A Robust and Efficient Clustering Algorithm for Network MIMO System

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Abstract— **In a practical network MIMO system, a limited number of transceivers form a super virtual cell, called cluster, to cooperatively transmit data to extremely improve the system performance in terms of sum capacity, user fairness, and coverage area. Clustering algorithm is thus identified as a key enabler to reap such enormous coordinated transmission gain. In this paper, a heuristic algorithm is proposed to dynamically bind together some base stations, which can adjust itself to the ever-changing interference condition. Through utilizing the predefined connection graph, the complexity of proposed scheme is reduced while retaining a similar performance to exhaustive searching algorithm. Compared with other previous clustering methods, the proposed one demonstrates its robustness against the unrealistic feedback channel and mostly matches the performance gain produced by exhaustive searching clustering strategy.**

Index Terms— **network MIMO, interference mitigation, adaptive clustering algorithm, distributive beamforming**

I. Introduction

Wireless cellular networks are being confronted by the ever-growing demand for massive high data rate communication applications. Apart from the universal frequency reuse pattern, the base stations (BSs) are deployed more densely than ever before. When frequency reuse factor of one is applied in a multi-input multi-output (MIMO) wireless network, the co-channel interference (CCI) becomes more serious. Therefore, an interference management in network level is in crucial need to guarantee the network performance.

Recently, network MIMO technology, also known as coordinated multi-point (CoMP) transmission, multi-base cooperation and so on, has been widely announced to be the most promising technology to mitigate the CCI in wireless cellular network [1]. Wyner pioneered this cooperative way to address the CCI issues in [2]. A closed-form system capacity for a cellular network is obtained under an assumption of a simple channel model. Other more realistic channel models were also considered to deal with the system capacity problem in the case of sharing the channel state information (CSI) and user data between all coordinated stations (see [1] [3]and references therein). The insight of all these research is that system performance of the cellular network with aggressive frequency reuse is never limited by CCI as joint transmission of all BSs thoroughly eliminates the interference in system. However, harvesting such high performance gain is an extremely challenging task in a practical cellular system. Theoretic analyse ignores the network MIMO's demand for the complex cooperative processing and the dramatic overhead signaling. Unfortunately, all of these assumptions are affected by the limited control unit (CU) capability and constrained backhaul link capacity, meanwhile it is difficult to keep precise synchronizing between a large set of coordinated BSs [4].

In order to maintain the complexity and signal overhead in an appropriate level, network MIMO can be performed among a limited number of BSs, which is called super virtual cell or BS cluster. This strategy comes from the fact that there is a tradeoff between the performance gain and the increase of overhead signal. On the other hand, this limited form of network MIMO can further reduce the processing complexity. Zhang et al. [5] proposed a coordinated transmission combining full intra-cluster and partial inter-cluster coordination. All BSs are clustered in a static fashion and multi-cell block diagonization precoding is used to jointly transmit data between BSs in the same clusters. The main setback is that it does no fully exploit the macro-diversity in the distributed multi-cell coordinated network. Sun et al in [6] dealt with the dynamic cell clustering problem in the case of multipoint downlink transmission. The whole network is pre-divided into several cluster patterns, and coordinating transmission is finally performed in the selected patter that maximizes the network throughput. Therefore, it not fully adjusts to the dynamic property of CSI. Authors in [7] focused on the full dynamic-clustering strategy, whereby the BSs were grouped by the criterion of maximizing the sum capacity of uplink channel. The complexity of such a scheme is high since it requires global CSI and transmission beamforming vector which is always alter-

Manuscript received August 10, 2013; revised September 2, 2012; accepted November 16, 2013.

