MAXIMIZING THE CAPACITY OF WIRELESS NETWORKS USING MULTI-CELL ACCESS SCHEMES

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ABSTRACT

We propose a novel method for improving wireless network capacity by resorting to a so-called "multi-cell access" (MCA) scheme. An MCA scheme is reminiscent of the conventional multiple access problem in multi-user networks. However, in an MCA scheme cells (rather than users) compete for access. Furthermore, an example of such a scheme is introduced whereby a cell obtains a credit that is a function of the channel gain of its scheduled user, and it is allowed to transmit with a probability that is computed based on the credit value. The network capacity under this scheme is analyzed and we propose an optimization method in the case where the probability distribution for access is binary.

1. INTRODUCTION

Today's wireless networks are optimized from the point of view of the physical layer, but are hindered by inefficient reuse of the spectral resource over the different cells (or transmit-receive pairs) composing the networks. Careful spectral reuse planning plays an important role in mitigating co-channel interference, which limits the link capacity of every transmit-receiver pair. However, static reuse schemes do not exploit information available on variations in the underlying physical layer. It is well known that significant capacity gains can be reached by exploiting some form of coordination between the different cells occupying the same spectral resource. Coordination may be done in either a centralized or decentralized manner. In the former case, channel gain information of all users in all cells is collected by a centralized coordinator that decides which users in which cells are allowed to transmit simultaneously on a given resource while incurring the least loss of capacity due to inter-cell interference. This gives an interesting trade-off between multi-user diversity due to intra-cell gain maximization and co-channel interference minimization. [1]. In this regard, some interesting results exist exploiting inter-cell coordination. In the downlink of CDMA data networks, using a binary power allocation is shown to provide gains over intermediate power allocation [2]. In [3], a centralized heuristic algorithm works by inserting co-channel users one by one, as long as the channel throughput increases. In [4] power-profile shaping based resource assignment allows the BS to transmit with different powers in different portions of the frame and users are allotted slots according to the amount of interference tolerated.

In all of the above approaches, the key underlying idea is that substantial gains are achieved by switching off transmission in cells which do not contribute enough capacity to outweigh the interference degradation caused by them to the rest of the network. However, in a realistic network, centralized multi-cell coordination is hard to realize, especially in fast fading environments.

In this paper, we address the problem of decentralized coordination. To this end, we introduce the concept of multi-cell access (MCA) schemes, whereby the network cells (rather than the users) directly compete for access to the spectral resource. Thus, at any given scheduling period, out of say N cells, only K cells will be allowed to be active simultaneously. The other cells will stay silent for that scheduling period, but can compete again during the next scheduling period. An interesting perspective on MCA schemes is to consider it as a generalized form of frequency reuse pattern design. In contrast with traditional cellular networks, the obtained pattern (formed by the K allowed cells out of possible N) is random, possibly highly irregular (Figure 1), and varies from one scheduling period to the next as a function of the channel state information of the cell users.

MCA schemes are somewhat similar to the modified *ALOHA* protocol proposed in [5], where the uplink transmit probability of users in the ALOHA protocol is adapted to exploit multi-user diversity to maximize the system throughput. Even though the goal of increased capacity is the same, the modified ALOHA protocol is for one common receiver (single-cell). MCA schemes, on the other hand, consider concurrent interfering transmissions (multi-cell), and do not only exploit multiuser diversity but also employ interference mitigation to obtain network capacity gains.

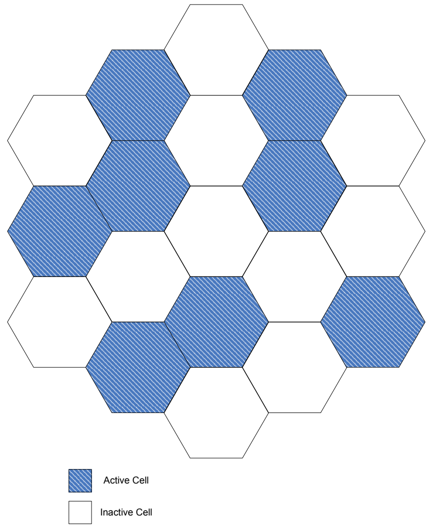

Fig. 1. Possible irregular reuse pattern at a given scheduling period due to multi-cell access.

