ignored. That is, full-dynamic scheme can achieve optimal performance but needs exhaustive information interchange which will bring more complexity. Considering the tradeoff between performance and complexity, our semi-dynamic clustering scheme aims at reducing the complexity without much loss of performance.

The affinity propagation was proposed by Frey and Duech in 2007 [9], to cluster images of faces, detect genes in microarray data, and identify representative sentence. Affinity propagation algorithm proved that it has efficiency convergence rate and high quality even with limited prior information. Hence, partial CSI rather than complete CSI is needed when affinity propagation algorithm is applied. It was later extended to the clustering of Vehicle Ad Hoc Networks [10] and Cognitive Radio Networks [11]. The convergence performance of affinity propagation algorithm is demonstrated in [12] and [13]. In CoMP picocells, pico BSs are usually dense deployed, therefore, complete CSI is always available. Affinity propagation algorithm is exactly suitable for this scenario, because of its high clustering quality with limited CSI and efficiency convergence rate. However, affinity propagation has been rarely used in the CoMP picocells. In [13], the author presents a decentralized BS clustering scheme based on affinity propagation.

In this paper, we propose a semi-dynamic clustering framework consisting of offline and online stages to maximize the SE and cellular throughput with low signaling and data cost in dense CoMP enabled picocells. Measurement BS cluster (MBC) for the CoMP users is decided based on geographical locations and the reference signal received power (RSRP) at the offline stage; and then, at the online stage we propose a clustering algorithm to choose CBC from MBC based on limited CSI. Moreover, the affinity propagation principle is used at the online stage to guide the proposed affinity propagation based online clustering (APOnC) algorithm. The proposed scheme is proved to be effective and only need limited CSI between local and neighboring cells, compared with existing static and full-dynamic clustering schemes.

The rest of this paper is organized as follows. We introduce the basic framework of CoMP in Section II. Then we present the procedures of semi-dynamic clustering scheme and propose our APOnC algorithm in Section III. In Section IV, performance of the proposed algorithms is evaluated by simulations. Finally, Section V summarizes this paper.

II. Basic CoMP Framework

In this paper, the downlink of a cellular network with B hexagonal cells is considered. Let $\mathbf{U}_b$ denote the user set served within the coverage of picocell b, $\forall b \in \{1, 2, ..., B\}$. Each user has a single transmit antenna and each BS has n_r receive antennas. In our model, round-robin (RR) scheduling scheme is applied and the multiple-input multiple-output (MIMO) channel is assumed to be flat fading.

A. Non-CoMP MIMO System

The single user MIMO (SU-MIMO) scheme is applied in the non-CoMP MIMO system shown in Fig.1(a). CCI affects the user performance especially when a UE locates at the edge of its serving cell. The received signal at user k served by BS b $(k \in U_b)$ is given by

$$y_{non} = \underbrace{h_k^b s_k^b}_{\text{desired signal}} + \underbrace{\sum_{j \in U_{b'}} h_j^{b'} s_j^{b'}}_{\text{interference signal}} + n_k^b \tag{1}$$

where s_k^b and $s_j^{b'}$ are the symbols transmitted by the desired UE k and interfering UE j occupying the same resource block (RB) respectively, the variance of transmitted symbol s_k^b is $E\left\{\left|s_k^b\right|^2\right\} = p_k^b \geq 0$. h_k^b is the channel gain from UE k to BS b, and n_k^b denotes the additive white Gaussian noise (AWGN) with zero mean and variance $E\left\{\left|n_k^b\right|^2\right\} = \sigma^2$.

Hence the non-CoMP SINR for user k served by BS b is

$$\mathrm{SINR}_{non} = \frac{\left|h_k^b\right|^2 p_k^b}{\sigma^2 + \sum\limits_{k \neq j, j \notin U_b} \left|h_j^b\right|^2 p_j^b}. \tag{2}$$

Based on Shannon's capacity formula, the achievable capacity of non-CoMP user k served by BS b is given by:

$$C_{non} = BW \log_2 \left(1 + \mathrm{SINR}_{non}\right), \tag{3}$$

where BW is the bandwidth of each subchannel.

B. CoMP MIMO System

In CoMP joint transmission, several BSs constructing a CBC jointly transmit data to the CoMP user, as shown in Fig.1(b). Joint transmission at BS side enables the mitigation of intra-cluster CCI and improves throughput especially for cell-edge users. A central unit (CU) controls signals and data flow. To simplify the analysis, one of the BSs in a CBC is chosen to be the CU and is called master BS, and the other BSs act as slave BSs. All BSs inside a CBC are connected with each other by fibers.