This work was supported by the National Basic Research Program of China under Grant No. 2009CB320401, the National Natural Science Foundation of China under Grant No. 61171099 and the National Science and Technology Major Project of China under Grant No. 2012ZX03003-007 and No.2012ZX03004005-002.

doi:10.4304/jcp.8.11.2750-2755

nated during BS clustering. [8] proves that only grouping several BSs close to each other in the same cluster can provide significant performance gain of fully cooperative processing. Based on this insight of how many BSs are in need to enjoy the advantage of network MIMO, Moon et al. designed an effective clustering algorithm after mapping BSs into vertices of a graph [9]. However the robustness against the inaccurate CSI feedback is not considered. In [10], a dynamic clustering scheme was presented to improve system performance while being resilient to the CSI error. Nonetheless, the complexity of computation is high as it exhaustively searches all BSs combination case to maximize its predefined utility function. It is therefore not suitable to large network.

In this paper, we consider the maximum of downlink sum rate in a network MIMO cellular system. The optimal problem of maximizing the sum rate is first formulated under the constraint of per-BS power constraint and limited cluster size. Thereafter a connection graph is developed based on the reasonable conclusion of grouping together several BSs close to each other, which results in a refined searching space of dynamic clustering procedure. After introducing an intuitive utility function, an adaptive heuristic algorithm is proposed to further speed the formation of dynamic clusters, wherein full intercell coordinated transmission is carried out by zero-force (ZF) beamforming. Simulation results demonstrate that the proposed scheme mostly match the performance of brute-force searching algorithm while maintaining low computational complexity and showing robust against CSI error introduced by feedback channel.

The remainder of the paper is structured as follows. In section II, after introducing the system model, we analyze the optimization problem to maximize the multicell sum capacity under the constraint of cluster set and ZF beamforming. Through representing the connection relationship between BSs in a graph, the proposed robust clustering algorithm is described in section III. Finally, the numerical results are presented and discussed in section IV and the paper is concluded in section V.

II. System Model

In this section, we consider the downlink transmission in a frequency division duplex (FDD) network MIMO system, which is composed of B single antenna BSs. The single antenna configuration is chosen for the reason of clear exposition, and the analysis can be easily extended to multiple antennas BSs. All single antenna mobile stations (MSs) are served by a BS in a round-robin manner at any current time slot. Several BSs bind together into a cluster, wherein geographically distributed antennas form a virtual antenna array to eliminate the intra-cluster interference by joint precoding. An architecture example of such a clustered network MIMO system is depicted in Figure 1. We focus on the linear precoding technology, which is more feasible in practical systems due to its low complexity [11] and its capability of achieving the maximal multiplexing gain [12]. $\mathbb{V}$ is denoted as the set of all disjoint BS clusters in the network; and $\mathcal{V}_i$ as the i-th BS clusters. Provided that the active BSs in cluster $\mathcal{V}_i$ are denoted as $\mathcal{U}_i$, the channel matrix of the cluster $\mathcal{V}_i$ can be given by

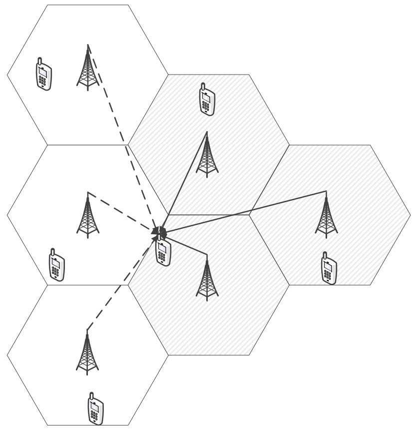

Figure 1. An architecture example of clustered network MIMO where all BSs are grouped into 2 cooperative area

$$\begin{aligned}\mathbf{H}^{(\mathcal{V}_i)} &= [h_{m,n}] \\ &= \left[\mathbf{h}_1^{(\mathcal{V}_i)^{\mathrm{T}}}, \cdots, \mathbf{h}_m^{(\mathcal{V}_i)^{\mathrm{T}}}, \cdots, \mathbf{h}_{|\mathcal{U}_i|}^{(\mathcal{V}_i)^{\mathrm{T}}}\right]^{\mathrm{T}} \\ & \quad m \in \mathcal{U}_i,\ n \in \mathcal{V}_i \end{aligned} \tag{1}$$

