Semi-dynamic Cooperative Cluster Selection for Downlink Coordinated Beamforming Systems

Dong Liu, Qian Zhang, Shengqian Han, Chenyang Yang
Beihang University, Beijing, China
Email: {liudong, qianzhang, sqhan}@ee.buaa.edu.cn, cyyang@buaa.edu.cn

Gang Wang, Ming Lei
NEC Laboratories, China
Email: {wang_gang, lei_ming}@nec.cn

***Abstract*—Coordinated multi-point (CoMP) transmission can significantly improve the spectral efficiency of cellular networks. To reduce the training overhead and the complexity for implementing CoMP, an effective way is to divide base stations (BSs) into cooperative clusters. However, with disjointed clusters, the cluster-edge users suffer from inter-cluster interference. In this paper, a scheme is designed to select a set of BSs to serve each user with CoMP coordinated beamforming, where the clusters of different users may overlap. To reduce the signaling overhead, the average net throughput of the network is maximized considering the training overhead. The proposed scheme depends on large-scale channel gains and can be operated in a semi-dynamic manner. A low complexity algorithm is proposed to form the clusters, which achieves similar performance to the optimal solution with exhaustive searching. Simulation results show the proposed algorithm outperforms the existing CoMP joint transmission with dynamic clustering and the Non-CoMP system.**

I. Introduction

Inter-cell interference (ICI) is a major bottleneck for improving spectral efficiency of universal frequency reuse cellular networks. Coordinated multi-point (CoMP) transmission is widely recognized as a promising technique to enhance system throughput by eliminating ICI [1]. Depending on whether data is shared among the coordinated base stations (BSs), CoMP can be roughly divided into CoMP joint transmission (CoMP-JT) and CoMP coordinated beamforming (CoMP-CB).

To facilitate CoMP transmission, more channel information should be available compared with the traditional single-cell transmission systems, i.e., Non-CoMP systems. In fact, the performance of CoMP transmission may even become inferior to Non-CoMP systems [2], since the training overhead for acquiring channel information may counteract the cooperative gain and the throughput of CoMP transmission largely depends on the users' location [3, 4], i.e., cell-edge users will benefit more from cooperative transmission than cell-center users.

To trade off the performance gain provided by CoMP with the resulting training overhead as well as the implementation complexity, multiple cells are usually formed into many cooperative clusters with limited number of BSs in each cluster [5, 6]. In [5], a fixed clustering method was provided to form pre-defined disjoint clusters, where the users located at the cluster-edge still suffer from severe interference from nearby clusters. In [6], a dynamic clustering method was proposed, where multiple cells were divided into non-overlapped clusters to maximize the instantaneous sum rate of multiple users served by CoMP-JT. When the training overhead is taken into account for gathering the channel information, the gain in net throughput becomes less significant. In [7], a precoding for CoMP-JT with overlapped cooperative clusters was proposed, where the clusters were formed by each user with a threshold based simple method.

Considering that CoMP-JT needs backhaul links with high capacity, CoMP-CB is more desirable for practical systems. In this paper, we strive to reduce the training overhead in gathering channel information for forming cooperative clusters and mitigate the inter-cluster interference for cluster-edge users. To this end, we design a semi-dynamic cooperative cluster selection scheme that maximizes the downlink average net throughput of the CoMP-CB system considering training overhead, where the cooperative clusters of different users can be overlapped. To provide a feasible scheme for practical use, we propose a low-complexity algorithm to select the cooperative cluster for each user, which performs closely to the optimal solution found by exhaustive searching. Simulation results show that the proposed algorithm outperforms other relevant schemes in the literature.

The rest of the paper is organized as follows. In Section II, we present the system model. The semi-dynamic cooperative cluster selection scheme is proposed in Section III and simulation results are provided in Section IV. The conclusions are drawn in Section V.

II. System Model

Consider a downlink network consisting of N_b BSs and N_u active single-antenna users. Each BS is equipped with N_t antennas. Each user is served by CoMP-CB with a cluster of cooperative BSs, including a master BS and a number of coordinative BSs. The cooperative clusters for different users may overlap and may be with different sizes. When the cluster size for a user is one, the user is in fact served with Non-CoMP transmission, i.e., the user receives the desired signal from its master BS and suffers interference from all the other BSs. Otherwise, the user receives the desired signal from its master

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BS while other BSs in the cluster avoid generating interference to it. An example of the considered system is shown in Fig. 1.

