A Distributed Clustering Algorithm for Coordinated Multipoint in LTE Networks

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***Abstract*—Coordination and cooperation among transmitters are fundamental paradigms to improve the performance of next generation mobile networks. By grouping multiple transmitters into clusters, interference can be managed to improve the performance at the end user's side. In this paper, we present a novel distributed clustering algorithm that adapts the cluster configuration according to the users distribution and the average cluster size. We compare the performance obtained with other clustering solutions in an LTE scenario using the open-source network simulator ns3. Our proposed algorithm is shown to significantly outperform the other approaches especially for the users with low signal-to-noise ratio (SNR), with a 26% improvement of throughput for the worst 10% of the low-SNR users compared to a greedy clustering.**

***Index Terms*—Cellular radio; MIMO systems; clustering; Long Term Evolution; coordinated beamforming.**

I. Introduction

Mobile data traffic is rapidly growing in volume: an 11-fold increase is expected over the years from 2013 to 2018 [1]. To face this trend, the standard mobile communication network is evolving into a heterogeneous network (HetNet) characterized by a huge density of base stations (BSs) and different transmitter tiers. This leads to new challenges concerning spectrum and interference management, especially for the users at the edge of the cell coverage area, which are more affected by intercell interference [2].

A very promising concept to achieve high spectral efficiency for interference-limited cellular networks is the cooperative communication between BSs, often referred to as coordinated multipoint transmission (CoMP). This technique encodes (for downlink; for uplink, it decodes) messages for multiple users, exploiting a distributed multiple-input multiple-output (MIMO) system. Multiple BSs are grouped to form a *CoMP cluster*, which is the elementary coordination unit. Interference among BSs belonging to the same cluster is then cancelled to achieve a multiplexing gain [3]. Two transmission schemes are considered for downlink CoMP transmission: joint transmission (JT) and coordinated scheduling/beamforming (CS/CB). In JT, the transmission to a *single* user is performed coherently by the BSs of the same CoMP cluster. Thus, interference is mitigated and the signal-to-interference-plus-noise ratio (SINR) is improved. As a special case, it may even be that only one BS of the cluster, e.g., the one with the best channel to the user, is allowed to transmit at a time, while the others are inactive [4]. Differently from JT, in CS/CB *multiple* users are allocated simultaneously in the same resource unit. Then, the CoMP cluster forms a distributed MIMO system, where cooperative beamforming is adopted. By exchanging channel state information (CSI) among the BSs, linear precoding beamforming can be applied to mitigate the interference perceived by the users. The higher the number of cooperating BSs, the higher the mitigation of the interference. However, in realistic systems the number of cooperating BSs is limited by coordination signaling [5]; thus, the set of transmitters should be partitioned into clusters of proper size.

The problem of network clustering has been treated in the literature especially following a *centralized* approach. In [6], a centralized clustering technique is proposed, where the users report the SINR gain expected when merging neighboring clusters and a central unit uses these data to optimize the network coordination. In [7] and [8], dynamic joint clustering and scheduling are studied by assuming limited CSI at the BSs, and adopting a greedy algorithm, respectively.

The use of a centralized approach leads to an increase of traffic signaling (CSI estimation, CSI feedback, synchronization) and infrastructure overhead [9] that may turn the network clustering procedure into a bottleneck. To reduce this overhead, a cooperative distributed approach may be adopted. In [10] a decentralized framework is presented in a simplified scenario, where BSs negotiate the composition of fixed size clusters. In [11], a dynamic coalition formation game is modeled for cooperative spectrum sharing; the BSs are serving one user and the spectrum is orthogonally divided among the BSs of the same cluster. Coalitions are formed by joining the BSs according to a utility value based on channel capacity and coalition size. Network topology is taken to be fixed, so rearrangements of the clusters are not considered.

In [12], coalitional game theory is used to develop a merge-and-split algorithm. A utility function is computed by each cluster, seen as a coalition, considering the signaling cost among the BSs and the gain obtained through cooperation. According to this computation, existing coalitions may be joined or split. This algorithm offers the additional advantage that cluster sizes are not fixed; a goal size can be set, which works well on average. However, this algorithm is only partially distributed; being based on game theory, it computes distributed utilities for each BS, but requires their coordinated exchange within each cluster, which may be expensive.