where $h_{m,n}$ is the channel gain between an MS m and an BS n, $\mathbf{h}_m^{(\mathcal{V}_i)}$brepresents the $1 \times |\mathcal{V}_i|$ ($|\mathcal{V}_i|$ is the cardinality of set $|\mathcal{V}_i|$) channel matrix from BSs in cluster $\mathcal{V}_i$ to MS m in its corresponding cluster. Let $\mathbf{d}^{(\mathcal{V}_i)}$ denote the intended signals for MSs in cluster $\mathcal{V}_i$, with $\mathrm{E}\left(\mathbf{d}^{(\mathcal{V}_i)}\mathbf{d}^{(\mathcal{V}_i)^*}\right) = \mathrm{diag}(\mathrm{P}_1, \mathrm{P}_2, \cdots, \mathrm{P}_{|\mathcal{V}_i|})$. Assuming that transmitted signal has the same power equal to P_{tx}, thus $P_1 = P_2 = \cdots = P_{|\mathcal{V}_i|} = P_{\mathrm{tx}}$. After expressing the linear precoding matrix of cluster $\mathcal{V}_i$ as $\mathbf{W}^{(\mathcal{V}_i)}$, the received signal vector of all MSs in cluster $\mathcal{V}_i$ is as follows

$$\begin{aligned}\mathbf{y}^{(\mathcal{V}_i)} &= \mathbf{H}^{(\mathcal{V}_i)}\mathbf{W}^{(\mathcal{V}_i)}\mathbf{d}^{(\mathcal{V}_i)} \\ &\quad + \sum_{\mathcal{V}_j \in \mathbb{V}\setminus\mathcal{V}_i} \mathbf{H}^{(\mathcal{V}_j \to \mathcal{V}_i)}\mathbf{W}^{(\mathcal{V}_j)}\mathbf{d}^{(\mathcal{V}_j)} + \mathbf{z}\end{aligned} \tag{2}$$

where $\mathbf{H}^{(\mathcal{V}_j \to \mathcal{V}_i)}$ is the channel matrix from all BSs in cluster $\mathcal{V}_j$ to all MS in cluster $\mathcal{V}_i$, and $\mathbf{z}$ represents the additive White Gaussian noise with zero mean and variance $\mathrm{E}(\mathbf{z}\mathbf{z}^*) = \sigma_n^2 \mathbf{I}_{|\mathcal{V}_i|}$. Thus the signal at receiver m in this cluster can be expressed as

$$\begin{aligned} y_m^{(\mathcal{V}_i)} &= \mathbf{h}_m^{(\mathcal{V}_i)}\mathbf{w}_m^{(\mathcal{V}_i)}d_m^{(\mathcal{V}_i)} + \sum_{k \in \mathcal{U}_i \setminus m} \mathbf{h}_m^{(\mathcal{V}_i)}\mathbf{w}_k^{(\mathcal{V}_i)}d_k^{(\mathcal{V}_i)} + \\ & \sum_{\substack{\mathcal{V}_j \in \mathbb{V}\setminus\mathcal{V}_i \\ b \in \mathcal{V}_j}} \mathbf{h}_m^{(\mathcal{V}_j \to \mathcal{V}_i)}\mathbf{w}_b^{(\mathcal{V}_j)}d_b^{(\mathcal{V}_j)} + z_m \end{aligned} \tag{3}$$

where $\mathbf{h}_m^{(\mathcal{V}_j \to \mathcal{V}_i)}$ represents the channel vector from all BSs in cluster $\mathcal{V}_j$ to MS m in BSs cluster $\mathcal{V}_i$. Then the SINR at the m-th receiver in this cluster can be calculated by