Let $\mathbf{W}^C$ be the zero-forcing (ZF) combining weight, matrix at the UEs' receiver and u be the single CoMP user in cluster C, then the signal after joint reception is given by:

$$\tilde{\mathbf{Y}}_{CoMP} = \underbrace{\mathbf{W}^C\mathbf{H}_u^C\mathbf{S}_u^C}_{desired\text{ signal}} + \underbrace{\sum_{j\in U_{b'},b'\in C'} \mathbf{W}^C\mathbf{H}_j^{C'}\mathbf{S}_j^{C'}}_{inter-cluster\text{ interference}} + \mathbf{W}^C n_k^C \tag{4}$$

where $\mathbf{H}_u^C$ is the channel gain matrix from UE u to BSs in Cluster C, $\mathbf{S}_u^C$ and $\mathbf{S}_j^{C'}$ are the symbol matrixes transmitted by the desired UE u and interfering UE j occupying the same RB respectively, and the second term in the right-hand-side indicates the interference from users in neighboring clusters.

The CoMP SINR for user k in cluster C is

$$\mathrm{SINR}_{CoMP} = \frac{\left|h_k^b\right|^2 p_k^b}{\left|\sigma\right|^2 + \sum\limits_{j\in U_{C'},C\neq C'} \left|h_j^b\right|^2 p_j^b}, \tag{5}$$

Based on Shannon's capacity formula, the achievable capacity of CoMP user k served by BS b is given by:

$$C_{comp} = BW\log_2\left(1 + \mathrm{SINR}_{comp}\right), \tag{6}$$

C. Pair CoMP SINR Gain

Here we set a CBC C consisting of BS b and BS b', and let b act as the master BS. UEs k and m belong to BSs b and b' respectively. The CoMP strategy can eliminate CCI from user m to user k. We define a variable to measure the desire of BS b to cooperate with BS b', $pcg(b, b')$, which is called the pair CoMP SINR gain and is given by:

$$pcg(b,b') = \frac{\mathrm{SINR}_{\mathrm{CoMP}}}{\mathrm{SINR}_{\mathrm{non}}} = \frac{\frac{\left|w_k h_k^b\right|^2 p_k^b}{|w_k\sigma|^2 + \sum\limits_{j\in U_{C'}} \left|w_k h_j^b\right|^2 p_j^b}}{\frac{\left|h_k^b\right|^2 p_k^b}{\sigma^2 + \sum\limits_{j\in U_{C'}} \left|h_j^b\right|^2 p_j^b + h_m^b p_m^b}}$$
$$= \frac{\left|w_k h_k^b\right|^2 \left[\sigma^2 + \sum\limits_{j\in U_{C'}} \left|h_j^b\right|^2 p_j^b + h_m^b p_m^b\right]}{\left|w_k h_k^b\right|^2 \left[\sigma^2 + \sum\limits_{j\in U_{C'}} \left|h_j^b\right|^2 p_j^b\right]}$$
$$= 1 + \frac{h_m^b p_m^b}{\sigma^2 + \sum\limits_{j\in U_{C'}} \left|h_j^b\right|^2 p_j^b} \tag{7}$$

III. Proposed Adaptive Clustering Scheme

A. Adaptive Semi-dynamic Clustering Scheme

In this section, two kinds of BS cluster are involved: measurement BS cluster (MBC) and CBC. *MBC* denotes the set of BSs which share measurement information such as power levels and channel state information (CSI), while *CBC* denotes the set of BSs which jointly receive and process data from the CoMP user. MBC is identical to CBC in static clustering strategy and is fixed by the network. While in full-dynamic and semi-dynamic schemes, the CBC is a subset of MBC. In Fig.2, we decompose the semi-dynamic clustering scheme into two stages: the offline stage identifies the MBC based on geographical location and RSRP, while the online stage chooses the CBC from MBC. The detailed procedure is described below:

Offline stage. In realistic systems, only a limited number of BSs can cooperate because of affordable communication overhead [8]. Hence, we set the MBC to include a central BS and six neighbouring BSs that surround it. The CoMP user sends CoMP request to the central serving BS, then the network launches offline stage and forms a MBC for the user based on geographical locations of BSs and RSRP:

Online stage. In a MBC for each user, CSI for example, comp-pair SINRs of Sounding Reference Signal (SRS) can be evaluated and fed back to BSs periodically. By analyzing them according to some criterions, we can select the CBC for the certain CoMP user. A lower

SINR_{SRS} means that the user suffers greater interference and needs more coordinating BSs to serve it. Furthermore, the clustering criterion takes SINR_{SRS} and backhaul overhead cost into consideration.

