# Coordinated Multi-point Transmission Systems with Dynamical Cell-clustering Strategies

Shang-hui Xiao [1, 2], Zhong-pei Zhang [1], Qin-min Wang[1], Zhi-ping Shi [1, 3]

[1] *National Key Lab of Commun., University of Electronic Science and Technology of China, Chengdu 611731, P.R. of China*

[2] *School of Physics and Electronic Engineering, Yibin University, Yibin 644007, P.R. of China*

[3] *National Mobile Communications Research Lab, Southeast University, Nanjing 211189, P.R. of China*

***Abstract*—This paper firstly presents the system structure and mathematical signal model for multi-point coordinating downlink transmission, and then gives a detailed discussion on dynamical cell-clustering strategies and scheduling utility metric in forming cooperation cluster of cells based on detected system parameters, where the user is serviced by a cluster selected from a set of clusters. Some simulation results are given to show that dynamical cell-clustering strategies are beneficial to user performance improvement owing to fairness across all the UEs comparing to static cell-clustering method.**

## I. INTRODUCTION

Traditionally, each user is typically associated with a particular one of the multiple base stations, where each base station transmits signals for users within its cell coverage. Thus, the user can be serviced by the given base station, while other base station in vicinity can generate interference, which partially reduced and mitigated by careful radio resource management techniques such as power control, frequency reuse, spreading code assignments [1] and advanced receiver processing [2]. However, these techniques are all implemented at single cell without inter-cell cooperation on the physical layer, and limit the achievable spectral efficiency gain and/or lead to insufficiency suppression to inter-cell co-channel interference (IC-CCI). Moreover, on the downlink (DL), receiver processing necessarily burdens the mobile users by adding complexity. An alternative very promising technology of facing IC-CCI is multi-points cooperative processing [3, 4], where different BSs together transmit signals for multiple users in joint transmission and/or interference management. This includes "clustering" of multiple base stations that defines possible cooperation among cells. How to select cooperative set (i.e. clusters) is critical issue for multiple BSs coordinating transmission.

This paper mainly presents some discusses and performance analysis on multiple points coordinating downlink transmission via dynamical cell-clustering strategies based on detected system parameters, in order for mitigating service disparities among users at cluster boundaries.

Manuscript received April 20, 2010.

Corresponding author: Shang-hui Xiao, an associate professor for Yibin University, is a Ph.D. candidate of University of Electronic Science and Technology of China, majoring in Communication and Information Systems. E-mail: xiaosh@uestc.edu.cn

CHINACOM 2010, August 25-27, Beijing, China

DOI 10.4108/chinacom.2010.152

## II. SYSTEM STRUCTURE FOR COORDINATED MULTI-POINT TRANSMISSION

Already in cellular MIMO systems with non-collocated transmit antennas [5], geographically dispersed multiple antennas connected to a central baseband processing unit via a high-speed fiber backbone are used as a cost-efficient way of building networks, which can provide improved resistance to shadowing and extended range. Such structures open up new transmission strategies. Recently, in [6], the technology component "Coordinated Multi-point (Co-MP) transmission" was outlined. Technology components that seem to be based on the same basic principles were also outlined in some other contributions, although using different terminology such as "base station cooperation", "collaborative MIMO", "network-MIMO".