$$\begin{aligned} \gamma_m^{(\mathcal{V}_i)} &= \frac{K_{\text{int}}}{K_{\text{intra}} + K_{\text{inter}} + \sigma_n^2} \\ K_{\text{int}} &= \left\| \mathbf{h}_m^{(\mathcal{V}_i)} \mathbf{w}_m^{(\mathcal{V}_i)} \right\|^2 P_{\text{tx}} \\ K_{\text{intra}} &= \sum_{k \in \mathcal{U}_i \setminus m} \left\| \mathbf{h}_m^{(\mathcal{V}_i)} \mathbf{w}_k^{(\mathcal{V}_i)} \right\|^2 P_{\text{tx}} \\ K_{\text{inter}} &= \sum_{\substack{\mathcal{V}_j \in \mathbb{V} \setminus \mathcal{V}_i \\ b \in \mathcal{V}_j}} \left\| \mathbf{h}_m^{(\mathcal{V}_j \to \mathcal{V}_i)} \mathbf{w}_b^{(\mathcal{V}_j)} \right\|^2 P_{\text{tx}} \end{aligned} \tag{4}$$

K_{intra} is the intra-cluster interference and K_{inter} is inter-cluster interference. In order to completely eliminate the intra-cluster interference part, we utilize the zero-force (ZF) precoder which is design as

$$\begin{aligned} \mathbf{W}^{(\mathcal{V}_i)} &= \frac{1}{\sqrt{C_{(\mathcal{V}_i)}}} \overline{\mathbf{W}}^{(\mathcal{V}_i)} \\ &= \frac{1}{\sqrt{C_{(\mathcal{V}_i)}}} \mathbf{H}^{(\mathcal{V}_i)^*} \left(\mathbf{H}^{(\mathcal{V}_i)} \mathbf{H}^{(\mathcal{V}_i)^*} \right)^{-1} \end{aligned} \tag{5}$$

Since all BSs are geographically distributed and their antennas cannot share their power, we apply the same per-BS power constraint as in [9-11]. And the power control parameter $C_{(\mathcal{V}_i)}$ can be given by

$$C_{(\mathcal{V}_i)} = \max_{l} \left[\overline{\mathbf{W}}^{(\mathcal{V}_i)} \overline{\mathbf{W}}^{(\mathcal{V}_i)^*} \right]_{l,l} \tag{6}$$

where $[\mathbf{W}]_{l,l}$ represents the $[l,l] - \text{th}$ elements of the matrix $\mathbf{W}$. Then equation (4) can be further calculated as follows

$$\begin{aligned} \gamma_m^{(\mathcal{V}_i)} &= \frac{\left\| \mathbf{h}_m^{(\mathcal{V}_i)} \mathbf{w}_m^{(\mathcal{V}_i)} \right\|^2 P_{\text{tx}}}{\sum\limits_{\substack{\mathcal{V}_j \in \mathbb{V} \setminus \mathcal{V}_i \\ b \in \mathcal{V}_j}} \left\| \mathbf{h}_m^{(\mathcal{V}_j \to \mathcal{V}_i)} \mathbf{w}_b^{(\mathcal{V}_j)} \right\|^2 P_{\text{tx}} + \sigma_n^2} \\ &= \frac{P_{\text{tx}}}{\sum\limits_{\substack{\mathcal{V}_j \in \mathbb{V} \setminus \mathcal{V}_i \\ b \in \mathcal{V}_j}} \left\| \mathbf{h}_m^{(\mathcal{V}_j \to \mathcal{V}_i)} \mathbf{w}_b^{(\mathcal{V}_j)} \right\|^2 P_{\text{tx}} + \sigma_n^2} \end{aligned} \tag{7}$$