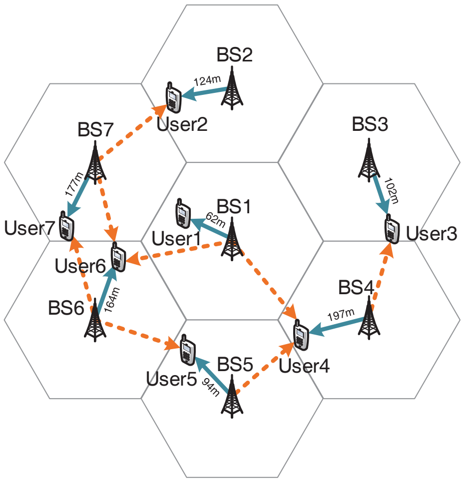

Fig. 1. An example layout of the considered system. A solid arrow stands for the connection between a user with its master BS, and a dash arrow represents the connection between a user with its coordinative BS.

A. Coordinated Beamforming With Overlapped Clusters

To describe the coordinated beamforming with overlapped clusters, we introduce *transmission matrix* $\mathbf{S} = [s_{ub}]_{N_u \times N_b}$ and *coordination matrix* $\mathbf{C} = [c_{ub}]_{N_u \times N_b}$ respectively to reflect the relationship of a user with its master BS and coordinative BSs, whose elements are either 0 or 1. Specifically, if BS b is the master BS of user u, $s_{ub} = 1$; otherwise, $s_{ub} = 0$. If BS b is a coordinative BS for user u, $c_{ub} = 1$; otherwise, $c_{ub} = 0$. In practice, the *transmission matrix* $\mathbf{S}$ can be determined easily. Each user can simply select a BS as the master BS from whom the average channel gain is the largest. If the *coordination matrix* $\mathbf{C}$ can be found under a certain criterion, each of the N_u users will obtain its coordinative BSs.

Denote b_u as the index of the master BS of user u, i.e., $s_{ub_u} = 1$. Denote $\mathcal{P}_u = \{b|c_{ub} = 1\}$ as the set of indices of the coordinative BSs for user u. Then, $\mathcal{C}_u = \mathcal{P}_u \cup \{b_u\}$ is the indices of all BSs in the cooperative cluster for user u, which is referred as the cluster for user u. In Fig. 1, the clusters for user 1, 5 and 6 are respectively $\{1\}$, $\{5, 6\}$ and $\{1, 6, 7\}$. Notice that user 1 is served by Non-CoMP transmission, and the clusters of these three users are overlapped.

To illustrate how the clusters are formed and the corresponding performance, we consider zero-forcing (ZF) precoder [8] to eliminate the multi-user interference (MUI) in each cell and coordinate the ICI inside each cooperative cluster. Note that the clustering scheme under ZF precoder can apply to other precoders, such as [9–11]. Denote $\mathcal{S}_b = \{u|s_{ub} = 1\}$ and $\mathcal{I}_b = \{u|c_{ub} = 1\}$ as the sets of indices of the users served by and coordinated by BS b, respectively. With ZF precoder, the overall number of users able to be served and coordinated by BS b is restricted by its number of antennas, i.e., $M_b \triangleq |\mathcal{S}_b| + |\mathcal{I}_b| = \sum_{u=1}^{N_u} (s_{ub} + c_{ub}) \le N_t, b = 1, \cdots, N_b$. The ZF beamforming vector for user u at its master BS b_u can be expressed as follows,

$$\mathbf{w}_{ub_u} = \frac{\Pi_{\bar{u}b_u} \mathbf{h}_{ub_u}}{||\Pi_{\bar{u}b_u} \mathbf{h}_{ub_u}||}, \tag{1}$$

where $||\mathbf{w}_{ub_u}|| = 1$, $\mathbf{h}_{ub} = \alpha_{ub}\mathbf{g}_{ub}$ is the composite channel between BS b and user u, α_{ub} and $\mathbf{g}_{ub} \in \mathbb{C}^{N_t \times 1}$ are respectively the large-scale channel gain and small-scale channel vector, $\Pi_{\bar{u}b_u}$ is the null space of $\mathbf{H}_{\mathcal{K}_u, b_u}$,

$$\Pi_{\bar{u}b_u} = \mathbf{I} - \mathbf{H}^H_{\mathcal{K}_u,b_u} \left(\mathbf{H}_{\mathcal{K}_u,b_u} \mathbf{H}^H_{\mathcal{K}_u,b_u}\right)^{-1} \mathbf{H}_{\mathcal{K}_u,b_u}, \tag{2}$$

and $\mathbf{H}_{\mathcal{K}_u,b_u}$ is the channel matrix from BS b_u to the users in a set $\mathcal{K}_u = \mathcal{S}_{b_u} \cup \mathcal{I}_{b_u} - \{u\}$, which includes the served and coordinated users of BS b_u except user u, $(\cdot)^H$ denotes the conjugate transpose, and $||\cdot||$ denotes the norm of a vector.