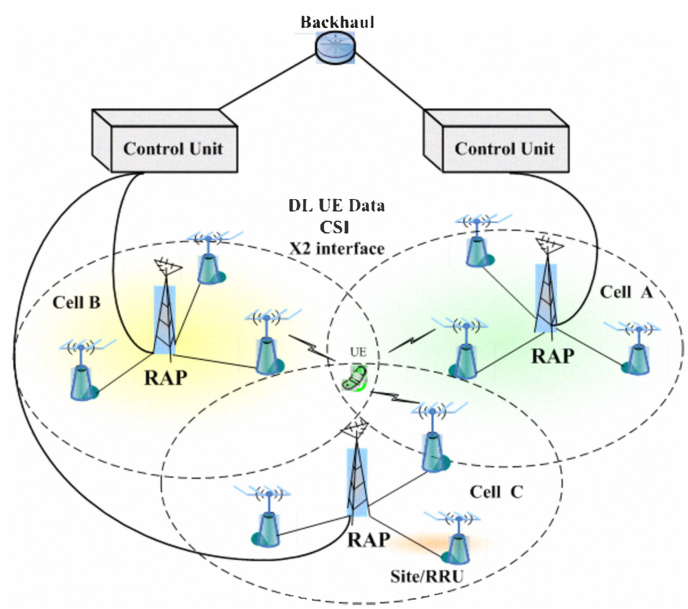


Fig.1 System setup of coordinated multi-point transmission systems

It has been shown that Co-MP techniques, in which geographically separated multiple different radio access points (RAPs) together transmit signal for different users equipments (UEs) by forming a distributed antenna array, as shown in figure 1, accordingly the IC-CCI mitigation becomes easy to implement, can significantly improve the system performance, especially for the spectral efficiency of cell-edge user over the cell. Several RAPs are connected to one control unit (CU) via high capacity backhaul links (optic fibers or wireless links) which undertake the needed exchange on user data and channel state information (CSI), whereas each RAP may contain one or multiple antenna elements.

Therefore, the Co-MP techniques, which can be easily deployed in a semi-distributed communication system with distributed antennas but centralized control functionally, have been comprehensively considered by some researchers and companies as promising techniques and good candidates for improving system capacity and cell-edge experience to meet the requirements set by LTE-Advanced. For the Co-MP DL transmission, it supports dynamic coordination in the scheduling and joint transmission, from multiple geographically separated BSs/RAPs. Moreover, multiple UEs can be served by one or multiple BSs/RAPs of the same or different CU simultaneously. The coordinated central controllers retrieve information from distributed BSs/RAPs and allocate resources to satisfy the QoS requirements of the UEs while maximizing the network performance. Thus, RAPs can cooperate to yield a scheduling decision where each RAP can be involved in data transmission to each UE. Further, scheduling decisions can be based upon a utility metric, which is a function of weighted rates that can be achieved for different UEs.

## III. Mathematical Signal Model for Co-MP Network MIMO Systems

In contrast to network-global cooperation strategy, which results in complex scheduling decision and high backhaul capacity, we may divide the Co-MP network into a number of the clustered super cells with local cooperation mode. A group of the RAPs to serve a Co-MP configured UE is defined as the clustered supercell, where each supercell contains a smaller group of adjacent cells. In general, the term "cluster" refers to a subset of the cells in the network that can cooperate in transmission of data to multiple UEs in a time-frequency block. The antennas of all the cells in the supercell participating in cooperation can be considered as a virtual antenna array within a "network coordinating MIMO system".

Suppose that there are $K$ mobile users arbitrarily distributed in coordinated multi-point transmission supercell system, with $N_t$ the number of transmit antennas at each RAP, and $N_r$ the number of receiver antennas at each UE, respectively. Suppose that $M_p$ is the total number of adjacent RAPs in a cooperation cluster, where $M_p < M$, so ($N_t$, $N_r$, $M_p$, $K$) can be used to represent the formed supercell in a cooperation cluster. The different links are independent and undergo frequency-flat Rayleigh fading. Therefore, $\mathbf{H}_{pk}$, the baseband matrix representation of the channel from RAP $p$ to UE $k$, has complex Gaussian elements. For any UE, the multiple RAPs cooperate and jointly transmit the signals intended for it. The transmit vector for UE $k$ from RAP $p$ is optimally precoded by the $N_t \times L_k$ matrix $\mathbf{W}_{pk}$ as $\mathbf{S}_{pk}=\mathbf{W}_{pk}\mathbf{X}_k$, where $\mathbf{X}_k$ denotes the zero-mean data symbol vector, of size $L_k \times 1$ at time m, meant for UE $k$. The received signal vector model at the $k$-th user in the supercell $Sc$ can be represented as follows [7]

