Dynamic Clustering Framework for Multi-cell Scheduling in Dense Small Cell Networks

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***Abstract*—This letter proposes a novel graph-based multi-cell scheduling framework to efficiently mitigate downlink inter-cell interference in small cell OFDMA networks. This framework incorporates dynamic clustering combined with channel-aware resource allocation to provide tunable quality of service measures at different levels. Our extensive evaluation study shows that a significant improvement over the state-of-the-art benchmarks can be achieved in terms of user spectral efficiency in return for reuse factor level via tuning the proposed Quality of Service (QoS) measures.**

***Index Terms*—Interference Coordination, Graph partitioning, Small cells**

I. INTRODUCTION

The rapid-increasing coverage and capacity demand in emerging wireless cellular systems necessitates the employment of multi-level hierarchical radio access networks, known as Heterogeneous Networks (HetNets) [1]. In such system, small cell networks are envisioned as a key deployment to address coverage and capacity issues [1]. However, the massive deployment of small cells in a dense area is going to face critically increased levels of inter-cell interference (known as co-tier interference) since the scarcity and high cost of the spectrum resource inevitably requires intense spectrum reuse.

The ICI management for dense small cell networks can be more challenging compared with macro-cell ones, due to several reasons: Firstly, due to arbitrary deployment of small cells, secondly due to small perimeter of such cells (dismissing the traditional area-based flexible frequency reuse methods) and finally as a result of interference nature where we face multiple aggressors unlike legacy macro cells with one or two dominant interferers.

The problem of multi-cell scheduling in presence of inter-cell interference is an NP-hard combinatorial problem [2]. There are different heuristic solutions to address this problem in the literature. Graph-based solutions are of particular interest in this case due to modularity and potential simplicity. However, some assume fixed number of clusters according to the number of sub-channels. This relies on the assumption that each user has prior knowledge on the required number of resources as QoS measure thereby replicating itself across different clusters to meet the measure [3]. While such assumptions would decompose the outcome solution to simple modules, in practice, the target QoS might be multi-objective depending upon instantaneous rate requirement as well as long term interference requirement, leaving the number of resources to be allocated as an optimization variable.

In this letter, while we rely on lessons learned from graph-based solutions in the literature ([3], [4]), we formulate our problem based on dynamic clustering to target adaptive yet feasible QoS measures in two levels: instantaneous QoS per user via tuning the weighting (priority factor) of users versus longer term QoS per cell via adjusting the number of admitted users per cluster. In this direction, we come up with sub-optimal yet efficient and low complexity solutions that are scalable for multi-cell scheduling for dense small cell networks.

II. SYSTEM MODEL

Here, the system is considered as a downlink multi-cell OFDMA cellular network that consists of a dense deployment of small cells. Each small cell is served by a single, randomly located, antenna denoted as small-cell Access Point (s-AP). The entire network is regarded either way as an enterprise or domestic environment that comprises L s-APs. Each s-AP serves M_l users and the total number of users in the system is the aggregation of the users of all L s-APs, such that $M_T = \sum_{l=1}^{L} M_l$. Here, $m(l) \in \mathrm{M}_l$ represents the user attached to s-AP l, for $L = \{l | \forall l \in 1,2,..,L\}$ assuming each user is served by only one s-AP. This system also includes a local entity that acts as the control unit that resolves the conflicts (in terms of interference) in the small cell network.

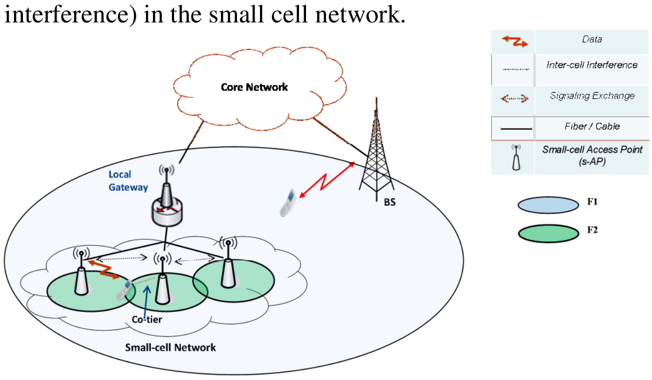

Figure 1 Small cell Network example

In Fig. 1, we illustrate an example deployment comprising a dense small cell network, as well as a Local Gateway (L-GW). Such L-GW [5] provides a medium between small cells and the internet backhaul.