In this letter, we present a novel *fully distributed* algorithm for the LTE downlink, based on the utility perceived by each BS. Our proposal can be seen as a further improvement over the game-theory based algorithm. Similarly to it, we use a (different) utility function based on the SINR, and also the cluster size is specified only on average. However, the

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important advantage over all existing algorithms (including the game theoretic ones) is that all the computations made by the BSs within our approach are fully distributed, and there is no need for additional signaling exchange.

We implemented our algorithm and evaluated its performance for a large LTE network through the open-source network simulator ns3 [13]. We compared it with static clustering, a greedy algorithm based on [5] and the coalition game theoretic algorithm inspired by [12], also originally implemented in the simulator. These benchmarks are fully representative of the existing clustering techniques.

Our distributed approach, where each BS decides about its participation to a coalition without negotiating it with the entire cluster, still achieves good performance, while being able to significantly decrease signaling. Also, it is even able to improve the performance for the worst users of the scenario; in particular, we observe a significant improvement for the low-SNR users, since the BSs are able to manage them more promptly, without the need to coordinate with the entire cluster it belongs to.

II. System Model

We consider a scenario with a set $\mathcal{S} = \{1, 2, ..., S\}$ of pico LTE BSs, each equipped with one omnidirectional antenna. A set $\mathcal{I} = \{1, 2, ..., I\}$ of users are placed according to a Poisson point process (PPP) with intensity λ, and associated with the BS with the strongest signal.

In LTE, the downlink channel is organized according to time division and orthogonal frequency division multiplexing. We consider time frames of 10 ms, each consisting of 10 sub-frames of 1 ms, while the downlink spectrum is divided into groups of adjacent sub-carriers, called sub-channels. The allocation atom is a time/frequency unit element called resource block (RB), i.e., a sub-channel in frequency for a sub-frame in time. We consider that each BS adopts a proportionally fair scheduler and allocates a single user in each RB. Assuming uniform power allocation over the entire bandwidth, if no coordination is adopted among the BSs, user i assigned to BS j is affected by interference received from the neighboring BSs and its SINR value is

$$SINR_i = \frac{|h_{ji}|^2 P_j}{\sigma^2 + \sum_{s \neq j, s \in \mathcal{S}} |h_{si}|^2 P_s} \tag{1}$$

where h_{mn} is the channel coefficient from BS m to user n, P_m is the power transmitted by BS m and σ^2 is a noise term. When coordination among a subset $\mathcal{K} = \{S_1, S_2, ..., S_K\}$ of the BSs is allowed, a BS cluster can be seen as a MIMO distributed system so as to exploit the use of linear precoding beamforming matrices to mitigate the mutual interference. If $\mathbf{H}(\mathcal{K}, \mathcal{Q}) \in \mathbb{C}^{K \times Q}$ denotes the matrix of channel coefficients, where $\mathcal{Q}$ is the subset of the Q users scheduled within the cluster, zero forcing (ZF) can be obtained by selecting the Moore-Penrose pseudoinverse of the channel as the precoding matrix $\mathbf{W}(\mathcal{K}, \mathcal{Q})$, with

$$\mathbf{W}(\mathcal{K}, \mathcal{Q}) = \left[\mathbf{H}^H(\mathcal{K}, \mathcal{Q})\, \mathbf{H}(\mathcal{K}, \mathcal{Q})\right]^{-1} \mathbf{H}^H(\mathcal{K}, \mathcal{Q}) \tag{2}$$

so that $\mathbf{W}(\mathcal{K}, \mathcal{Q})\, \mathbf{H}(\mathcal{K}, \mathcal{Q}) = \mathbf{I}_Q$ (identity matrix of size Q).

If cluster $\mathcal{K}$ manages user i and internal interference is cancelled, the resulting SINR is

$$SINR_i = \frac{P_j}{|w_i|^2 \sigma^2 + \sum_{s \in \mathcal{S} \setminus \mathcal{K}} |h_{si}|^2 P_s} \tag{3}$$

where w_i is the beamforming coefficient for user i.

The benefits of CoMP depend on the size of the clusters and the BS distribution within the clusters. The larger the clusters, the more effective the interference cancellation but also the higher the overhead. Thus, the cluster size is the result of a trade-off; we consider a realistic cluster size of about 4 BSs.

We compare the performance of our algorithm with three different feasible algorithms. We emphasize that we have not considered the exhaustive search among all the possible cluster combinations because it is infeasible from a practical point of view due to the high computational complexity.