$$\begin{aligned}\mathbf{y}_{Sc\_k} &= \sum_{p=1}^{M_p} \mathbf{H}_{(Sc,p)\_k} \mathbf{W}_{(Sc,p)\_k} \mathbf{A}_{(Sc,p)\_k} \mathbf{X}_{Sc\_k} \cdots \\ &+ \sum_{p=1}^{M_p} \mathbf{H}_{(Sc,p)\_k} \sum_{\substack{j=1\\ j\neq k}}^{K} \mathbf{W}_{(Sc,p)\_j} \mathbf{A}_{(Sc,p)\_j} \mathbf{i}_{Sc\_jk} \cdots \\ &+ \sum_{\substack{\overline{Sc}=1\\ \overline{Sc}\neq Sc}}^{C} \sum_{\overline{p}=1}^{M_p} \mathbf{H}_{(\overline{Sc},\overline{p})\_k} \sum_{i=1}^{K} \mathbf{W}_{(\overline{Sc},\overline{p})\_i} \mathbf{A}_{(\overline{Sc},\overline{p})\_i} \mathbf{i}_{\overline{Sc}\_ik} + \mathbf{n}_{Sc\_k} \\ &= \mathbf{D} + \mathbf{J} + \mathbf{Q} + \mathbf{n}_{Sc\_k}\end{aligned} \tag{1}$$

where $\mathbf{D}$ is the desired signal vector, $\mathbf{J}$ is the intra-cluster interference signal vector, $\mathbf{Q}$ is the inter-cluster interference signal vector. $\mathbf{X}_{Sc\_k}$ is the $L_k \times 1$ data symbol vector for UE $k$ in the cluster ($C$ denotes total number of the entire supercell). $\mathbf{H}_{(Sc,p)\_k}$ is the $N_r \times N_t$ channel matrix from RAP $p$ in the supercell $Sc$ to UE $k$. $\mathbf{W}_{(Sc,p)\_k}$ is the $N_t \times L_k$ precoding matrix for UE $k$ at the $p$th RAP in the supercell $Sc$. $\mathbf{n}_{Sc\_k}$ is the additive white Gaussian noise at UE $k$ in the supercell $Sc$, with zero mean and variance.

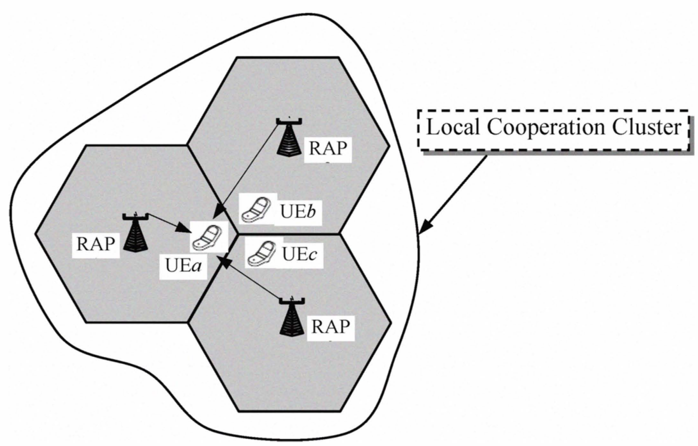


Fig. 2 Co-MP operation via local coordination mode with the three neighboring RAPs

As shown in figure 2, the three neighboring RAP 1, 2, and 3 together in the clustered supercell cooperatively transmit data streams to UE $a$, $b$, $c$. Denoting the channel transmission matrix observed by UE-$i$ and RAP-$j$ as $h_i^j$, RAP1 obtains the knowledge of $h_a^1$ from UE$a$, and $h_b^1$ from UE$b$ via backhaul from RAP2, and $h_c^1$ from UE$c$ via backhaul from RAP3.

After coordinated beamforming among RAP 1, 2, and 3, the sum capacity for UE $a$, $b$, $c$ can be approximated as