After eliminating the MUI and ICI, the signal to interference plus noise ratio (SINR) at user u can be expressed as

$$\gamma_u = \frac{\lambda_{uu} \left|\mathbf{g}^H_{ub_u} \mathbf{w}_{ub_u}\right|^2}{\underbrace{\sum_{\substack{j \neq u \\ b_j \notin \mathcal{C}_u}} \lambda_{uj} \left|\mathbf{g}^H_{ub_j} \mathbf{w}_{jb_j}\right|^2}_{\text{inter-cluster interference}} + \sigma^2} \triangleq \frac{S_u}{I_u + \sigma^2}, \tag{3}$$

where $\lambda_{uj} \triangleq \alpha^2_{ub_j} p_{jb_j}$ is the average power received at user u from the signals sent to user j, p_{jb_j} is the transmit power allocated to user j at BS b_j, and σ^2 is the variance of additive white Gaussian noise, and $|\cdot|$ denotes the magnitude. In this paper, we assume that each BS equally allocates the total transmit power P to its served users, therefore $p_{jb_j} = \frac{P}{\sum_{i=1}^{N_u} s_{ib_j}}$.

B. Training Overhead

To facilitate downlink precoding, the channel information should be available at a central unit (CU). In time division duplex (TDD) systems, the channel is estimated at the BS through uplink training by exploiting the reciprocity of uplink and downlink channels. The uplink training occupies the time or frequency resources. After taking into account the uplink training overhead, the net downlink data rate of user u can be expressed as

$$R_u(\mathbf{C}) = (1 - v_u X) \log_2(1 + \gamma_u), \tag{4}$$

where v_u represents the percentage of the resources taken by the uplink training for user u depending on its channel coherent time and coherent bandwidth, and X reflects the occupied uplink resources to ensure the orthogonality among the training signals of multiple users [12].

For CoMP with non-overlapped clusters, only the training signals for the users within a cluster should be orthogonal and X simply equals to the number of the scheduled users in each cluster. When the clusters are overlapped, however, the training signals for the users in overlapped clusters should also be orthogonal. The value of X can be computed using the method proposed in [12], which depends on the sizes of the clusters as well as the number of overlapped clusters.

III. Semi-dynamic Cooperative Cluster Selection

In this section, we propose a scheme to determine the cooperative cluster for each user that maximizes the downlink net throughput.

Dynamically forming cooperative clusters based on small-scale fading channels yields a frequently changing clusters and leads to large signaling overhead among BSs and users, making it infeasible in practical systems. Therefore, in the sequel, we select cooperative cluster for each user based on large-scale channels, aiming at maximizing the average net throughput rather than the instantaneous net throughput. As a result, the proposed scheme can be implemented in a semi-dynamic manner.

A. Problem Formulation

From (4) the average net throughput can be obtained as

$$\bar{R}(\mathbf{C}) = \sum_{u=1}^{N_u} \mathbb{E}\left\{R_u(\mathbf{C})\right\} = \sum_{u=1}^{N_u}(1 - \upsilon_u X)\mathbb{E}\left\{\log_2\left(1 + \gamma_u\right)\right\}. \tag{5}$$

Proposition 1: When the entries of $\mathbf{g}_{ub}$ are independent and identically distributed (i.i.d.) unit variance complex Gaussian variables and when $\sigma^2 \to 0$, we have

$$\bar{R}(\mathbf{C}) = \sum_{u=1}^{N_u}(1 - \upsilon_u X) \sum_{\substack{j \neq u \\ b_j \notin \mathcal{C}_u}} \xi_{uj}\Big(- \ln\left(\rho_{uj}\right) + \sum_{k=1}^{K_u - 1} \frac{1}{k} + \frac{(-\rho_{uj})^{K_u} \ln(\rho_{uj})}{(1 - \rho_{uj})^{K_u}} - \sum_{k=1}^{K_u-1} \binom{K_u - 1}{k} \frac{(1 - \rho_{uj}^k)(-\rho_{uj})^{K_u - k}}{k(1 - \rho_{uj})^{K_u}}\Big), \tag{6}$$

where $K_u = N_t - M_{b_u} + 1$, $\rho_{uj} = \frac{\lambda_{uj}}{\lambda_{uu}}$, and $\xi_{uj} = \frac{1}{\ln 2} \prod\limits_{\substack{m \neq j \\ b_m \notin \mathcal{C}_u}} \frac{\lambda_{uj}}{\lambda_{uj} - \lambda_{um}}$.

