Adaptive Partitioned Interference Management in Cellular Networks

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***Abstract*—This paper proposes an adaptive and scalable approach to resource allocation in cellular networks. We introduce an adaptive strategy to form clusters of coordinating base stations, referred to as scheduling cells (SCs), based on the local traffic demand. A system parameter is proposed which adjusts the level of coordination between the base stations. A proportional fair coordinated resource allocation scheme is discussed which allows informed reuse of resources within each cluster. The performance is evaluated for a system with one frequency channel. The proposed framework can adaptively form clusters of coordinating base stations in an autonomous cellular network with an irregular deployment of base stations.**

I. Introduction

A. Background and motivation

An ever increasing traffic demand translates into the need for exceedingly high spectral efficiencies in cellular networks. The low frequency re-use of traditional voice-centric designs is no longer adequate. While aggressive spectrum re-use seems to be the inevitable solution, reducing the frequency re-use factor on its own — in non-CDMA systems — would induce excessive interference.

In traditional cellular networks, the area centered at a base station (BS) defines a cell whose size depends on the BS power budget. The network is then formed by the deployment of the BSs according to a regular pattern modeled with hexagons. The BSs are partitioned into groups of geographically adjacent cells, known as frequency reuse clusters. The frequency reuse factor (FRF) defines the size of the clusters and in a sense determines the level of frequency reuse in the network. System resources are uniformly distributed among the BSs (or cells) of each cluster and reused according to a pre-defined pattern. Despite the uniform allocation of resources to the BSs in each cluster, the traffic load on the BSs will not be uniform at all times. Consequently, a more adaptive approach to resource allocation is required for a more aggressive frequency reuse — an indisputable requirement for future networks.

More recently, the Fractional Frequency Reuse (FFR) technique was proposed as a more aggressive alternative to the traditional frequency reuse approach. Two different frequency reuse patterns are applied: One with a conservative reuse for the weak terminals at the cell edge and a more aggressive reuse pattern for the stronger terminals, generally located closer to the BS. Soft frequency reuse (SFR) and partial frequency reuse (PFR) are the two widely investigated variations of this technique [1]. Ali and Leung have proposed a more elaborate dynamic frequency allocation technique in [2]: The FFR frequency allocation pattern is employed. However, the frequency allocation is based on the the average performance of all terminals in the network on all available frequency resources. The proposed centralized approach tremendously increases the complexity which renders the approach not practical. In [3] the concept of static scheduling cells were first introduced, where we proposed an adaptive localized resource allocation technique.

In this paper, we introduce a new approach to frequency reuse in cellular networks. We propose a BS clustering method which adapts to the time variations of the network. Not only does this approach improve the efficiency of resource allocation in traditional cellular networks, but more importantly it is crucial in adaptation and scalability of autonomous cellular networks with irregular BS deployments.

B. Overview

In order to provide service to a set of K wireless terminals, a set of A BSs are deployed - geographically distributed across a given coverage area. Each BS has a backbone connection to the wired network and is equipped with a single antenna. Each terminal is assigned to the BS with the strongest channel gain. The communication between the BSs and the terminals are established on one frequency channel.

We define a scheduling cell (SC) as a collection of BSs with coordinated resource allocation. Resource allocation

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in a SC is completely independent from the rest of the network. At one extreme, one can define the entire network to be one SC. In this case a fully coordinated resource allocation would result in optimal performance. Nevertheless, the resource allocation would be extremely complex to implement. At the other extreme, if we viewed each BS as one SC, the level of frequency reuse could result in unacceptable interference levels.

The choice of BSs forming a SC plays an important role in the performance of the system. We propose an adaptive SC formation strategy based on the following three factors:

- The number of assigned terminals to each BS
- Channel gain of terminals to their assigned BS
- Channel gains of terminals to all interfering BSs in the network

To this end, the network is modeled as a graph. The scheduling cells are formed according to a proposed algorithm which employs the spectral graph partitioning technique [4].

The paper is organized as follows. Section II presents the concept of a scheduling cell and discusses the adaptive clustering algorithm. In section III the resource allocation strategy in each SC is discussed. The time scale of adaptation is discussed in section IV. Section V presents the system model and elaborates on the numerical results. In the end, section VI concludes the paper with the main results.