In the small cell network, the problem of network optimization can be translated to weighted sum rate maximization problem where the weighting factors can be tuned accordingly to maintain fairness or other per user service requirements of the network. Let $\{w_{m,n}, m \in M_T, n \in N\}$ be arbitrary user weights taking into account instantaneous QoS requirements and $R_{m(l),n}$ the achievable user's data rata in terms of spectral efficiency on each sub-channel, represented as: $R_{m(l),n} = log_2(1 + \rho SINR_{m(l),n})$,where ρ is a constant related to the target Bit Error Rate (BER) according to $\rho = -1.5/\ln(5 \cdot BER)$ [2]. The corresponding Signal-to-Interference-and-Noise Ratio (SINR) can be expressed as: $SINR_{m(l),n} = P_{l,n} G_{m(l),l,n} / (\sum_{i \neq l \in I_{m(l),n}} P_{i,n} G_{m(l),i,n} + \eta)$.

Here, $P_{l,n}$ is the small cell transmit power and $G_{m(l),l,n}$ is the channel gain between s-AP l and UE m in the sub-channel n. Moreover, η is the power of the thermal noise and $I_{m(l),n}$ accounts for the set of the interferers in a specific sub-channel n. The optimization problem here is to find the optimal resource allocation in order to maximize the weighted sum-rate:

$$max \sum_{l=1}^{L} \sum_{m(l)=1}^{M_l} \sum_{n=1}^{N} w_{m(l),n} R_{m(l),n} a_{m(l),n} \quad (1)$$

Subject to:

$$a_{m(l),n} \in \{0,1\}, \forall \mathrm{l} \in \mathrm{L}, n \in \mathrm{N} \quad (2)$$

$$\sum_{n=1}^{N} P_{l,n} \leq P_{l,max} \quad (3)$$

$$\sum_{m(l) \in M_l} a_{m(l),n} \leq 1, \forall \mathrm{\ l} \in \mathrm{L}, n \in \mathrm{N} \quad (4)$$

where $a_{m(l),n}$ is the binary variable corresponding to the allocation decision for the sub-channel n to user m of s-AP l, *i.e.* $a_{m(l),n} = 1$ if user $m(l)$ is allocated sub-channel, where $N = \{\mathrm{n} | \forall \mathrm{n} \in 1,2,..,\mathrm{N}$ is the set of sub-channels. Moreover, $P_{l,n}$ accounts for the s-AP transmit power per sub-channel. Hence, the optimization problem is weighted sum-rate maximization over the network in presence of inter-cell interference subject to power constraint of $P_{l,max}$ per node l as in (3) and orthogonal allocation at intra-cell as in (4).

III. Proposed Graph-Based Framework

The generic weighted rate maximization problem as described in (2) is a non-convex optimization problem with non-linear constraints and was shown to be NP-hard [2]. To address this issue, in this work, we introduce an alternative formulation using graph partitioning-based framework. Here we introduce three main phases of Graph Construction, Graph Manipulation and Channel Assignment as detailed below:

A. *Graph Construction*

The interference graph $G(V, E)$ consists of V vertices corresponding to the users in the system such that $|V| = M_T$ and E edges that show the downlink interference conditions between users. The interference graph is a weighted graph connecting each pair of users u, v in the system through weighted edges $E(u, v), \forall \mathrm{u}, \mathrm{v} \in \mathrm{V}$.