Proof: See Appendix A. ■

In practice, we can use (6) as an approximated average net throughput, which is accurate for high SNR.

The values of ξ_{uj}, ρ_{uj} and λ_{uj} are all related to the large-scale channel gains α_{ub}, $u = 1, \ldots, N_u$, $b = 1, \ldots, N_b$. To compute $\bar{R}$ in (6) for selecting coordinative BSs for each user, the CU needs to know the values of α_{ub}. In practical systems, each user can measure the large-scale channel gains by averaging the channels in multiple time slots and then report to the CU. Because a user will gain little from choosing the faraway BSs as its coordinative BSs, we introduce a measurement set $\mathcal{F}_u$ and user u only estimates the large-scale channel gains from the BSs in $\mathcal{F}_u$, which can be determined by using one of the following two ways:

1) Fix the size of $\mathcal{F}_u$ for all users, and each user reports $|\mathcal{F}_u|$ strongest large-scale channels to the CU.
2) The size of $\mathcal{F}_u$ depends on the location of user u, and its measurement set is formed using the same method to form a cluster in [7] as

$$\mathcal{F}_u = \left\{ b \,\middle|\, \frac{\alpha_{ub}^2}{\max\left\{\alpha_{uj}^2\right\}_{j=1}^{N_b}} > \beta \right\},$$

where $0 < \beta \leq 1$.

Although the interference from each of the BSs outside the measurement set is very weak, the total interference from those BSs may not be ignorable. If the CU simply ignores the interference when selecting cluster for each user, it will select too many coordinative BSs for the user, which degrades the system performance due to the increased training overhead and reduced antenna resource available for other users. Therefore, each user also needs to measure and report its average total received power, denoted as $\bar{I}_u$, which can be easily implemented. Then, the CU can obtain the average total interference power for user u outside its measurement set as $\bar{I}_u^{\text{out}} = \bar{I}_u - \sum\limits_{b_k \in \mathcal{F}_u} \lambda_{uk}$. When the CU computes $\bar{R}$ in (6), the required interference powers for user u outside its measurement set, $\{\lambda_{uj} | b_j \notin \mathcal{F}_u\}$, can be estimated as random variables as follows

$$\lambda_{uj} = \frac{\theta_j}{\sum\limits_{b_i \notin \mathcal{F}_u} \theta_i} \bar{I}_u^{\text{out}}, \tag{7}$$

where $\{\theta_j\}$ are i.i.d. random variables uniformly distributed in $[0, 1]$. In the next section, we show that such an estimation has negligible impact on computing the value of $\bar{R}$.

After obtaining the large-scale channel gains and interference, the semi-dynamic coordinative BSs selection problem can be formulated as the following optimization problem,

$$\max_{\mathbf{C}} \quad \bar{R}(\mathbf{C}) \tag{8a}$$

$$s.t. \quad c_{ub}s_{ub} = 0, c_{ub} \in \{0, 1\}, \tag{8b}$$

$$c_{ub} = 0 \ (b \notin \mathcal{F}_u), \tag{8c}$$

$$\sum_{u=1}^{N_u}(c_{ub} + s_{ub}) \leq N_t, \tag{8d}$$

where (8b) and (8c) indicate that the coordinative BSs for user u should be selected from its measurement set excluding its master BS, and (8d) indicates that the total number of served and coordinated users at BS b should be less than its number of antennas.

B. Semi-dynamic Coordinative BSs Selection Algorithm

The complexity of solving problem (8) by exhaustive searching is $O(2^{N_u N_b})$, which grows exponentially with N_u and N_b. In the following, we propose a low-complexity algorithm to find the coordination matrix $\mathbf{C}$, where the cooperative links are added one-by-one based on a Non-CoMP system.