Static Clustering. A simple clustering procedure defines static groups of neighboring BSs, without rearranging them over time. Signaling among the BSs is limited to the coherent combining signal coordination within the cluster and no central control unit (C-CU) is needed for dynamic updates. Even though this scheme has the least amount of signaling exchange, it is inefficient for what concerns interference management, since it does not consider the distribution of the users. Moreover, the cluster size is fixed and cannot be adapted to the actual amount of interference to be cancelled.

Greedy Clustering [5]. In this case, a BS is randomly chosen and a cluster is formed iteratively with the BSs maximizing the joint capacity, until a predefined cluster size is reached. The scheme increases network fairness and cluster efficiency, even though the CoMP benefits are higher for the clusters formed in the earlier stages that can exploit more degrees of freedom. Moreover, a C-CU is needed to get CSI from the BS and run the clustering algorithm. As in static clustering, the cluster size is fixed. Even though we refer to the implementation of [5], other algorithms [8], [10] are also based on greedy clustering and obtain similar performance.

Game Theoretic Clustering, inspired by [12] and based on a coalitional merge-and-split. Consider cluster C_i comprising a subset $\mathcal{K} = \{S_1, S_2, ..., S_K\}$ of BSs, where the set of users assigned to BS k is $\mathcal{M}_k = \left\{m_1^k, m_2^k, ..., m_n^k\right\}$. Given that user m is assigned to BS k within cluster $\mathcal{K}$ and scheduled in RB r, its SNR and SINR are

$$SNR_{r,m,k} = \frac{P_k}{|w_{r,m}|^2 \sigma^2} \tag{4}$$

$$SINR_{r,m,k}(\mathcal{K}) = \frac{|h_{r,km}|^2 P_k}{\sigma^2 + \sum_{s \in \mathcal{K} \setminus \{k\}} |h_{r,sm}|^2 P_s} \tag{5}$$

where $h_{r,mn}$ is the channel coefficient from BS m to user n in RB r. Thus, we define the cluster utility as

$$u(\mathcal{K}, \mathcal{M}_k, \mathcal{R}_m) = \sum_{\substack{k \in \mathcal{K} \\ m \in \mathcal{M}_k \\ r \in \mathcal{R}_m}} \frac{\log_2(1 + SNR_{r,m,k})}{\log_2(1 + SINR_{r,m,k}(\mathcal{K}))} - \beta\, \xi(z - z_0)$$

where $\mathcal{R}_m$ is the subset of RBs where user m is scheduled, $\xi(z - z_0) = 1/(1 + e^{-(z - z_0)})$ is a sigmoid function where z is the cluster size, z_0 is equal to the reference cluster size, and β

is an adjusting parameter. The utility function has two terms: the former is proportional to the capacity gained by canceling the interference within the cluster, the latter is the cost due to the coalition size, which serves to obtain a non super-additive game and drive the average cluster size towards a predefined value (z_0=4 in our setup). The role of the sigmoid is to penalize the utility of clusters bigger than z_0 while allowing for some flexibility. Given an initial set $\mathcal{C} = \{1, 2, ..., C\}$ of clusters, a coalition is randomly chosen; the C-CU computes the utilities for all possible merges among clusters and/or when clusters are split. The following rules are adopted.

- **Merge Rule:** Two coalitions $\mathcal{C}_j$ and $\mathcal{C}_i$ can be merged if $u(\mathcal{C}_j) + u(\mathcal{C}_i) < u(\mathcal{C}_i \bigcup \mathcal{C}_j)$.
- **Split Rule:** A coalition $\mathcal{C}_j = \bigcup_{i=1}^{k} \mathcal{C}_{ji}$ can be split into $\mathcal{C}_{j1}, \mathcal{C}_{j2}, ..., \mathcal{C}_{jk}$ if $\sum_{i=1}^{k} u(\mathcal{C}_{ji}) > u(\mathcal{C}_j)$.

The configuration that provides the best utility value according to split and merge rules is formed and added to the set of clusters. The external cluster interference is neglected.

As in the previous case this scheme needs the use of a C-CU to manage all the CSI from the BSs and to apply split-and-merge and rearrange the network clustering. In this specific algorithm, the cluster size is not fixed and can be tuned through β. Thus, cluster configurations are adaptive, i.e., clusters are larger where the user density is higher.

The proposed Dynamic and Distributed Clustering. We avoid using a C-CU and, at the same time, provide a dynamic network clustering able to follow the evolution of the network. The re-configuration of the clusters is shifted from the C-CU to the BSs that we assume to be capable of collecting CSI from all the users. We consider that the clustering configuration is known at each BS and all BSs synchronously exchange data and CSI over a logical X2 interface, see [14].