After referring the sum capacity of each active MS in every time slot as the evaluation metric, an optimal problem of finding those disjoint BSs cluster sets can be formulated as follows

$$\begin{aligned} \mathbb{V} = \arg \max_{\mathcal{V}_1, \mathcal{V}_2, \cdots, \mathcal{V}_{|\mathbb{V}|}} & \sum_{\mathcal{V}_i \in} \sum_{m \in \mathcal{V}} \log_2 \left(1 + \gamma_m^{(\mathcal{V}_i)} \right) \\ \text{s.t.} \quad & \mathcal{V}_1 \cup \mathcal{V}_2 \cup \cdots \cup \mathcal{V}_{|\mathbb{V}|} = \mathbb{V} \\ & \mathcal{V}_1 \cap \mathcal{V}_2 \cap \cdots \cap \mathcal{V}_{|\mathbb{V}|} = \emptyset \end{aligned} \tag{8}$$

This problem can be solved by brute-force searching all possibility of BS combinations. Assume that this optimal problem finally generates N_c clusters each with N_B BSs, then $B = N_c N_B$. According to the permutation and combination theory on the grouping problem, we can calculate the number of all possibilities as follows

$$\begin{aligned} N &= \frac{C_B^{N_B} C_{B-N_B}^{N_B} \cdots C_{N_B}^{N_B}}{N_c!} \\ &= \prod_{t=0}^{N_c - 1} \frac{\binom{B - tN_B}{N_B}}{N_c!} = \frac{B!}{(N_B!)^{N_c} N_c!} \end{aligned} \tag{9}$$

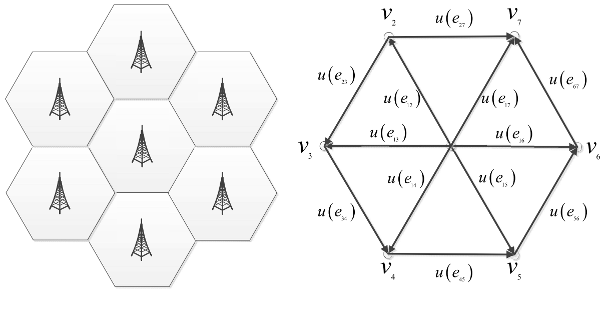

Figure 2. An example of graph demonstrating connection relationship between 7 BSs

Since this figure will increase quickly as network size B is increased, exhaustive searching is unfavorable in a large-scale wireless network. Dynamically managing those BSs need a sub-optimal yet efficient cluster forming algorithm.

III. Robust and Efficient Clustering Algorithm

In this section, we detail the proposed effective and robust clustering algorithm with the assistance of connection graph, which is a useful tool to aid the analysis of sum rate maximum under the constraint of disjoint BS clusters. Thereafter, a utility function is designed to speed the adaptive clustering procedure under the consideration of retaining robustness against the feedback channel errors.

Firstly, we map all BSs to vertices in a connection graph, and denote these nodes as $\text{V} = \{v_1, v_2, \cdots, v_B\}$. Any two BSs in the network are theoretically possible to cooperatively transmit data. Therefore, any two nodes in this graph are connected by an edge, which represents the cooperative relationship between them. If several BSs in the vicinity form a cluster, they can achieve the majority of performance gain introduced by fully cooperative processing [8]. In other word, there is no need to build cooperative relationship between some BSs if the distance between them exceeds a predefined threshold, which is the nearest distance between two vertices in this research. Figure 2 illustrates an example of this simplified connection graph consists of seven BSs in a two-dimensional hexagonal cellular network.

In order to further increase the speed of searching the possible cluster combinations, a utility function is in need to weight the cooperative chance between all edges. It can be observed from equation (4) that the SINR is limited by the intra-cluster interference when the inter-cluster interference is completely cancelled by multi-cell ZF beamforming. If dynamically clustering converts the most percentage of the interference observed by each receiver into an intra-cluster component, the SINR will be maximized. Interference channel gain is a direct metric to measure the strength of interfering signal. [9] analyzes this intuition in a special two cells case with a mathematical justification. Accordingly, a utility function, which represents the interfering strength between several