B. The Proposed Affinity Propagation Based Online Clustering Algorithm

In the proposed APOnC algorithm, we introduce a concept called "exemplar", an input key variable called "similarity" and two information variables called "responsibility" and "availability". The exemplar for BS i represents the master BS of the cluster including BS i.

The *similarity* $s(i,k)$ indicates how well BS k is suited to be the exemplar for BS i. Especially, $s(k,k)$ is referred to as "preference" and BSs with larger *preference* values are more likely to be chosen as exemplar BSs. The *similarity* matrix is the unique input of APOnC algorithm and has a direct impact on the performance. Through the analysis of online stage, we define the non-diagonal elements of *similarity* matrix based on pcg described in Section II.C. The BS with lower SINR_{non} is more possible to be an exemplar. Nevertheless, more cooperations mean more signaling and data exchanging cost. So a negative variable c is introduced to indicate the cost. Therefore, we define $s(i,k)$ as follows

$$s(i,k) = \begin{cases} \log(pcg(i,k)), & i \neq k \\ \beta \cdot \left[\log(1/\text{SINR}_{\text{non}}^{\text{i}}) - \text{c}\right], & i = k \end{cases} \tag{8}$$

where β is a coordinative parameter to adjust the size of clusters, c is the indicator of signaling and data exchanging cost, and $\beta \cdot \left[\log(1/\text{SINR}_{\text{non}}^{\text{i}}) - \text{c}\right]$ is the definition of *preference*, where BSs with lower SINR_{non} have larger *preference* values, are more likely to be chosen as exemplar BSs.

The *responsibility* $r(i,k)$ is sent from BS i to candidate exemplar BS k as shown in Fig.3(a). $r(i,k)$ reflects the accumulated evidence of how well-suited BS k is to serve as the exemplar BS for BS i, taking into consideration other potential exemplars for BS i. Each BS updates *responsibility* following the rule:

$$r(i,k) = s(i,k) - \max_{\substack{k' \neq k \\ k' \in adj(i)}} \{a(i,k') + s(i,k')\} \tag{9}$$

Where $a(i,k')$ is the *availability* sent from candidate exemplar BS k' to BS i as shown in Fig.3(b). $a(i,k)$ reflects the accumulated evidence for how appropriate it would be for BS i to choose BS k as its exemplar. Each BS updates *availability* and *self-availability* following the rules

$$\begin{aligned} a(i,k) &= \min(0, r(k,k) + \sum_{\substack{i' \notin \{i,k\} \\ i' \in adj(k)}} \max\{0, r(i',k)\}) \\ a(k,k) &= \sum_{\substack{i' \neq k \\ i' \in adj(k)}} \max\{0, r(i',k)\} \end{aligned} \tag{10}$$

C. Algorithm Flow

The proposed semi-dynamic clustering scheme with APOnC algorithm consists of three major steps: step A is for MBC initialization in offline stage, step B is online information broadcasting, where $ITER$ is the maximal iteration of $iter$, and step C is the selection of CBC.

The proposed algorithm can be implemented in each cluster using only local information and limited CSI between neighboring cells, where the CSI can be exchanged via backhaul links.

For the complexity of the affinity propagation algorithm, the running time depends on the number of iterations. If there are n samples, when updating responsibility $r(i,j)$, it will cost $O(n-1)$ time, and there are n^2 values in responsibility matrix R. Then update availability $a(i,j)$, it will take $O(n-2)$ time for each value. As the result, each iteration requires $O(2*n^3-3*n^2) = O(n^3)$ time.

The convergence of affinity propagation algorithm has been proven in [13], [13], which can guarantee the practicality of the proposed Algorithm 1.

IV. SIMULATION RESULTS

A dense HetSNet consisting of nineteen small BSs (picocell BSs) was simulated as shown in Fig.4. The channel model based on 3GPP TR 25.996 urban micro scenario includes shadow fading, large scale pathloss, and multi-path fading. The value of heuristic cost parameter c is chosen by “try and error method” in simulation. And the simulation will give a guidance for the application in piratical scenario. We assume that the distance between two adjacent BSs is 50m and there are 15 uniformly distributed UEs within each cell. RR schedular is employed in each

Algorithm 1 Semi-dynamic clustering scheme with APOnC algorithm.