II. Scheduling cell

Let us define the topology of the network by the interference matrix $\mathbf{H} = [h_{li}] \in \mathbb{R}^{K \times A}$, where h_{li} denotes the channel gain between terminal l and BS i. High channel gains between terminals and BSs result in a dense topology which calls for coordination in resource allocation. On the other hand, a sparse topology is formed as a result of low channel gains between terminals and their corresponding interfering BSs. Naturally, the size of a scheduling cell[1] should depend on the topology of the network. Although a large scheduling cell implies high coordination in resource allocation and hence a better system performance, it in turn increases the cost and complexity. On the other hand, too small a scheduling cell results in excessive interference levels.

Let us model the cellular network as a fully connected weighted graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. The set of vertices $\mathcal{V}$ represents the set of BSs $\mathcal{A}$. Each edge connects two BSs in the network. The weight on the edge is defined based on the notion of interference between BSs. This notion is introduced in section II-A which gives rise to the definition of the *similarity index*. Subsequently in section II-B, a clustering algorithm is proposed which partitions the set of BSs into scheduling cells.

[1]The size of a scheduling cell is defined as the number of BSs belonging to the scheduling cell.

A. Similarity index

For any two BSs i and j, the transmission from BS i creates a level of interference on each terminal assigned to BS j. Similarly, the transmission from BS j induces interference on the terminals assigned to BS i. If one of the two BSs i or j induces high levels of interference on the links associated to the other BS, coordination in resource allocation between the two BSs is required. In other words, the two BSs should be members of the same scheduling cell. In order to quantify the tendency of two BSs to reside in the same scheduling cell, the concept of similarity between two BSs is introduced.

Based on the interference coming from BS j, the signal-to-interference-plus-noise ratio (SINR) at terminal l assigned to BS i can be written as:

$$\text{SINR}_{lij} = \frac{h_{li} p_i}{h_{lj} p_j + \eta_0 W} \tag{1}$$

where p_i is the transmit power of BS i and $\eta_0 W$ denotes the background noise power. With no interference from BS j, the signal-to-noise ratio (SNR) for terminal l is

$$\text{SNR}_{li} = \frac{h_{li} p_i}{\eta_0 W} \tag{2}$$

Let us form the vector $\mathbf{x}_{ij}$ by the SINR_{lij} levels of all terminals assigned to BS i. Similarly, let $\mathbf{y}_i$ be the vector of the SNR_{li} levels. The loss in performance due to the effect of interference from BS j on BS i is quantified by the following index,

$$c_{ij} = \frac{f(\mathbf{y}_i)}{f(\mathbf{x}_{ij})} \tag{3}$$

where, $f(\mathbf{x}_i)$ (or $f(\mathbf{y}_{ij})$) is a measure of cell performance based on the information provided by $\mathbf{x}_i$ (or $\mathbf{y}_{ij}$). In this paper, we have assumed $f(\mathbf{z})$ to be equal to the median value of the elements of $\mathbf{z}$. The index c_{ji} is defined by exchanging i and j in (1) and (3).

A large c_{ij} and/or c_{ji} implies large levels of interference between BSs i and j, in which case coordination between the two BSs is required. The similarity index between BS i and BS j is then defined as:

$$s_{ij} = \frac{1}{2}\left(c_{ij} + c_{ji}\right) \tag{4}$$

The similarity matrix $\mathbf{S} = [s_{ij}] \in \mathbb{R}^{A \times A}$ is then formed by the similarity indices of all pairs of BSs in the network.

B. Clustering algorithm

Given a fully connected weighted graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with the weight matrix $\mathbf{W} = [w_{ij}] \in \mathbb{R}^{V \times V}$, let us define the connectivity between two sets $\mathcal{E}, \mathcal{F} \subset \mathcal{V}$ as

$$c(\mathcal{E}, \mathcal{F}) = \sum_{e \in \mathcal{E}, f \in \mathcal{F}} w_{ef} \tag{5}$$

Let $\{\mathcal{V}_1, \cdots, \mathcal{V}_Q\}$ be a Q-partition of $\mathcal{V}$ and $\bar{\mathcal{V}}_q$ be the complement of the set $\mathcal{V}_q$. The clustering problem is to find a partition which minimizes

$$\sum_{q=1}^{Q} \frac{c(\mathcal{V}_q, \bar{\mathcal{V}}_q)}{|\mathcal{V}_q|} \tag{6}$$

where $|\mathcal{V}_q|$ is the size of $\mathcal{V}_q$. The solution of this problem has been shown to be NP hard. Spectral clustering is a way to solve a relaxed version of the problem and lends itself to a standard linear algebra problem which is easy to solve [4].