1) Initialize $\mathbf{C}^{(0)} = \mathbf{0}$, $\bar{R}_{\max}^{(0)} = \bar{R}(\mathbf{C}^{(0)})$, which is the average net throughput when all users are served by Non-CoMP transmission, where $\mathbf{0}$ is an all-zero matrix.
2) Iteration, $i = 1$:

a) Find the optimal cooperative link maximizing the average net throughput from the following problem by exhaustive searching,

$$\max_{\mathbf{D}^{(i)}} \quad \bar{R}(\mathbf{C}^{(i-1)} + \mathbf{D}^{(i)}), \tag{9a}$$

$$s.t. \quad \sum_{u=1}^{N_u}\sum_{b=1}^{N_b} d_{ub}^{(i)} \le 1, \; d_{ub}^{(i)} \in \{0,1\}, \tag{9b}$$

$$d_{ub}^{(i)} = 0 \; (b \notin \mathcal{F}_u), \tag{9c}$$

$$d_{ub}^{(i)} c_{ub}^{(i-1)} = 0, \tag{9d}$$

$$d_{ub}^{(i)} s_{ub} = 0, \tag{9e}$$

$$\sum_{u=1}^{N_u} (c_{ub}^{(i-1)} + d_{ub}^{(i)} + s_{ub}) \le N_t, \tag{9f}$$

where $\mathbf{D}^{(i)} = [d_{ub}]_{N_u \times N_b}$ denotes the newly added cooperative link that is a 0-1 matrix and the number of "1"s in $\mathbf{D}^{(i)}$ is no larger than 1 as shown in constraint (9b); constraints (9c), (9d) and (9e) indicate that each user can only choose the newly added coordinative BSs from its measurement set excluding its master BS and the chosen coordinative BSs, and constraint (9f) indicates that the total number of served and coordinated users at each BS should be limited by its number of antennas. The search space of this problem is $O(N_u N_b - i)$, which shrinks with the increase of iteration times i.

b) Denote $\mathbf{D}_{\text{opt}}^{(i)}$ as the optimal value of $\mathbf{D}^{(i)}$. Then, $\bar{R}_{\max}^{(i)} = \bar{R}(\mathbf{C}^{(i-1)} + \mathbf{D}_{\text{opt}}^{(i)})$. With the increase of the number of cooperative links, the training overhead grows and the available antennas diminish, which finally leads to reduction in the average net throughput. If $\bar{R}_{\max}^{(i)} > \bar{R}_{\max}^{(i-1)}$, update $\mathbf{C}^{(i)} = \mathbf{C}^{(i-1)} + \mathbf{D}_{\text{opt}}^{(i)}$ (i.e., add a new cooperative link into the system), $i = i+1$ and go back to step 2)-a) . Otherwise, stop the iteration and $\mathbf{C}^{(i-1)}$ is the final result of the coordination matrix.

The computational complexity of this algorithm is $O(N_u^2 N_b^2)$, which is much smaller than $O(2^{N_u N_b})$. In the next section, we show that the proposed algorithm performs closely to the optimal solution of problem (8).

IV. Numerical and Simulation Results

In this section, we evaluate the proposed semi-dynamic cooperative cluster selection algorithm by simulations.

To reduce the computational complexity for simulation, a cellular network with one tier of seven cells is considered, i.e., N_b = 7, as shown in Fig. 1. Each BS is located in the center of the hexagon cell and wraparound is considered to remove the boundary effects. The number of antennas at each BS is four. The measurement set size of each user is fixed as three, i.e., $|\mathcal{F}_u| = 3$. We use the cell-edge SNR to reflect the impact of different kinds of cells, which is defined as the received SNR of a user located at the cell-edge without interference. For the typical system setting of the macro cell in 3GPP, i.e., when the maximum transmit power of each BS is 46 dBm, the cell radius is 250 m, the value of the receiver noise is -95 dBm and the path-loss is modeled as $36.3 + 37.6\log_{10}(d_{ub})$ in dB where d_{ub} is the distance from BS b to user u in meters, the cell-edge SNR is 15 dB accordingly.

The uplink training overhead of user u, v_u, is set in a range of $0 \sim 4\%$ according to a proposal for LTE systems with training period from 2 ms to 160 ms [13], and the typical value of v_u is 1% for a 10 ms training period. The value X is obtained by using the method proposed in [12] to guarantee the training signal orthogonality among the users with overlapped cooperative clusters. For example, $X = 3$ for the layout in Fig. 1. The average net throughputs obtained in the following are averaged over 500 drops, each of which contains 1000 realizations of i.i.d. Gaussian small-scale channels. At each drop of users, one user is uniformly distributed in each cell.

In order to evaluate the performance of the proposed cooperative cluster selection scheme, the following approaches are simulated:

1) *Non-CoMP system* (with legend "Non-CoMP"): Each user is only served by one BS and suffers from ICI from all the other BSs.