Input:

The set of BSs, $\mathbf{N} = \{1, 2, ...N\}$;

The set of UEs, $\mathbf{U}_{CoMP} = \{1, 2, ...U_{CoMP}\}$ and $\mathbf{U}_{Non} = \{1, 2, ...U_{non}\}$;

Output:

Ensemble of CBCs, $\mathbf{C} = \{C_1, C_2, ...C_U\}$;

A) Initialization:

Determine MBC for each user in offline stage;

Calculate *similarity* matrix $\mathbf{S}$ according to (8);

Set initial *availability* matrix $\mathbf{A} = [\mathbf{0}]_{\mathbf{N}\times\mathbf{N}}$, *responsibility* matrix $\mathbf{R} = [\mathbf{0}]_{\mathbf{N}\times\mathbf{N}}$ for each user;

B) Iteration:

repeat

a)Update *responsibility* $\mathbf{R}(\mathbf{i}, :)$ by (9) and broadcast;

b)Update *availability* $\mathbf{A}(:, \mathbf{k})$ by (10) and broadcast;

Oscillatory decay: (α and $\beta \in [0, 1]$)

$\mathbf{R}(\mathbf{iter}) = \alpha \cdot \mathbf{R}(\mathbf{iter}) + (\mathbf{1} - \alpha) \cdot \mathbf{R}(\mathbf{iter} - \mathbf{1})$,

$\mathbf{A}(\mathbf{iter}) = \beta \cdot \mathbf{A}(\mathbf{iter}) + (\mathbf{1} - \beta) \cdot \mathbf{A}(\mathbf{iter} - \mathbf{1})$,

until Convergence or $iter = ITER$

C) Exemplar judgment:

for $ibs = 1$ to N **do**

$exemplar(ibs) = \underset{k \in adj(ibs)}{\arg\max} \{a(ibs, k) + r(ibs, k)\}$

end for

BS. For further performance analysis, we classify all UEs into central and edge UEs based on the distance between UE and its serving BS. As shown in Fig.4, the red points denote the small cell BSs, and the green and blue points denote central and edge users respectively.

The simulation results are given in terms of UE SE cumulative distribution function (CDF) to indicate system gain, and estimated signaling and data cost based on the size of CBC to indicate backhaul cost.

Non-CoMP scheme and two CoMP clustering schemes are also evaluated for comparison with our proposed scheme:

1) **Non-CoMP**:
   In this scheme, each user transmits to its serving BS, while it will cause CCI to its neighboring cells.
2) **Static CoMP clustering scheme (static-CoMP)**:
   In this scheme, cluster formulation is fixed and MBC equals CBC. Three adjacent BSs are grouped into one CBC for a CoMP user.
3) **Signal-interference matrix (SIM) based CoMP clustering scheme (sim-CoMP)** [7] :
   In this scheme, MBC for the CoMP user includes the serving BS and its neighboring BSs at offline stage. The user compares the ratio of the biggest interference component and the signal component with a threshold. The online clustering of CBC depends on the ratio.

The SE CDF curves of both central and edge UEs for each scheme are given in Fig.5. It can be observed that SE CDF curves of the three CoMP schemes are on the right of that of non-CoMP, because CoMP can efficiently combat the interference. Moreover, our proposed clustering scheme provides the best SE for both central and edge users in the three CoMP schemes. With non-CoMP set as baseline, the throughput gain of CoMP over non-CoMP is more evident for edge users than for central users. The reason is that the edge users suffer from higher CCI and lower SINR, hence they have more demands and opportunities to be coordinated. In other words, CoMP strategy is more effective for enhancing cell-edge performance.

Fig.6 illustrates the average throughput and the gain over the non-CoMP scheme of different schemes. We can see that CoMP schemes can achieve higher throughput than non-CoMP system. In addition, due to the effective information interchange mechanism, our proposed semi-dynamic clustering scheme with APOnC algorithm obtains the highest average throughput and largest gain. From both Fig. 5 and Fig. 6, the effectiveness of CoMP compared with non-CoMP schemes can be observed, moreover, the APOnC CoMP scheme achieves a better performance than the existing CoMP schemes.