Algorithm 1 outlines this technique. The eigenvectors computed in step 2 correspond to the Q smallest eigenvalues of the Laplacian matrix $\mathbf{L}$. Given the generated node coordinates $\mathbf{g}_v$ in step 4, in step 5 the K-means clustering technique clusters the nodes according to algorithm 2.

Algorithm 1 Spectral clustering

Require: Parameter Q.

1: Compute the Laplacian matrix $\mathbf{L} = \mathbf{D} - \mathbf{W}$, where $\mathbf{D}$ is a diagonal degree matrix with $d_{ii} = \sum_{j=1}^{V} w_{ij}$.
2: Compute the first Q eigenvectors $\mathbf{u}_1, \cdots, \mathbf{u}_Q$ of $\mathbf{L}$.
3: Let $\mathbf{U} \in \mathbb{R}^{V \times Q}$ be the matrix containing the vectors $\mathbf{u}_1, \cdots, \mathbf{u}_Q$ as columns.
4: Let $\mathbf{g}_v \in \mathbb{R}^Q$ be the vector corresponding to the row v of matrix $\mathbf{U}$.
5: Cluster the points $\mathbf{g}_1, \cdots, \mathbf{g}_V$ into $\mathcal{B}_1, \cdots, \mathcal{B}_Q$ clusters with the K-means clustering algorithm.
6: Form clusters: $\mathcal{V}_q = \{v | g_v \in \mathcal{B}_q\}$.

The K-means clustering algorithm is the most common clustering algorithm in the literature. As illustrated in algorithm 2, this technique requires each vertex to lie in a vector space with coordinates $\mathbf{g}_v$.

Given the node coordinates of the vertices of a graph, the weights between any two vertices can be defined as the Euclidean distance between the two as

$$w_{ij} = ||\mathbf{g}_i - \mathbf{g}_j|| \tag{7}$$

In our clustering problem, although the weight matrix $\mathbf{W}$ has been defined through the introduction of the similarity matrix, the BSs themselves do not lie in the corresponding vector space. Thus the K-means clustering algorithm cannot be directly applied to solve the clustering problem.

Algorithm 2 K-means clustering

Require: Parameter Q.

1: Randomly cluster $\{\mathbf{g}_1, \mathbf{g}_2, \cdots, \mathbf{g}_V\}$ into Q clusters $\{\mathcal{B}_1, \mathcal{B}_2, \cdots, \mathcal{B}_Q\}$.
2: For each cluster $\mathcal{B}_q$ find the coordinates of the clusterhead $\mathbf{m}_q = \frac{1}{|\mathcal{B}_q|} \sum_{v \in \mathcal{B}_q} \mathbf{g}_v$.
3: Given the current set of clusterheads $\{\mathbf{m}_1, \cdots, \mathbf{m}_Q\}$, reassign node $\mathbf{g}_v$ to cluster $\mathcal{B}^*$ where,

$$\mathcal{B}^* = \arg \min_{1 \le q \le Q} ||\mathbf{g}_v - \mathbf{m}_q||^2$$

4: Iterate steps 2 and 3 until the assignments converge.

Algorithm 3 illustrates the proposed clustering strategy in the cellular network. The idea is to apply the spectral clustering algorithm L times on $\mathcal{G}$, based on which an association matrix $\mathbf{D} = [d_{ij}] \in [0,1]^{A \times A}$ is formed. The association factor d_{ij} represents the fraction of times BS i and BS j reside in the same cluster. The scheduling cells are formed according to the association matrix $\mathbf{D}$: BSs with an association factor larger than a threshold (T) form one scheduling cell. This iterative approach has been considered due to the fact that the K-means clustering algorithm is extremely sensitive to the initialization in the first step of algorithm 2. Iterative clustering was first proposed in [5].

Algorithm 3 Forming the scheduling cells

Require: Parameters Q and T.

1: Initialize the association matrix: $\mathbf{D} \leftarrow \mathbf{0}_{A \times A}$.
2: **for** $l = 1$ to L **do**
3:    Cluster the BSs based on algorithm 1 with $\mathbf{W} = \mathbf{S}$.
4:    **if** i and j are members of the same cluster **then**
5:       $d_{ij} \leftarrow d_{ij} + \frac{1}{L}$.
6:    **end if**
7: **end for**
8: **if** $d_{ij} > T$ **then**
9:    **if** BS i or j is already part of a SC **then**
10:       Join the other node to that SC.
11:    **else**
12:       Form a new SC with BSs i and j as members.
13:    **end if**
14: **end if**
15: BSs which are not members of any SC form stand-alone SCs.