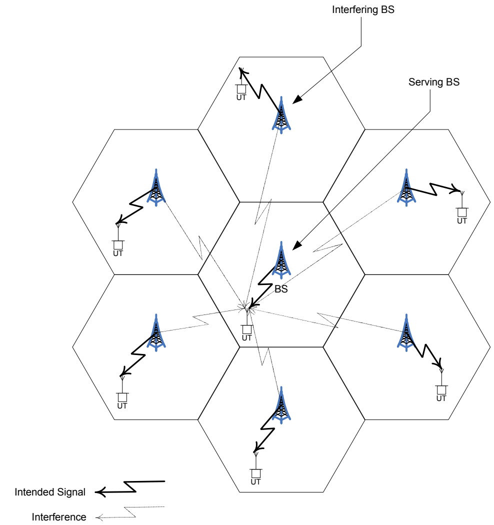

Fig. 2. An interference limited cellular system employing full resource reuse.

In this paper we propose:

- A fully decentralized MCA scheme governed by a random access mechanism in which the probability of access for each cell is a function of a *credit* obtained by this cell.
- A typical instance of credit is given by the instantaneous rate of the scheduled user in the cell.
- An analysis of the mean network capacity function given the fading statistics.
- An optimization procedure for the basic case where the probability of access has a binary distribution $(0, 1)$.

In the case of the probability of access taking binary values only, the probability is simply a step function of the credit which, in this case, is the user rate; the cell is active if its best user exhibits a rate beyond a given threshold and remains silent if the rate falls below the threshold. We show that the advantage of this method is that it combines multi-user diversity with multi-cell coordination in a low-complexity and decentralized manner. The optimal threshold is computed numerically and tested in the context of a realistic wireless network. Overall network capacity gains are calculated over a traditional interference-limited network, and compared with the case of all cells being active.

2. SYSTEM MODEL

Consider a multicell system, such as the one depicted in Figure 2, in which a set of access points (AP) communicate with user terminals (UT), all using the same spectral resource.

2.1. Signal Model

We consider the downlink of an N cell system with U_n users distributed randomly in each cell n. The received signal at user u_n is given by

$$Y_{u_n} = \sqrt{G_{u_n,n}} X_{u_n} + \sum_{\substack{i=1 \\ i \neq n}}^{N} \sqrt{G_{u_n,i}} X_{u_i} + Z_{u_n},$$

where $G_{u_n,i}$ is the channel gain between any arbitrary AP i and user u_n in cell n, and X_{u_n} is the signal from the serving AP. The noise Z_{u_n} is additive white Gaussian. The signal to interference-plus-noise ratio (SINR) is then given by

$$\Gamma_{u_n} = \frac{G_{u_n,n} P_{u_n}}{N_0 + \sum_{\substack{i=1 \\ i \neq n}}^{N} G_{u_n,i} P_{u_i}},$$

where $P_{u_i} = \mathrm{E}[|X_{u_i}|^2]$ and $N_0 = \mathrm{E}[|Z_{u_n}|^2]$ is the thermal noise power. Using the Shannon capacity, summing over all the cells, we can express the network capacity of the system (in $\mathrm{bits/Hz/sec/cell}$) as

$$\mathcal{C} = \frac{1}{N} \sum_{n=1}^{N} \log\Big(1 + \Gamma_{u_n}\Big). \tag{1}$$

Previously reported scheduling algorithms try to optimize the network capacity $\mathcal{C}$ given information on the $G_{u_n,n}$ and perhaps also the $G_{u_n,i}$ of all cells. This sets significant requirements to the amount of feedback in the system, as well as the complexity of the algorithms. A distributed solution is thus highly desirable from an implementaion point of view.