This interference graph is constructed in L-GW. For the graph construction, we introduce a metric corresponding to the relative channel loss between the s-AP l to the UE m versus other cell users in the system. This metric encapsulates the path loss and shadowing effect as $Loss_{l,m}$. Notice that this metric is not dependent on the frequency selectivity and thus provides the average information on the quality of the BS-to-user link. This parameter characterizes the interference metric λ_m for a user and is defined as follows:

$$\lambda_m = \frac{\sum_{i \neq l \in L} Loss_{i,m}}{Loss_{l,m}}, \forall m \in V \quad (5)$$

This interference metric is used to update the weights on the edges corresponding to pairs of users. An edge logically shows the level of signal degradation to both users assuming they utilize the same resource. The weights of the edges are continuous and can be defined as a function of the mutual interference metric for each pair of users u, v such that:

$$E(u, v) = E(v, u) = \max\{\frac{\lambda_u}{\lambda_v}, \frac{\lambda_v}{\lambda_u}\} \quad (6)$$

In OFDMA, the allocation of the same resource to users at the same small cell violates the orthogonal intra-cell resource allocation constraint. Therefore, the weight of the edges between users of the same cell is set extremely high to ensure that each cluster will eventually include (at most) one user per each cell.

B. *Graph Manipulation*

Here, we implement a novel graph-partitioning scheme that enables grouping the users of the entire network into dynamic clusters with minimum intra-cluster interference. Intuitively, the graph manipulation starts from a node with the best neighborhood (minimum degree). Selecting a node with the minimum degree as starting point ensures that several paths (candidate solutions) are available for the next-node search. Thereafter, we traverse iteratively the graph by adding the node that minimizes the sum weight towards the already chosen nodes. Fixing the first node with minimum degree can potentially lead to the construction of more efficient sub-graphs (i.e. graphs that have the highest number of nodes under a pre-defined sum-weight threshold). The upper bound of each cluster is set as a constraint (denoted as E_{bound}) targeting long term QoS requirement per cell. This reflects the high level of tune-ability in this algorithm in a larger time-scale (in addition to the faster QoS measure per user handled by the instantaneous weighting as outlined in (1) of problem formulation). When this bound is reached, a cluster is extracted and the algorithm continues to form new clusters, removing the traces of the pre-selected nodes. The complexity of the proposed graph-partitioning method is proportional to the sum of the number of edges and the nodes in the graph. Considering the computational complexity for the sorting of the M nodes ($O(\mathrm{MlogM})$) and the partitioning of the sorted nodes to clusters ($O(M^2/2 + M/2)$), this heuristic method results in complexity in order of ($O(M^2/2 + M/2 + \mathrm{MlogM})$).

As mentioned above, the outcome number of clusters and the users therein is dynamic depending upon the target long term QoS requirement. Hence, the partitioning is adaptive implying the number of clusters and the included users can change rapidly to deal with the dynamic environment having numerous small cells. The number of clusters created by the proposed scheme is adaptive and ranges between $m^* \leq |K| \leq |M_T|$where $m^* = \max(|M_l|)$**.** The lower bound is derived by the fact that users of the same cell cannot share the same cluster whereas the maximum equals to the total number of users in the system M_T in case of full orthogonalization.

Another interesting feature of this algorithm is the uniqueness in finding the best set of users forming each cluster. This is achieved by the continuous weighting in the interference graph to ensure that the novel local search results in a unique solution.

Below we illustrate the flow chart of proposed algorithm as in Fig. 2:

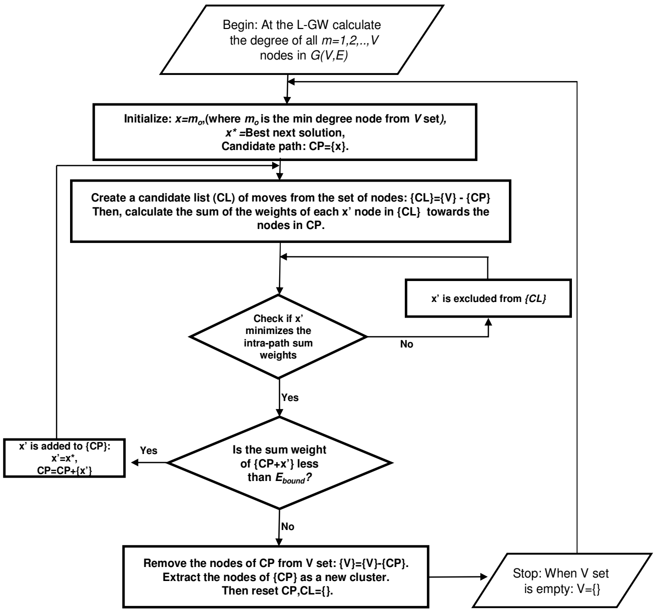

Figure 2 Flowchart of the graph-partitioning algorithm

C. Channel Assignment

Having formed the clusters, the channel assignment strategy iteratively assigns clusters to sub-channels with the maximum weighted sum-capacity. In particular, the L-GW calculates the sum of the weighted rates for different clusters. Then, it assigns each sub-channel to the cluster with the highest achievable weighted sum rate.

However, dynamic clustering and channel assignment strategy implies that the effective reuse factor can be less than 1. As a result, the number of utilized sub-channels (resources) per small cell will be variable depending on the channel variations as well as QoS requirements. In other words, the level of allocated power per resource will be dependant to resource allocation policy even in case of uniform power allocation.

The aforementioned challenge requires an iterative power allocation algorithm on top of the channel assignment strategy, similar to [7]. This algorithm is an iterative power allocation scheme that decouples the problem as we described above.

The following steps show an overview of the channel assignment algorithm including the power allocation policy. All the sub-channels are firstly sorted based on their average qualities and two separate pools are created, one with sorted sub-channels and another for the clusters. The algorithm starts with maximum power budget $P_{l,max}$ for all s-APs

Step 1, 2: Starting from the sub-channel with best quality, the weighted sum capacity (e.g. sum of intra-cluster utilities) is calculated for all clusters (according to the power budget) and the one with the maximum value is mapped to the sub-channel.

Step 3: The allocated sub-channel is removed from the pool and the weighted sum capacities are updated based on the iterative power allocation algorithm as [7]. In particular, the s-APs with allocated sub-channels in previous iteration (to their users) will have an updated (lower) power budget for the next iteration.

Step 4: The process continues to the next sub-channel with best quality and it repeats until all sub-channels are assigned to clusters.

IV. Numerical Results

In this study we focus on a 3x3 grid of indoor small cells where each s-AP and corresponding users (4 users per apartment) are randomly distributed in each apartment. We run Matlab Monte Carlo simulations with the simulation parameters derived from 3GPP standard [5] as in Table I. For the evaluation of our proposed algorithm, we set E_{bound} (through empirical evaluation) to provide relatively high interference isolation between the clusters while keeping the cell spectrum utilization in an acceptable level (on average 60%). Nevertheless, by increasing (or decreasing) this bound, we can target higher (or lower) spectrum re-use at the cost of less interference isolation.

TABLE I. Simulation Parameters

Cell Radius	7m
Snapshots	5000
s-AP transmission power	20dBm
UE Noise figure	10dB
s-AP/UE antenna gains	3dBi/0dBi
Number of Interfering s-APs	8
Frequency Reuse Factor	1
Frequency Selectivity	Rayleigh Fading Channel (4-tap)
Sub-Channels	12 RBs (5 MHz)
PF constant (Tc)	100
Path Loss Model	$PL(dB) = 127 + 30 \cdot \log_{10}(R/1000)$ *where R is the UE-s-AP distance*

Concerning the intra-cell scheduling, Proportional Fair (PF) Scheduling [6] is used for a multi-channel system in each Small cell to provide a fair allocation of resources between multiple users. Each user feedbacks the achievable data rate to its serving s-AP l per sub-channel $n=1,2,...,N$ and the s-AP calculates the ratio of the achievable spectral efficiency $R_{m,n}(t)$ to the average spectral efficiency $\bar{R}_m(t)$ for each user $m=1,2,..,M$ and time-slot $t=1,2,..,T$ Thereafter, each s-AP forms a matrix consisting of the ratios of the achievable rate to the average spectral efficiency for the allocated users, corresponding to their individual weighted rates:

$$w_{m,n}R_{m,n}(t) = \frac{R_{m,n}(t)}{\bar{R}_m(t)}, \forall \mathrm{m} \in M_T, \forall \mathrm{n} \in \mathrm{N}, , \forall t \in T \quad (7)$$