Parameter Q defines the maximum number of clusters in a K-clustering problem. In the proposed algorithm, Q limits the maximum number of clusters in each iteration l. A higher Q results in a lower number of BSs per scheduling cell which translates into less coordination in resource allocation. The effect of Q on the cluster size is studied in section V.

A larger T in algorithm 3 requires two BSs to have a larger association factor to join the same scheduling cell. Naturally with a fixed Q, increasing T increases the number of SCs in the network. In this paper, the performance evaluation is conducted assuming a fixed value for T and the size of the scheduling cells are controlled with varying Q.

III. Coordinated resource allocation

Resource allocation is coordinated among the BSs inside a scheduling cell. It is assumed that each BS has the channel state information of its assigned terminals to all BSs in the scheduling cell. In addition, the transmission power level of the BSs at each time slot is chosen in a centralized fashion and hence is known by all BSs.

After resource allocation in time slot t, the average rate of terminal l is updated according to

$$\bar{r}_l(t) = \left(1 - \frac{1}{t}\right)\bar{r}_l(t-1) + \frac{1}{t} r_l(t) \tag{8}$$

where, $r_l(t)$ is the data rate of terminal l in time slot t and is equal to

$$r_l(t) = c_l(t)\log_2\left(1 + \frac{\text{SINR}_l(t)}{2}\right) \tag{9}$$

where $c_l(t)$ is proportional to the number of frequency resources assigned to terminal l in time slot t and $\text{SINR}_l(t)$ is the SINR level of the link of terminal l in time slot t. Clearly, if terminal l is not allocated any resources in time slot t, $r_l(t)$ is set to zero.

A system with one frequency channel is considered. The resource allocation problem for time slot t is formulated as:

$$\max \sum_{k_l \in \mathcal{K}(c)} \log \bar{r}_l(t) \tag{10}$$

where $\mathcal{K}(c)$ is to set of terminals in scheduling cell c. For ease of notation the scheduling cell index c is dropped in the rest of this section.

Let $\mathbf{p}(t) = \{p_1, \cdots, p_{|A|}\}$ be the transmission power vector of the BSs in the scheduling cell at time slot t. Given a power vector $\mathbf{p}_0$, the interfering signal power received at each terminal from all BSs inside the cell is available. Thus, BS i can estimate the supported data rates $r_l(t)$ for its assigned terminals. The frequency channel can then be allocated to one terminal at each BS based on the proportional fairness criterion,

$$k_a^*(t) = \arg\max_{k_l \in \mathcal{K}_a} \frac{r_l(t)}{\bar{r}_l(t-1)} \quad , \forall a \in \mathcal{A} \tag{11}$$

For a given power vector $\mathbf{p}_0$, the set of chosen terminals in a scheduling cell form the cochannel user set $\mathcal{K}(\mathbf{p}_0) = \{k_a^*(t)\}_{a\in\mathcal{A}}$ at time slot t. The coordinated resource allocation problem is to find the power vector $\mathbf{p}^*$ which maximizes the system utility in (10). It can be shown that the original optimization problem can be approximated by maximizing the sum of the marginal utilities [6],

$$\max_{\mathbf{p}} \sum_{k_l \in \mathcal{K}(\mathbf{p})} \frac{r_l(t)}{\bar{r}_l(t-1)} \tag{12}$$

In this paper, we consider a binary power control scheme, i.e. $p_i \in \{P_{\text{max}}, 0\}$. An exhaustive search is conducted to find the optimal power vector.

The complexity of the coordinated resource allocation is directly proportional to the size of each scheduling cell which can be adjusted by parameter Q.

IV. Time scale of adaptation

While a static set of scheduling cells would result in an inefficient resource allocation, a very fast rate of adaptation would require a tremendous amount of signaling which would be impractical. The rate of adaptation should clearly be a function of the rate of the time variations in the network. We propose the adaptive clustering algorithm to update the scheduling cells at the rate of variations in the large-scale fading channel gains. For the sake of argument, let us assume that the shadow fading gains change with displacements in the order of tens of wavelengths. For a system with a center frequency of 2GHz and terminal velocity of 30Kmph, a terminal travels ten wavelengths in 0.18 seconds which is equivalent to 18 frames in the Long Term Evolution (LTE) air interface technology. Thus, a typical value of 10 updates per second is proposed (i.e. once every 10 frames). Coordinated resource allocation, however, is performed every transmission-time-interval (TTI) or once every subframe of 1ms for LTE.