2) *Fixed Clustering* (with legend "Fixed"): Each user is served by a pre-defined cluster with a master BS and a coordinative BS by CoMP-CB.

3) *Dynamic Clustering* (with legend "Dynamic"): The s-trategy is proposed in [6], where every two BSs forms a non-overlapped cluster dynamically in each time slot to jointly serve the users within the cluster using CoMP-JT.

4) *Optimal Semi-Dynamic Clustering* (with legend "Optimal"): This is the optimal semi-dynamic cooperative cluster selection obtained from problem (8) by exhaustive searching.

In Fig. 2, we first compare the simulated average net throughput and the numerical result computed from (6) for $\sigma^2 \to 0$. The users' location and their cooperative clusters are set as shown in Fig. 1. The simulation results are obtained from (4) using ZF precoding in (1), and are averaged over 1000 small-scale channel realizations. We can see that the numerical result approaches the simulation result with less than a 10% gap when the cell-edge SNR $>$ 10 dB. We also show the impact of the interference estimation in (7) on computing $\bar{R}$. When the CU employs (7), the obtained $\bar{R}$ is close to the simulation result. When the CU ignores these interference, i.e., simply sets $\lambda_{uj} = 0$ $(j \notin \mathcal{F}_u)$, the interference power will be under-estimated and the resulting $\bar{R}$ exceeds the true value.

In Fig. 3, we show the simulation results of average net throughput versus the cell-edge SNR. We can see that the proposed cooperative cluster selection algorithm performs close to the optimal solution, and outperforms the Non-CoMP system significantly when the cell-edge SNR is high. Compared with the fixed clustering, the proposed scheme achieves larger performance gain over Non-CoMP system at high cell-edge SNR. This is because the fixed clustering scheme suffers from severe inter-cluster interference for the users located at the cluster-edge, which can be reduced significantly by the proposed scheme with overlapped clusters. The dynamic

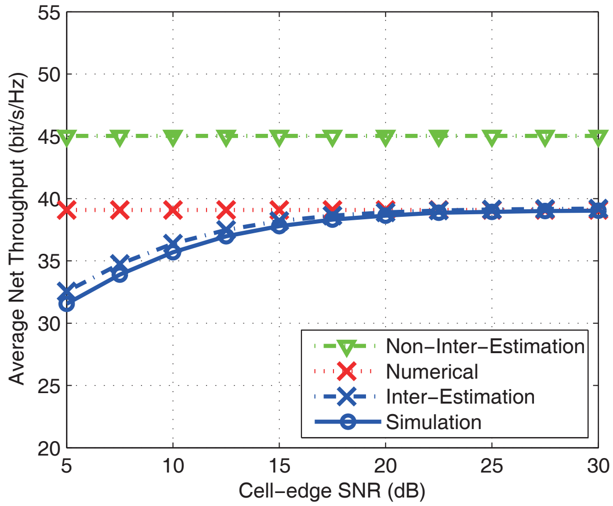

Fig. 2. The accuracy of the approximation of $\bar{R}$ for $\sigma^2 \to 0$ and the necessity of reporting interference, the uplink training overhead per user $v_u = 1\%$.

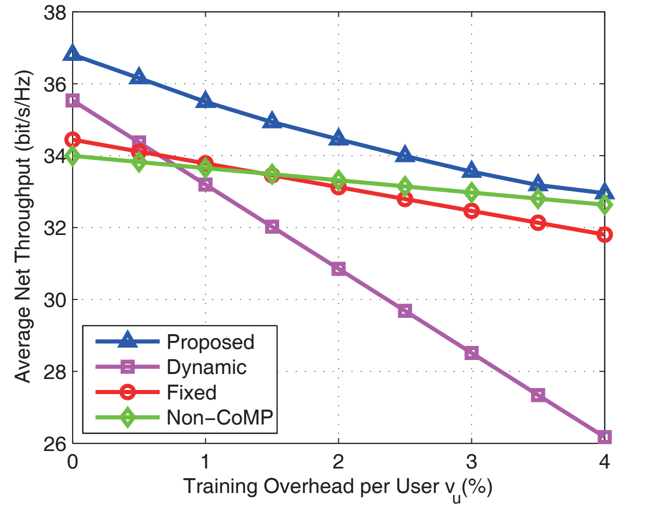

Fig. 4. Average net throughput vs training overhead per user v_u. The cell-edge SNR is set as 15dB.