Each BS has a counter initially set to a random value that decreases by 1 every transmission time interval (TTI). Given a cluster configuration $\mathcal{C}$, when the timer expires, the BS computes the value of its utility for each coalition in $\mathcal{C}$:

$$u_k(\mathcal{C}_i) = \sum_{m \in \mathcal{M}_k, r \in \mathcal{R}_m} \frac{\log_2(1 + SNR_{r,m,k})}{\log_2(1 + SINR_{r,m,k}(\mathcal{C}_i))} - \sum_{\substack{s \in \mathcal{C}_i \setminus \{k\} \\ m \in \mathcal{M}_s \\ r \in \mathcal{R}_m}} \frac{\log_2(1 + SNR_{avg})}{\log_2(1 + SINR_{r,m,s}(\{s,k\}))} \frac{1}{z} - \beta \xi (z - z_0) \tag{6}$$

where SNR_{avg} is a reference SNR for all the users, and $SINR_{r,m,s}(\{s, k\})$ is given by (5) with a reference fixed power in the numerator. The first term of the utility represents the gain achieved by BS k within cluster $\mathcal{C}_i$, while the second gives the contribution to interference mitigation of BS k in the cluster. The latter makes the cluster stable, and considers not only the improvement of BS k but also the effects on the other BSs. To keep the terms comparable, the second one is divided by the number of BSs in cluster $\mathcal{C}_i$. As in the game theoretic approach, the third term regulates the average size of the clusters through the choice of β. After computing the utilities for all the clusters, the BS joins the one providing the highest utility, or stay within the current cluster if no improvement is achievable.

III. Performance Evaluation

First of all, we compare the complexity of the considered algorithms. The greedy strategy requires the evaluation of $\mathcal{O}(S)$ steps. The game theoretic clustering requires $\mathcal{O}(C)$ steps, where $C = \mathcal{O}(S/z_0)$. For each step, $\mathcal{O}(M + D)$ operations are required, where M is the number of possible merges and D is the number of splits; note that $M = \mathcal{O}(C)$ and $D = \mathcal{O}(2^{z_0})$. Finally, our proposed algorithm requires $\mathcal{O}(S)$ step, each with $\mathcal{O}(C)$ operations.

This means that the complexity of our approach is comparable with the game theoretic clustering (actually, it is slightly lower, since the term D is missing). The greedy algorithm obviously has lower computational complexity (linear vs. quadratic in S) but in our algorithm the quadratic term is scaled down by z_0, thus they are comparable in practical cases. Besides, as shown next, the slight increase in complexity is more than justified by the performance enhancement. More in general, our proposed algorithm offers the additional advantage of better reconfigurability and highly reduced signaling exchange, since all the decisions are made by the BSs in a fully distributed manner.

To evaluate the performance quantitatively, with reference to a realistic LTE system, we used the open-source network simulator ns3 [13]. This simulator, based on object oriented programming, represents the entire protocol stack, from the physical to the application layer. Thanks to its modular structure, the previously discussed clustering algorithm can be implemented within an LTE compliant system.

The scenario consists of 40 pico base stations with transmission power equal to 30 dBm placed on a rectangular lattice structure, and a user distribution modeled using a PPP with $\lambda = 100$ users/(entire area). Neighboring BSs are positioned at distance 1.3 km from each other and equipped with one antenna. The total downlink power of 30 dBm is equally divided among the used RBs. The total downlink bandwidth is 5 MHz and is divided into 25 RBs with a frequency reuse factor equal to 1. Moreover, we assume a fully loaded scenario, i.e., the downlink traffic saturates each BS buffer, so all the RBs are used during each frame.

The detailed system parameters are reported in Table I; in short, the simulator includes realistic propagation and interference models and fully LTE-compliant specifications.