V. System model and numerical results

A cellular network composed of 21 BSs with regular deployment according to the hexagonal pattern is considered. Each BS is located at the center of the cell with an omni-directional antenna. An inter-site-distance of 500 meters is assumed. The channel gains between the terminals and BSs are modeled based on the ITU recommendations in an urban-macro environment [7]. The simulation parameters are provided in table I. In order to comply with the LTE air interface technology the system bandwidth has been chosen to be equal to that of a subcarrier in the standard. In addition, each time slot has been chosen to be equal to a subframe size of 1ms. In each time slot 14 transmissions (in time) occur for the scheduled terminal which corresponds to the 14 OFDM symbols in a resource block [8].

TABLE I
SYSTEM PARAMETERS

System parameter	Value
Carrier frequency	2GHz
Bandwidth (W)	15KHz
Subframe size (time slot duration)	1ms
Number of simulated subframes (t_s)	40
BS power budget ($P_{\max}$)	18.22dBm
Noise figure at terminal	7dB
Background noise power spectral density	-174dBm/Hz
Terminal velocity	30Kmph
Number of BSs (M)	21
Total number of terminals	$4, 6, 8, 10$ per BS
Traffic model	Full buffer
Clustering algorithm threshold (T)	0.7

The system performance of the proposed technique is compared with that of a cellular network with universal frequency reuse (UFR) and a network with static clusters of 3 BSs. For a fair comparison, the same resource allocation scheme proposed in section III has been employed for the three networks.

The proposed clustering algorithm clusters the BSs in the network adaptively. The average size of the cluster is a function of the clustering parameter Q. In figure 1 the average size of the clusters is depicted for different values of this parameter. The curve has been plotted for different number of terminals which, as illustrated in this figure, approximately yield the same result. A higher Q results in more clusters which consequently decreases the average cluster size in the network. Essentially Q is a system parameter, equivalent to the frequency reuse factor in the traditional networks, which adjusts the level BS coordination and hence the complexity in resource allocation.

Monte-Carlo simulations are employed to evaluate the performance of the system. In the ITU report 2135 [7], a *drop* is defined as an independent deployment of terminals and BSs. During the simulation of a drop, the shadow fading and slow fading channel gains are assumed to be constant. The mobility of the terminals, however, change the channel gains from one subframe to the next according to the Doppler effect. In this paper, 1000 drops have been considered and the performance of each drop is evaluated over 40 subframes. The following performance evaluation metrics have been considered:

- Network average spectral efficiency: Let $\bar{\eta}_l$ be the average spectral efficiency of terminal l defined as,
$$\bar{\eta}_l = \frac{\bar{r}_l(t_s+1)}{W}$$
where the terminal average rates are calculated over $t_s = 40$ subframes. The average spectral efficiency of the network is defined as the sum spectral efficiency of all terminals in the network normalized by the number of BSs M,
$$\bar{\eta} = \frac{\sum_{l=1}^{K} \bar{\eta}_l}{M}$$
- Cell edge spectral efficiency: Let $\mathbf{s} = [\bar{\eta}_1, \cdots, \bar{\eta}_K]$ be the vector of average spectral efficiencies of all terminals in the network. The 5% point of the cumulative distribution function (CDF) of the elements of $\mathbf{s}$ is defined as the cell edge spectral efficiency of the network.

The performance of the proposed technique is evaluated for two values of $Q = 4$ and $Q = 8$ which correspond to average cluster sizes of 1.7 and 3.3 respectively. The average spectral efficiency and the cell edge spectral efficiency are illustrated in figure 2 and figure 3 respectively.

Clearly, the coordinated resource allocation scheme yields a better performance than the universal frequency reuse strategy. The level of improvement depends on the level of coordination between the BSs which can be tuned by adjusting parameter Q. It is important to note that static clustering is only possible when the BSs are identical and regularly deployed. In an autonomous cellular network, the BSs can have different power budgets and are deployed in an irregular fashion. In this case a static clustering of the network is not possible. The proposed framework, on the other hand, can adaptively form the scheduling cells based on the time varying network topology.