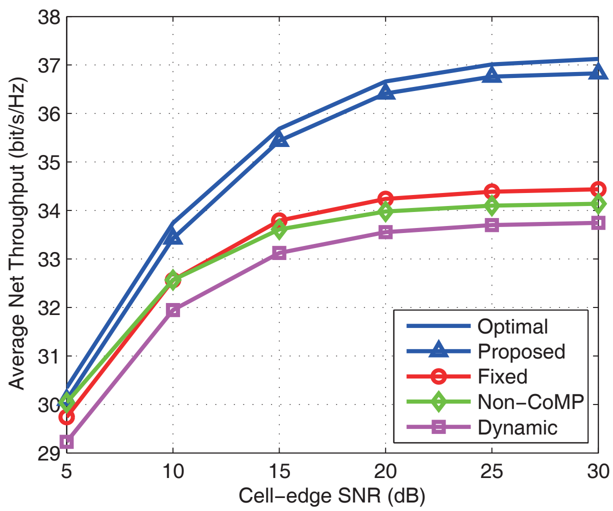

Fig. 3. Average net throughput vs cell-edge SNR, the uplink training overhead per user $v_u = 1\%$.

clustering is inferior to the Non-CoMP system and the fixed clustering. This is because the dynamic clustering needs to measure all the instantaneous channels from all users to all BSs when forming the clusters, which introduces large training overhead, while other schemes only need to measure the instantaneous channels within the cooperative cluster when computing the downlink precoding.

In Fig. 4, we show the simulation results of average net throughput versus the training overhead per user. When the training overhead is low, both the fixed clustering and the dynamic clustering outperform the Non-CoMP system. With the increase of the training overhead, the performance of the dynamic clustering reduces sharply since it needs the users to estimate the instantaneous channels from all the BSs, and the performance of the fixed clustering reduces relatively slowly since the clusters are pre-defined, introducing non-extra training overhead in the formation of clusters. By adaptively selecting cooperative cluster for each user, the proposed semi-dynamic clustering achieves better performance than Non-CoMP systems under any training overhead. If the training overhead is very high, few cooperative links are selected and the system determined by the proposed scheme degenerates into the Non-CoMP system. If the training overhead is very low, the dynamic clustering outperforms the Non-CoMP and CoMP with fixed clustering. However, it is still inferior to the proposed scheme even considering that it employs CoMP-JT while we employ CoMP-CB. This is because the clusters formed by it are non-overlapped while the clusters formed by us can be overlapped.

V. Conclusion

In this paper, a downlink cooperative cluster selection scheme was proposed for CoMP-CB, where the cooperative clusters for different users are allowed to overlap. By adaptively forming the cooperative cluster for each user according to its average channel gains and training overhead, the proposed scheme achieves high average net throughput compared with the Non-CoMP systems and other CoMP systems with fixed or dynamic clustering. The proposed scheme is based on large-scale channel information and with low complexity, which can be implemented in a semi-dynamic manner.

Appendix A
Proof of Proposition 1

To derive the expectation of $\log_2(1+\gamma_u)$, we first characterize the distributions of S_u and I_u in (3) as follows.

Define $\hat{\mathbf{g}}_{ub_u}^H = \mathbf{g}_{ub_u}^H / \|\mathbf{g}_{ub_u}^H\|$, then S_u can be expressed as

$$S_u = \lambda_{uu} \|\mathbf{g}_{ub_u}\|^2 \|\hat{\mathbf{g}}_{ub_u}^H \mathbf{w}_{ub_u}\|^2, \quad (10)$$

where $\lambda_{uu} \left\|\mathbf{g}_{ub_u}\right\|^2$ follows Gamma distribution, i.e., $\lambda_{uu} \left\|\mathbf{g}_{ub_u}\right\|^2 \sim \mathbb{G}(N_t, \lambda_{uu})$, and $\|\hat{\mathbf{g}}_{ub_u}^H \mathbf{w}_{ub_u}\|^2$ follows Beta distribution [14], i.e., $\|\hat{\mathbf{g}}_{ub_u}^H \mathbf{w}_{ub_u}\|^2 \sim \mathbb{B}(K_u, M_{b_u} - 1)$. Due to the independence of $\lambda_{uu} \left\|\mathbf{g}_{ub_u}\right\|^2$ and $\|\hat{\mathbf{g}}_{ub_u}^H \mathbf{w}_{ub_u}\|^2$ [15], we can show that S_u follows Gamma distribution as $S_u \sim \mathbb{G}(K_u, \lambda_{uu})$.