TABLE I
MAIN SYSTEM PARAMETERS

Parameter	Value
1-st sub-channel frequency	2110 MHz
Total Downlink Bandwidth	5 MHz
Sub-Carrier Bandwidth	15 kHz
Resource block bandwidth	180 kHz
Resource block carriers	12
Resource block OFDM symbols	7
BS downlink TX power	30 dBm
Noise power spectral density	-174 dBm/Hz
Pathloss at d meters, in dB	$128.1 + 37.6 \log_{10} d$
Shadow fading	log-normal with $\sigma = 8$ dB
Frame duration	10 ms
TTI (sub-frame duration)	1 ms
Target Bit Error Rate	5×10^{-5}
BS distance	1.3 km
User distribution	PPP with $\lambda = 100$

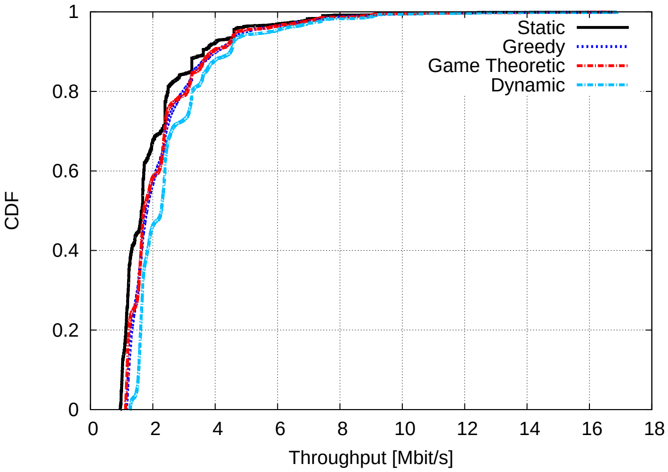

Fig. 1. Total Throughput CDF

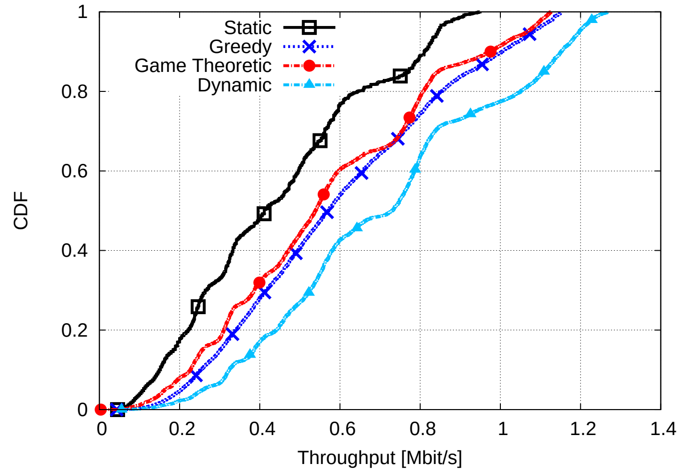

Fig. 2. Throughput CDF of the low-SNR users

We evaluate the per-user downlink throughput. To test the adaptivity of the algorithms, we initially set all the clusters to size 1 and we re-distribute the user positions as an independent PPP every 1 s. To improve the readability of the results, we call "low-SNR users" and 'high-SNR users" those users obtaining a throughput lower and higher than the average, respectively. We set β to obtain the same average cluster size for each clustering scheme.

Fig. 1 depicts the throughput CDF for all users. As expected, the static scheme achieves the worst performance due to its lack of adaptation. An improvement is obtained by the greedy and game-theoretic schemes. In these cases, the clusters are re-arranged according to the user distribution and, in the game theoretic case, larger clusters can be employed if needed. However, since this latter scheme uses a cluster-wise computation of utility, its improvements come at a higher complexity and signaling cost. Moreover, we see that the proposed dynamic algorithm obtains further performance improvements, in spite of the lower required signaling.

To better emphasize the benefits of our scheme, Fig. 2 shows the throughput CDF of the low-SNR users. Notice that low-SNR users are more significantly affected by interference, thus the performance improvement becomes more significant. Our proposal brings an improvement to the top-90% throughput of the low-SNR users by at least 15% versus all the competitors, and by 43% versus the static approach. For the worst-case low-SNR users that are in the bottom-10% of the throughput, a higher improvement is present, about 26% (and 53% versus the static approach). The improvement provided by the scheme proposed is then twofold. On the one hand, it avoids the need for a C-CU through a distributed approach; on the other hand, it increases the throughput achieved by the low-SNR users adapting the clusters to the user distribution.

IV. Conclusion and Future Works

We proposed a novel dynamic distributed clustering algorithm for CoMP that adapts the cluster configuration to the user distribution according to a predefined average cluster size. We compare the throughput performance with other clustering solutions developed in the literature, using the LTE module of the ns3 simulator. Our approach decreases the signaling exchange while at the same time improving the network performance, in particular for the low-SNR users. For future work, we will expand the model to different scenarios with multiple traffic models and various HetNet setups. Also, the clustering algorithm will be designed not only to improve the SINR of the users but also to fit their quality requirements, and different scheduling policies will be considered.

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