VI. SUMMARY AND CONCLUSION

In this paper an adaptive approach to resource allocation in cellular networks is proposed. The presented technique forms coordinating cluster of BSs (referred to as scheduling cells) according to the time-varying traffic distribution in the network. A system parameter is introduced which can be adjusted for a required level of coordination between the BSs. The network performance

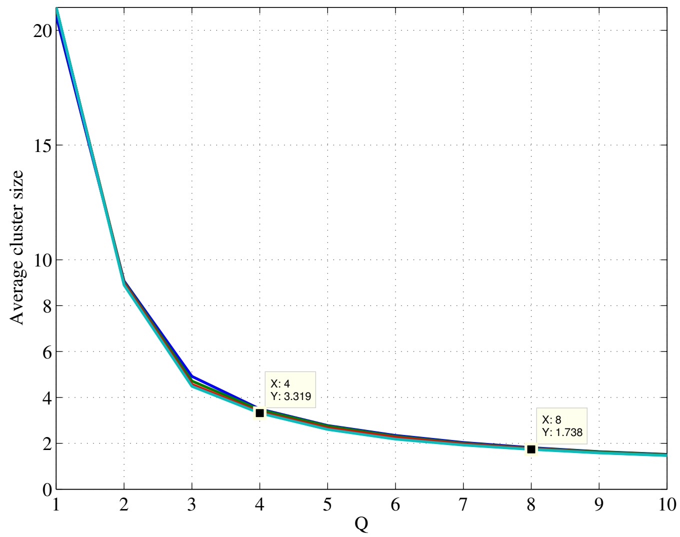

Fig. 1. Average cluster size

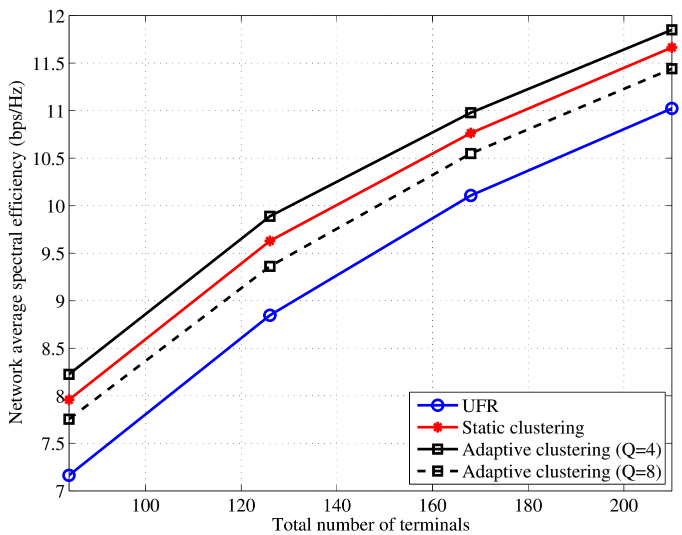

Fig. 2. Average spectral efficiency comparison

has been evaluated for a traditional cellular network where all BSs are identical (same power budget) with a regular hexagonal deployment pattern. The performance of the proposed approach is compared with that of universal frequency reuse and that of static clusters of three BSs. The results illustrate how the performance improves as the level of coordination between BSs is increased.

The introduced concept is particularly important in autonomous cellular networks where there is no regularity in the BS deployment and the BSs are not necessarily identical. In this scenario, static clustering of the BSs is not possible. However, the proposed framework can be directly applied to form clusters of coordinating base

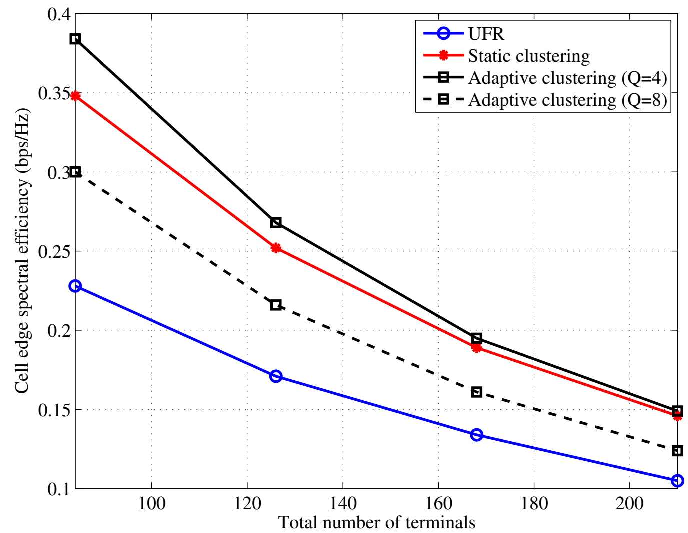

Fig. 3. Cell edge spectral efficiency comparison

stations which adapt to the time variations in the network topology.

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