$$\begin{aligned} R_{sum} &= \log\left[\det(\mathbf{I}+\frac{\mathbf{W}_1^H h_a^1 \mathbf{W}_1}{tr(\mathbf{W}_2^H h_a^2 \mathbf{W}_2+\mathbf{W}_3^H h_a^3 \mathbf{W}_3)/N_r+I_{oa}})\right] \\ &+\log\left[\det(\mathbf{I}+\frac{\mathbf{W}_2^H h_a^2 \mathbf{W}_2}{tr(\mathbf{W}_1^H h_b^1 \mathbf{W}_1+\mathbf{W}_3^H h_b^3 \mathbf{W}_3)/N_r+I_{ob}})\right] \\ &+\log\left[\det(\mathbf{I}+\frac{\mathbf{W}_3^H h_c^3 \mathbf{W}_3}{tr(\mathbf{W}_1^H h_c^1 \mathbf{W}_1+\mathbf{W}_2^H h_c^2 \mathbf{W}_2)/N_r+I_{oc}})\right] \end{aligned} \quad (2)$$

where $\mathbf{I}$ denotes the identity matrix. $\mathbf{W}_1$, $\mathbf{W}_2$, $\mathbf{W}_3$ are the precoding matrices at RAP 1, 2, and 3, respectively. $I_{oa}$, $I_{ob}$, $I_{oc}$ are the pre-antenna average interference and noise powers observed by UE $a$, $b$, and $c$, respectively, i.e., excluding the received power from cells in the set of cooperative transmission points. Clearly the maximization of the above metric (2) requires solving $\max_{\mathbf{W}_1,\mathbf{W}_2,\mathbf{W}_3} R_{sum}$.

## IV. DYNAMIC CELL-CLUSTERING STRATEGIES

Corresponding to each clustering, there can be some UEs that will be in clustering boundaries. To overcome this issue, dynamic multiple clustering of cells is provided. Instead of forming fixed coordinating transmission sets based on geometry of cell layout, it is better to form coordinating and transmission points dynamically based on the UE link gains to the various cells for a particular time. For a given UE belonging to a supercell, it may be beneficial to designate a set of cells which are participating in the actual transmission for the UE. The cells in actual transmission to a UE are called active cells for the UE. The active cells can be defined from the UE perspective based on signal strengths from the cells (normally cells with strong signal strength are chosen among cells within the supercell). The designation of active cells can reduce the UE feedback overhead and the backhaul load due to unnecessary coordination among the cells.

Dynamic clustering can be utilized to adapt cooperation strategies to an actual deployment and can be based upon location and/or priority of active users, which can vary over time. Moreover, dynamic clustering can mitigate a need for network planning and cluster boundaries, while potentially yielding an enhanced throughput/fairness tradeoff. By introducing adaptive algorithm for dynamic clustering in the way that the RAPs form clusters in order to serve the selected UEs, the sum-rate increases significantly together with fairness across UEs. This is since clusters change dynamically, and therefore there are no cluster regions constantly at the edge and always very prone to CCI. The dynamic cluster-forming algorithm is given for sum-capacity maximization as shown in Table 1. In order for fairness to be achieved across UEs, each cluster formation phase starts from a random cell and not from a specific one. Therefore, on average, there are no RAPs favored more than others.

Tab. 1 Dynamic clustering algorithm for sum-capacity maximization

| |
|---|
| **Step-1**: Specify the cluster size, i.e. the number of cooperating RAPs. |
| **Step-2**: Star from a random cell that has not been chosen as far. This corresponds to one RAP and some specific UEs, assigned to this RAP, that need to be served at this time slot. |
| **Step-3**: Find the RAP and the UEs associated with it in order to maximize the joint capacity with the initial RAP and UEs. Continue in the same way until the coordinating cluster is formed and the specified cluster size is reached. |
| **Step 4**: Go to step 2 until all the RAP clusters are formed. |

With dynamic clustering, all the cells in Co-MP systems can dynamically select clustering strategies, which can effectuate distributed decisions based on a finite order strategy constraint to converge to an optimized set of clusters at a given point in time, with low complexity of multiple RAPs scheduling and data sharing. Furthermore, a utility based distributed negotiation framework can be leveraged by multiple RAPs to dynamically yield the clustering strategies decisions.