For evaluation purposes, our proposal is compared with two cases of Reuse-1 and Reuse-3 scenarios without any explicit inter-cell interference management. In these benchmarks, PF scheduling is used for a multi-channel system in each small cell to provide a fair allocation of resources between multiple users. Furthermore, we evaluate also our proposal against two graph-based ICIC approaches ([3], [4]) achieving generally promising results among conventional fixed graph partitioning and graph coloring algorithms. In particular for [3], to ensure a fair comparison between the two schemes, we assume that the demand factor (e.g. the number of required resources) for each user is extracted by the number of resources a user takes using our adaptive multi-cell scheduling algorithm in both cases although in practice such information might not be readily available for algorithm in [3].

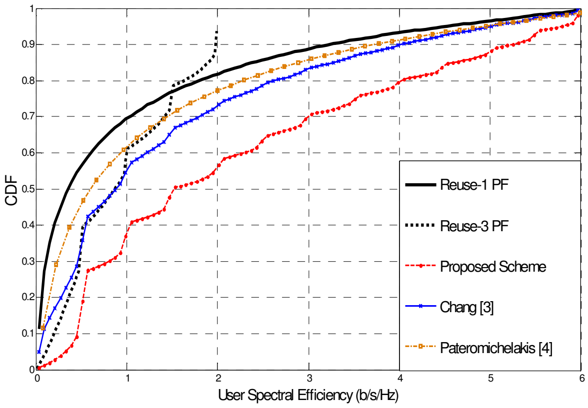

Figure 3. CDF of User Spectral Efficiency comparison

Fig. 3 presents the CDF of user spectral efficiency. Here, the improvement of our proposal is notable against the benchmarks. Targeting the 10th percentile of the CDF as QoS measure up to 55% improvement is observable over the Reuse-3 PF. Additionally, our algorithm shows 70% enhancement over [3], [4] and 91% over Reuse-1 PF. Targeting the 90th percentile, the improvement is also promising (26% over [3], [4], 40% over Reuse-3 PF and 63% over Reuse-1 PF).

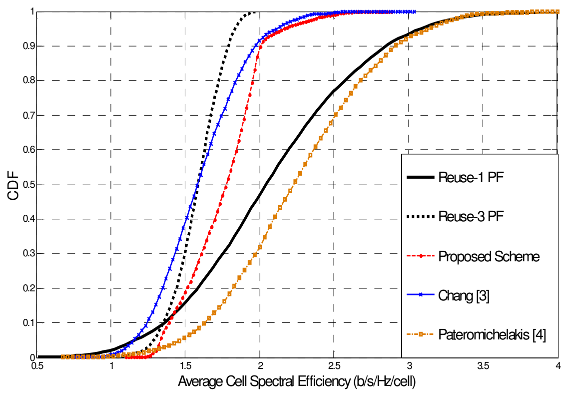

Figure 4. CDF of Average Cell Spectral Efficiency comparison

On the other hand, Fig. 4 shows the CDF of average cell spectral efficiency to highlight the main trade-off. Here, regarding the median of the CDF curves our proposal shows an improvement of 11% over Reuse-3 PF and [3]. Additionally for the mean values, our proposal shows an improvement of 27% over Reuse-3 PF and 4.5% over [3]. Note that, Reuse-1 PF and [4] show better results regarding spectral efficiency due to high spectrum reuse at the cost of degrading experienced QoS per user in particular for highly interfered ones as depicted in Fig. 3.

V. CONCLUSION

This paper proposed a multi-cell scheduling framework to efficiently mitigate ICI in dense deployments of small cells via adaptive QoS measures. The outcome of this work shows promising results when tested in dense scenarios consisting of small cells. Here, we managed to achieve significant improvement in user spectral efficiency over the benchmarks while we kept high cell-spectral efficiency via empirical tuning of reuse factor across the cells. Therefore, the proposed framework can efficiently mitigate the effect of inter-cell interference between dominant interferers, resulting in a better performance trade-off between user and cell-spectral efficiency.

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