In dense small cell systems, the complexity influences the system performance and practicability. Hence we also use the running time of sim-CoMP and our scheme to evaluate the algorithm complexity in Fig.7. We can see that when the number of BSs increases, the running time of the three schemes become larger. It also can be seen from Fig. 7, running time of APOnC CoMP scheme is larger than that of the other two schemes, but is acceptable. The APOnC CoMP scheme achieves higher throughput at the cost of acceptable complexity, which make our scheme capable for dense HetSNet scenario.

V. Conclusion

In this paper, we have proposed a semi-dynamic clustering CoMP scheme for dense small cell networks to improve user throughput with consideration of backhaul cost and complexity. Our scheme consists of offline and online stages to implement efficient clustering. MBC for the CoMP users is decided based on geographical locations and RSRP at the offline stage; and then, at the online stage we propose a novel affinity propagation based online clustering (APOnC) algorithm to choose CBC from MBC based on limited CSI. The proposed scheme is proved to be effective and only need limited CSI between local and neighboring cells, compared with existing static and full-dynamic clustering schemes. The performance of the proposed scheme is evaluated by comparing with some existing schemes in the simulation. The results show that our scheme can increase user spectral efficiency and cell throughput especially for edge users. Moreover, our scheme requires reduced complexity as compared with other clustering algorithms, proving to be more practical in dense small cell systems.

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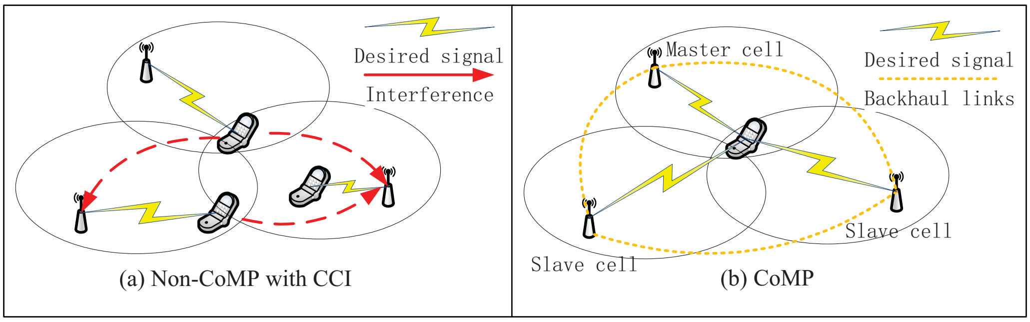