BSs, can be given by

$$u(e_{i,j}) = \sum_{m\in\mathcal{U}_i} \left\| \mathbf{h}_m^{(\mathcal{V}_j\to\mathcal{V}_i)} \right\|^2 + \sum_{n\in\mathcal{U}_j} \left\| \mathbf{h}_n^{(\mathcal{V}_i\to\mathcal{V}_j)} \right\|^2 \quad (10)$$

Furthermore, feedback error is unavoidable in a FDD wireless system. Since the proposed utility function is sensitive to this unrealistic feedback channel, we make a modification of this function as follows

$$\begin{aligned} u(e_{i,j}) &= \sum_{m\in\mathcal{U}_i} \mathrm{E}\left(\left\| \mathbf{h}_m^{(\mathcal{V}_j\to\mathcal{V}_i)} \right\|^2 \right) \\ &\quad + \sum_{n\in\mathcal{U}_j} \mathrm{E}\left(\left\| \mathbf{h}_n^{(\mathcal{V}_i\to\mathcal{V}_j)} \right\|^2 \right) \end{aligned} \quad (11)$$

Based on this utility function and above simplified connection graph, a robust and efficient clustering algorithm is proposed as follows to heuristically binding those BSs who are close to each other in the context of interference strength.

Robust algorithm 1 Proposed robust and effective clustering algorithm

Input: Channel gain between B BSs and assigned MSs
Output: cluster set $\mathbb{V}=\left\{\mathcal{V}_1 \cdots \mathcal{V}_{\lceil B/N_c \rceil}\right\}$

specify the maximum number of BSs in a cluster to be N_c
build a simplified graph to represents the BSs and related cooperative relationship
initialize $u(e_{i,j})$ for all edges before none cluster is formed
while $\exists e_{i,j} : u(e_{i,j}) > 0$ **do**
  $e_{a,b} = \arg\max_{e_{i,j}} u(e_{i,j})$
  if $|\mathcal{V}_a| + |\mathcal{V}_b| \le N_c$ **then**
    merge BS set indexed by a and b into the same cluster set
    set the edge value between all nodes in this set to be zero
    concatenate the channel matrix in this cluster set as a virtual one
    recalculate the utility value for all other remaining edges according to eq. (11)
  else
    update $u(e_{a,b}) \Leftarrow 0$
  end if
end while

This modification of utility function also benefits the design of data routing. Since the utility value is changed in a long-term scale, there is no need to perform data routing on a slot-to-slot basis, which can release the pressure on limited backhaul link transportation. Moreover, as opposed to vector variable of CSI in previous dynamic cluster algorithm [6] [7] [8], information exchanged to the clustering algorithm is scalar variables of channel gain, which can further reduce the overhead signaling. All these advantages make the proposed clustering algorithm suitable for large-scale wireless network.

IV. Simulation Results and Discussions

To illustrate the performance of proposed BS-clustering algorithm, we evaluate it in a two-dimensional hexagonal cellular network as shown in Figure 1. The number of BSs is limited to be seven due to the complexity of exhaustively searching for the optimal solution of $\mathbb{V}_{opt}$ in all possible BS combinations. These BSs are divided into two clusters; one compromises four BSs and the other three BSs. In addition, one MS is randomly dropped in each cell during each channel realization, corresponding to the round-robin schedule. The channel coefficient from BS n to MS m is given by

$$h_{m,n} = \Gamma_{m,n} \sqrt{\frac{\eta_{m,n}}{l_{m,n}}} \quad (12)$$

where $\Gamma_{m,n}$ represents the small-scale Rayleigh fading channel with zero mean and unite variance, and $\eta_{m,n}$ is the log-normal shadowing fading with 8dB standard deviation. $l_{m,n}$ models the path-loss fading between BS n to BS m, and it is set according to the model in baseline test scenario [11]. Additionally, we set transmission power $P_{tx} = 30$ dBm and noise covariance $\sigma_n^2 = -100$ dBm.