Denote $I_{uj} = \lambda_{uj}\|\mathbf{g}_{ub_j}^H \mathbf{w}_{jb_j}\|^2$ as the interference power from user j to user u. It was proved in [16] that I_{uj} follows exponential distribution with mean λ_{uj}. Moreover, $I_u = \sum\limits_{\substack{j \neq u \\ b_j \notin \mathcal{C}_u}}^{N_b} I_{uj}$ is the sum of independent exponential random variables whose probability density function can be found from [17] as

$$f_{I_u}(x) = \sum_{\substack{j \neq u \\ b_j \notin \mathcal{C}_u}} \delta_{uj} e^{-\frac{x}{\lambda_{uj}}}, \tag{11}$$

where $\delta_{uj} = \frac{1}{\lambda_{uj}} \prod\limits_{\substack{m \neq j \\ b_m \notin \mathcal{C}_u}} \frac{\lambda_{uj}}{\lambda_{uj} - \lambda_{um}}$ when $\lambda_{um} \neq \lambda_{uj}$ $(m \neq j)$.

Since S_u is independent from I_u, with (11) we can first take the expectation over I_u for $\sigma^2 \to 0$, which is [18, eq.(28)]

$$\begin{aligned} &\mathbb{E}_{S_u, I_u}\left\{\log_2(1+\gamma_u)\right\} = \mathbb{E}_{S_u, I_u}\left\{\log_2\left(1 + \frac{S_u}{I_u}\right)\right\} \\ &= \sum_{\substack{j \neq u \\ b_j \notin \mathcal{C}_u}} \frac{\delta_{uj}\lambda_{uj}}{\ln 2} \mathbb{E}_{S_u}\left\{\varepsilon + \ln\left(\frac{S_u}{\lambda_{uj}}\right) - e^{\frac{S_u}{\lambda_{uj}}} \mathrm{Ei}\left(-\frac{S_u}{\lambda_{uj}}\right)\right\}, \end{aligned} \tag{12}$$

where $\mathrm{Ei}(x) = -\int_{-x}^{\infty} \frac{e^{-t}}{t} dt$ denotes the exponential integral. Then, take the expectation over S_u, which is

$$\begin{aligned} &\mathbb{E}_{S_u}\left\{\varepsilon + \ln\left(\frac{S_u}{\lambda_{uj}}\right) - e^{\frac{S_u}{\lambda_{uj}}} \mathrm{Ei}\left(-\frac{S_u}{\lambda_{uj}}\right)\right\} \\ =&\varepsilon + \int_0^\infty \left(\ln(\tfrac{x}{\rho_{uj}}) - e^{\frac{x}{\rho_{uj}}} \mathrm{Ei}(-\tfrac{x}{\rho_{uj}})\right) \frac{x^{K_u-1}e^{-x}}{(K_u-1)!} dx. \end{aligned} \tag{13}$$

The integral in (13) can be derived from [19, eq.(6.228.2), eq.(8.365.4)] as

$$\Psi(K_u) - \ln(\rho_{uj}) + \frac{\rho_{uj}}{K_u} {}_2F_1(1,1;K_u+1;1-\rho_{uj}), \tag{14}$$

where $\Psi(x)$ and ${}_2F_1(a,b;c;x)$ are respectively the Psi (Digamma) function and the Gauss Hypergeometric function. Since K_u is an integer, we have

$$\Psi(K_u) = -\varepsilon + \sum_{k=1}^{K_u-1} \frac{1}{k} \tag{15}$$

and

$$\begin{aligned} &\frac{\rho_{uj}}{K_u} {}_2F_1(1,1;K_u+1,1-\rho_{uj}) \\ =&\rho_{uj} \int_0^1 \frac{(1-t)^{K_u-1}}{1-(1-\rho_{uj})t} dt \\ =&\frac{(-\rho_{uj})^{K_u}\ln(\rho_{uj})}{(1-\rho_{uj})^{K_u}} - \sum_{k=1}^{K_u-1}\binom{K_u-1}{k}\frac{(1-\rho_{uj}^k)(-\rho_{uj})^{K_u-k}}{k(1-\rho_{uj})^{K_u}}. \end{aligned} \tag{16}$$

Finally, by substituting (13) into (12), defining $\xi_{uj} \triangleq \frac{\lambda_{uj}\delta_{uj}}{\ln 2}$, and further considering (5), Proposition 1 is proved.

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