Fig. 1. CoMP and Non-CoMP system

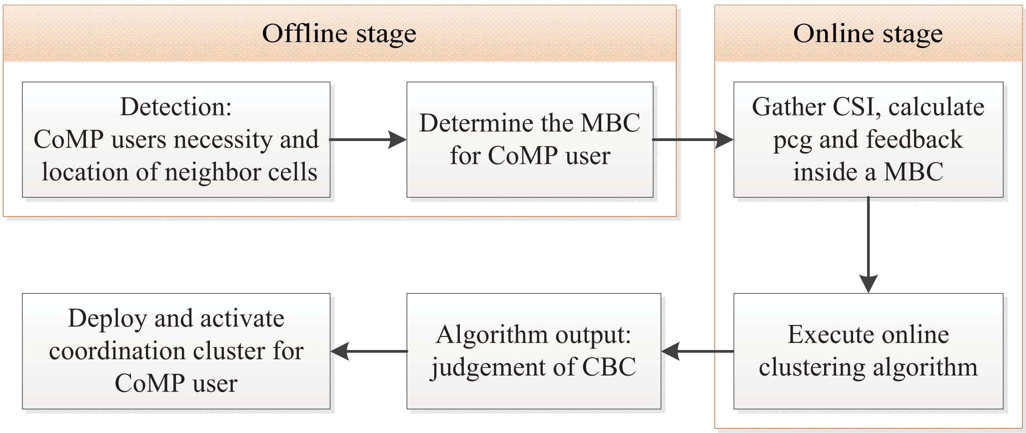

Fig. 2. Framework of CoMP system

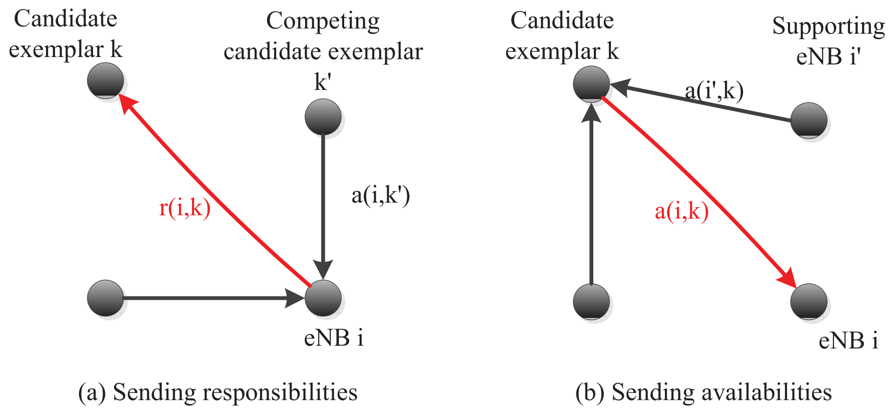

Fig. 3. Schematic diagram of *responsibility* and *availability*

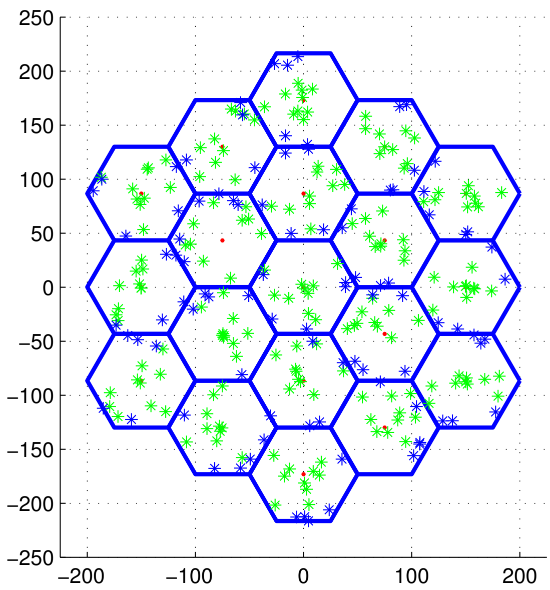

Fig. 4. System model of small cells and users.

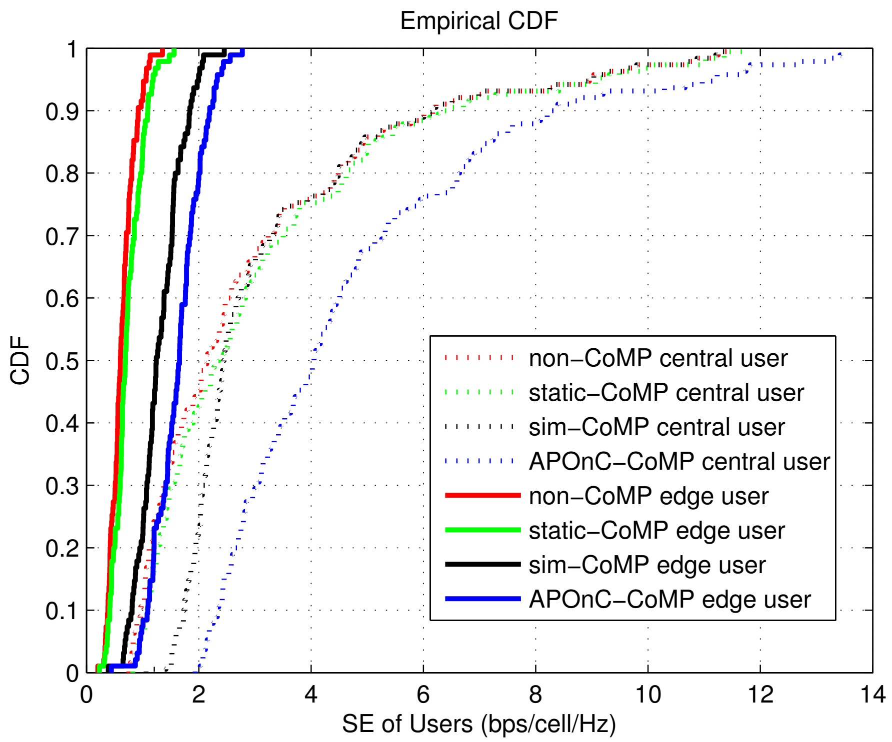

Fig. 5. CDF of central and edge users

Fig. 6. Average user throughput of different clustering schemes