A coordinating strategy $\boldsymbol{S}$ can be defined as a set of RAPs, UEs, underlying antenna weights and power spectral densities (PSD) at RAPs that serve UEs covered by the strategies $\boldsymbol{S}$. The set of RAPs covered by coordinating strategy $\boldsymbol{S}$ can be referred as $\mathbf{B}(\boldsymbol{S})$ and the set of UEs covered by coordinating strategy $\boldsymbol{S}$ can be referred as $\mathbf{U}(\boldsymbol{S})$. Moreover, a rate achieved by a UE $k$ under coordinating strategy $\boldsymbol{S}$ at time $t$ per allocated resource can be $\mathbf{R}_{k,t}(\boldsymbol{S})$, a utility-metric (U-M) associated with coordinating strategy $\boldsymbol{S}$ at time $t$ can be U-M$_t(\boldsymbol{S})$, and a relative priority of UE $k$ at time $t$ based on, for instance, quality of service (QoS), fairness, etc. can be $\beta_{k,t}$. For example, fairness can be supported by $\beta_{k,t}$ being inversely proportional to an amount of data that UE $k$ has received. Scheduling decisions is aimed at maximizing the utility-metric U-M$_t(\boldsymbol{S})$ associated with coordinating strategy $\boldsymbol{S}$ at time $t$ for network-MIMO systems. According to the above, the utility-metric can be evaluated as follows

$$\mathbf{U\text{-}M}_t(S) = \sum_{k\in\mathbf{U}(S)} \beta_{k,t}\mathbf{R}_{k,t}(S) \quad (3)$$

A cooperation order can be defined as a number of the RAPs included in a given coordination strategy, which can be referred as $|\mathbf{B}(\boldsymbol{S})|$, i.e., cardinality of the RAPs set $\mathbf{B}(\boldsymbol{S})$. If $X_{\boldsymbol{S}}$ denotes a maximum cooperation order that can be allowed in the network-MIMO system, $|\mathbf{B}(\boldsymbol{S})|$ can be a member of a set $\{1,2,\cdots\cdots,X_{\boldsymbol{S}}\}$, i.e., $|\mathbf{B}(\boldsymbol{S})| \in \{1,2,\cdots\cdots,X_{\boldsymbol{S}}\}$. A first order cooperation strategy can be similar to a classic wireless MIMO communication model that lacks coordination between the RAPs. Thus, all the UEs covered by second order and higher order cooperation strategies can be served by multiple points included in the cluster in a cooperative manner.

Intuitively, a globally optimal cooperation can be include a large number of finite order cooperation strategy since high gain long loops on RAPs and UEs can be infrequent. An overall network-MIMO systems can be a direct sum of local cooperation strategy, where cooperation order of the local strategies can be constrained to a maximum value $X_S$.

$$\left|\mathbf{B}(S_l)\right| \cap \left|\mathbf{B}(S_m)\right| = \Phi, \quad \forall l \neq m \tag{4}$$

Moreover, an over utility-metric at a given time $t$ can be a sum of utility-metric corresponding to the local cooperation strategy at the given time $t$,

$$\mathbf{U}\text{-}\mathbf{M}_t(S_l) = \sum_l \sum_{k \in \mathbf{U}(S_l)} \beta_{k,t} \mathbf{R}_{k,t}(S_l) \tag{5}$$

Therefore, subsets of the RAPs and subsets of the UEs are dynamically grouped over time to yield the time varying set of local cooperation strategies. In contrast, conventional techniques that allow grouping of the RAPs typically define static clusters, which remain constant over time, i.e., the same RAPs are grouped together over time.

## V. Linear Precoding Design for Local Cooperation Clusters

With zero-forcing (ZF) approach [8], the RAPs antenna precoding matrices are selected such that each UE's data symbols do not interference with each other in local cooperation cluster. Also, in the dirty paper coding (DPC) approach [9, 10], when the interference is known causally at the transmitter, UE′s codebooks can be chosen such that given a UE order [π(1), π(2), …, π(*K*)], a UE with index π(*k*) does not suffer any interference from UEs with lower indexes, i.e., π(*j*) with $j<k$. When DPC is combined with the limited form of ZF, the interference still present from DPC will be nullified out due to ZF precoding matrix. In this case, the precoding matrix for π(*i*)′s data symbols have to be orthogonal to the channels of UEs π(*k*) with $i>k$ only. Thus, the ZF precoding matrix must be satisfied