Three other approaches are also simulated for comparison. The brute-force search with instaneous CSI in [10] is referred as algorithm 1, and the brute-force algorithm with average CSI is algorithm 3, respectively. The heuristic algorithm with instaneous CSI in [13] is called algorithm 2. Additionally, the proposed algorithm is named the proposed robust algorithm.

Firstly, the average sum-rate of the whole network is examined as a function of the distance d between two nearest MSs. Since the transmission power and network layouts are fixed, the CCI is reduced as the distance becomes longer. As shown in Figure 3, two algorithms based on instaneous CSI always outperform the other schemes based on average CSI. However, the performance does not differ too much, which is 0.3 bps/Hz/Cell for d = 200m and 0.15bps/Hz/Cell for d = 1200m. This comes from the fact that the instaneous CSI features the current interference circumstance more correctly than average information does. Additionally, the robust algorithm shows almost the same improvement over the static BS-clustering strategy as algorithm 3 does. Taking the computational complexity into account, the proposed robust scheme is superior to exhaustive search in the case of densely deployed network. Remark that the average sum-capacity performances of all schemes are decreased as the cell size becomes larger. Although the average power of both intended and interference signal becomes weaker as the distance get longer, the power of intended signal decays much more quickly than that of interference signal because a MS is always much closer to its home BS than to its interfering neighbor BSs. Therefore, the average sum-rate is reduced as distances get large.

Secondly, Figure 4 demonstrates the cumulative distribution function (CDF) concerning MS rate for different dynamic clustering algorithm. As expected, the clustering algorithm based on brute-force search with instaneous

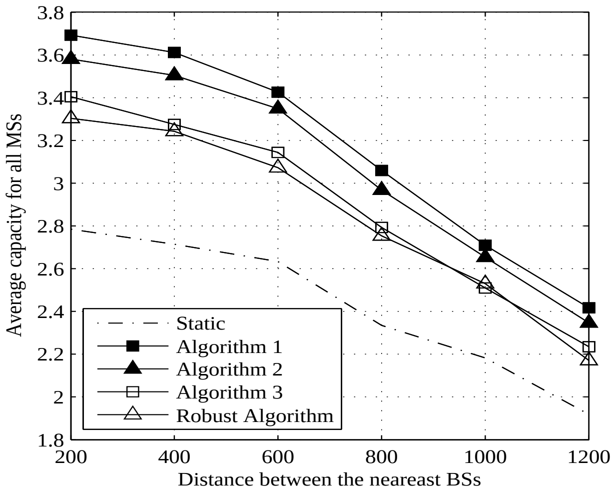

Figure 3. Average capacity (bps/Hz/cell) versus distance between nearest BSs for 7 hexagon cells with $N_t = 2$ $N_r = 1$

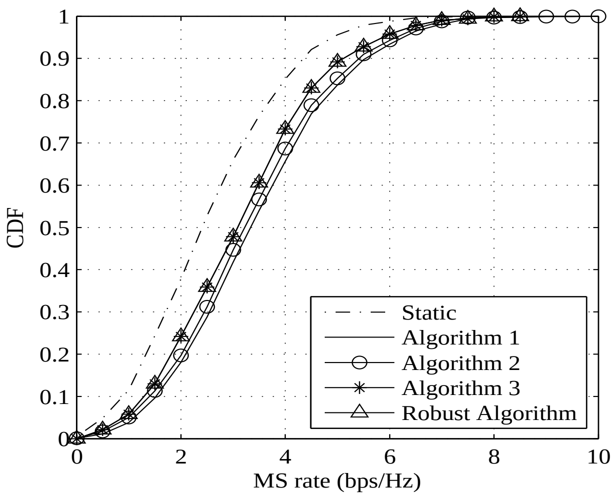

Figure 4. The cumulative distribution function of MS rate with 200 MSs in each cell

CSI (algorithm 1) outperforms all other counterparts. The heuristic algorithm with instaneous CSI (algorithm 2) performs closely with algorithm 1, which indicates that heuristic strategy maintains majority performance of the optimal algorithm at the cost of lower computation complexity in the ideal case of instaneous CSI. In particular, the proposed robust clustering scheme shows the same performance with the brute-force algorithm with average CSI. This simulation result implies that exhaustive search is not capable of enhancing the fairness performance of dynamic clustering scheme when average CSI is considered to combat the feedback error in a practical network.