$$\mathbf{H}_{Sc\_\pi(k)} \mathbf{W}_{Sc\_\pi(i)} \begin{cases} = 0, \forall i > k \\ = \mathbf{I}_K, \forall i = k \end{cases} \tag{6}$$

where $I_K$ is an identity matrix with the dimension equal to the number of selected users. Hence, the selected precoding matrix is the Moore-Penrose pseudoinverse of the channel matrix,

$$\mathbf{W}_{Sc\_\pi(i)} = \mathbf{H}^{\dagger}_{Sc\_\pi(k)} \left[\mathbf{H}_{Sc\_\pi(k)} \mathbf{H}^{\dagger}_{Sc\_\pi(k)}\right]^{-1} \tag{7}$$

Note that other choice of precoding (MMSE etc.) can be considered. In practice each column of $\mathbf{W}_{Sc\text{-}k}$ is normalized to unity, which is equivalent to adding an additional scaling factor to the power allocation matrix $\mathbf{A}_{Sc\text{-}k}$. In order to guarantee that each antenna has an average power constraint $P$, the power allocation matrix is

$$\mathbf{A}_{Sc\_k} = \sqrt{P \Big/ \max_{i=1,\cdots,N_t M_p} \left\| \mathbf{W}^{[i]}_{Sc\_k} \right\|_F^2} \times \mathbf{I}_K \tag{8}$$

Where $\mathbf{W}^{[i]}$ is the row vector of $\mathbf{W}$ which corresponding to the $i$-th antenna, $\|.\|_F$ represents the Frobenius norm. The power allocation matrix is computed by the CU that gathers CSI and selects users. The Signal to Interference plus Noise Ratio (SINR) of the $k$-th UE, when linear precoding is employed is

$$SINR_k = \frac{\left\| \mathbf{H}_{(Sc,p)\_k} \mathbf{W}_{(Sc,p)\_k} \right\|^2}{\sum_{j \neq k} \left\| \mathbf{H}_{(Sc,p)\_k} \mathbf{W}_{(Sc,p)\_j} \right\|^2 + \left( \max_{i=1,\cdots,N_t M_p} \left\| \mathbf{W}^{[i]}_{Sc\_k} \right\|_F^2 \sigma^2 \right) / P} \tag{9}$$

Where $\mathbf{W}_{(Sc,p)\_k}$ is the beamforming vector for the $k$-th UE and $\mathbf{H}_{(Sc,p)\_k}$ is the channel vector between the $k$-th UE and all the antennas of the cooperation cluster. The term $\sum_{j \neq k} \left\| \mathbf{H}_{(Sc,p)\_k} \mathbf{W}_{(Sc,p)\_j} \right\|^2$ corresponds to the intra-cluster interference. With zero-forcing precoding intra-cluster interference is eliminated and SINR becomes

$$SINR_k = \frac{P}{\max_{i=1,\cdots,N_t M_p} \left\| \mathbf{W}^{[i]}_{Sc\_k} \right\|_F^2 \sigma^2} \tag{10}$$

## VI. Numerical Simulation and Analysis

A network consisting 19 cells overall has been considered. RAPs are located in the centre of each cell. Spatial channel model (SCM) is used for the simulation where the large-scale fading and small-scale fading are considered. In order for the cost and the complexity to be affordable, cooperation clusters in practice need to be of a limited size. Increasing the cluster size will increase the amount of cooperation possible but at the same time will typically increase the complexity of network architecture and scheduling.

As illustrated in figure 3, the average sum-rate is plotted against the system SNR. The system SNR is the average SNR which a UE located at the edge of the cell receives from a RAP, without taking into account the CCI. The average sum-rate performance of the different clustering approaches can be shown in Fig.3. From figure 3, it can be seen that static cell-clustering coordination (i.e., Static Co-MP) techniques outperform single cell non-cooperation (i.e., Non Co-MP) processing since the amount of CCI is significantly reduced. The dynamic cell-clustering strategies (i.e., Dynamic Co-MP) provides significant sum-rate gains and enhances the fairness of the system comparing to static cell-clustering scheme since it exploits the knowledge of instantaneous CSI in the formation of clusters. A dynamic cell-clustering strategy with clustered supercell size of 2 outperforms static cell-clustering schemes with large cluster sizes.