Finally, we examine the robustness of the proposed scheme against the feedback error at $d = 200\mathrm{m}$. A noisy feedback channel is assumed with the variance of feedback noise is σ_f^2. It is observed in Figure 5 that the two algorithms with average CSI (algorithm 2 and proposed robust algorithm) maintain constant performance as the feedback error is increased, while the performance of

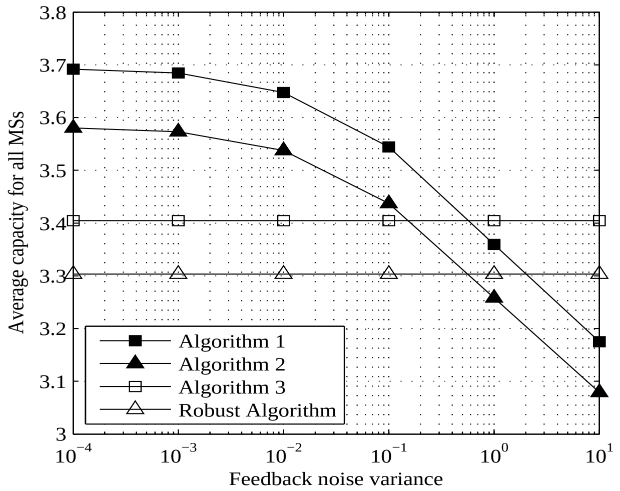

Figure 5. Average capacity versus feedback error noise σ_f^2 when $d = 200\mathrm{m}$

other two algorithms with instantaneous information is speedily decreased. This comes from the fact that the clustering algorithm based on average CSI is affected by the long-term channel fading characteristics, namely path-loss and shadowing fading, which is constant from the statics point of view. Particularly, the performance gap is small (0.1bps/Hz/Cell) between the proposed robust algorithms and exhaustive searching one. However the computational complexity of proposed scheme is much lower than that of brute-force searching, which renders the proposed algorithm more extendable to large cellular network.

V. Conclusions

Dividing the whole network into several clusters is a promising way to bring the advanced multi-cell processing technology into practice. In this paper, the problem of dynamically organizing all BSs into clusters is addressed to fully explore the macro-diversity in network MIMO system. After formulating the optimal problem of maximizing the sum capacity of all active MSs under the constraint of per-BS transmission power, a heuristic clustering algorithm is proposed based on the concept of connection graph. The utility function is designed to heuristically search the candidate BSs to form a cluster according to the sum of average interference channel gain. When the intra-cluster interference is suppressed by this adaptive clustering algorithm, the inter-cluster interference is completely eliminated by multi-cell ZF beamforming. This scheme is more effective than the optimal exhaustive searching one because connection graph restricts and simplifies the searching space for the proposed algorithm. Furthermore, inaccurate CSI is unavoidable in a practical wireless system. But the performance of proposed algorithm cannot be aggravated by this phenomenon since average interference channel gain is long-term interference information which is mainly determined by the large-scale channel fading. Through simulation results, the proposed heuristic approach shows a similar performance with the optimal one at the expense of lower computational complexity, while maintaining robust against the inaccurate CSI obtained through a noisy feedback channel.

ACKNOWLEDGMENT

The work is fully sponsored by the National Basic Research Program of China (also called 973 Program) under Grant No. 2009CB320401, the National Natural Science Foundation of China under Grant No. 61171099 and the National Science and Technology Major Project of China under Grant No. 2012ZX03003-007 and No.2012ZX03004005-002.

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