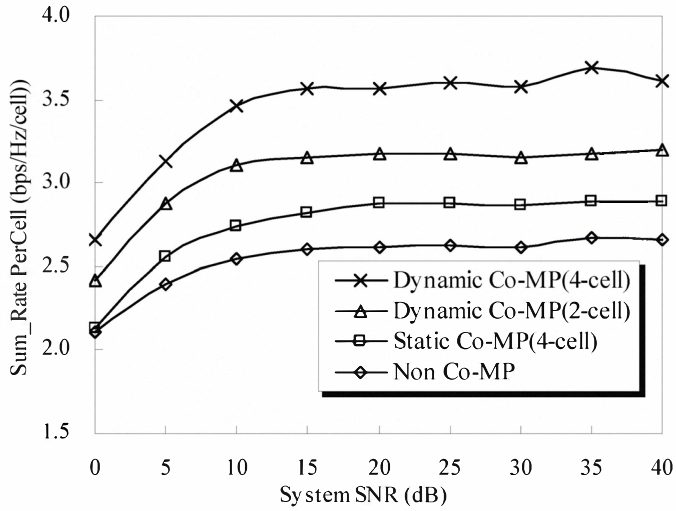


Fig. 3 The average achievable sum-rate performance per cell of the different cell-clustering approaches

The cumulative distribution function (CDF) of the user rates for two different clustering strategies can be shown in figure 4, where 100 users per cell are assumed. Except from sum-rate increase, dynamic cell-clustering enhances significantly fairness amongst the UEs of the network MIMO systems. This can be seen by the fact that the CDF of the dynamic cell-clustering strategy is steeper than the one corresponding to the static cell-clustering scheme.

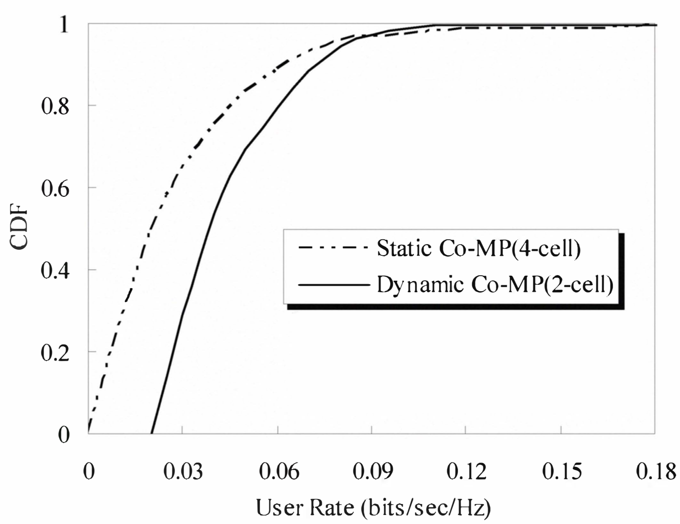


Fig.4 The cumulative distribution function (CDF) of two different cell-clustering strategies

## VII. CONCLUSIONS

In realistic cellular systems, coordinated multi-point coordination transmission inevitably requires increased signaling overhead and inter-RAP communications. Therefore in practice, only a limited number of RAPs by clustering can cooperate and jointly process the downlink transmission signals in order for the complexity and overhead to be practically affordable.

With dynamic cell-clustering which leverages the knowledge of the instantaneous channel state, all the cells in Co-MP systems can dynamically select clustering strategies. Moreover, dynamic clustering, based upon location and/or priority of active users, can be utilized to adapt cooperation strategies to an actual deployment and can mitigate a need for network planning and cluster boundaries, while potentially yielding an enhanced throughput/fairness tradeoff. By introducing adaptive algorithm for dynamic clustering in the way that the RAPs form clusters in order to serve the selected UEs, the sum-rate increases significantly together with fairness across UEs comparing to static clustering schemes.

## ACKNOWLEDGMENT

This work was supported by the National High Technology Research Project of China ("863") (No. 2009AA01Z234), the National Basic Research Program of China ("973") (No. 2007CB310604), and the open research fund of National Mobile Communications Research Lab in Southeast University (No. W200818).

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