3. ACCESS SCHEME

We now proceed to present the MCA scheme based on a random access mechanism requiring only local channel information. This enables us to find the expected network capacity for such a system. Furthermore, we show how to optimize this expected network capacity when the probability of access has a binary distribution, given the fading statistics.

In the proposed MCA scheme, a cell obtains permission to transmit when it has enough credit. To keep the algorithm distributed, the credit is only based on the intra-cell channel state information. The credit measures how worthwhile to the overall network capacity a given cell is at a given instant of time. In this paper, the credit measure is given by *the channel gain of the scheduled user in the cell in question*.

3.1. Probabilistic access

In the proposed framework we further extend the random access protocol idea to the multi-cell scenario, i.e. a cell will be transmitting to its scheduled user with a probability derived from the credit. Thus, the MCA scheme here lets the access point transmit to its user with the best channel gain, with a given probability $\mathrm{P}(g)$, where g is the channel gain of the user. The function $\mathrm{P}(g)$ can take on any shape as long as it satisfies $0 \leq \mathrm{P}(g) \leq 1$ and $\mathrm{P}(g_2) \geq \mathrm{P}(g_1)$ for $g_2 > g_1$.

3.2. Expected Network Capacity

In view of the random access mechanism described above, we wish to evaluate the multi-cell network capacity. First, the expectation of a cell being activated is

$$F = \int_0^\infty \mathrm{P}(g) f_G^{(U)}(g) \;\mathrm{d}\, g,$$

where $\mathrm{P}(g)$ is the probability of cell activation for a cell whose best user exhibits a channel gain g, and $f_G^{(U)}(g)$ is the corresponding pdf for the distribution of the best channel gain in a cell with U independent users.

3.2.1. Interference modeling

To allow a decentralized algorithm, we model the interference so that it is independent of the individual realizations of the inter-cell channel gains.

To this end we use the *interference-ideal network* assumption, valid for large full reuse networks [6] which states that the total interference that the users receive is weakly dependent on its location in the cell if many sources of interference are present (dense network).

Thus we obtain, for large N,

$$\sum_{\substack{i=1\\ i\neq n}}^{N} G_{u_n,i} P_{u_i} \approx G_I \sum_{\substack{i=1\\ i\neq n}}^{N} P_{u_i}.$$

where G_I is the average interference gain value.

Using a standard path loss model [7] and $N = 19$ cells, Monte Carlo simulations show that, for $99\,\%$ of the users, the out-of-cell interference differs by less than $1\,\mathrm{dB}$ from that given by the interference-ideal assumption.

Finally, in this work a binary power allocation policy is considered i.e. all the AP's transmit with a power of either 0 or $P_{\max}$, as this has been shown to achieve close to optimal power control policy [8].

Thus, for a network with a large number of cells, the expected value of the interference becomes

$$I = G_I (N-1) F P_{\max}.$$

The expected network capacity of the system is then

$$\begin{aligned} \mathrm{E}[\mathcal{C}] = \int_0^\infty & \mathrm{P}(\tilde{g}) f_G^{(U)}(\tilde{g}) \\ & \cdot \log_2\left(1 + \frac{\tilde{g} P_{\max}}{N_0 + I}\right) \mathrm{d}\,\tilde{g}. \end{aligned} \tag{2}$$

The interference-ideal assumption facilitates us in evaluting the expression of the expected capacity, but the assumption breaks down if a significant number of cells are not on, and the expected capacity will differ from the real capacity. Another approximation used in the derivation of (2) is the interchange of the expectation operator and the logarithm. Since the logarithm is a convex function the error of this interchange is bounded by Jensen's inequality. Though, we will show in the simulations that the expected capacity in (2) is close enough to the real capacity in (1) to be used in the maximization of system capacity.

3.3. Optimization Of Network Capacity

The problem is then to find the function $\mathrm{P}(g)$ satisfying the criteria in Section 3.1 which maximizes $\mathcal{C}^*$, the average network capacity:

$$\mathcal{C}^* = \max_{\mathrm{P}(g)} \{\mathrm{E}[\mathcal{C}]\}. \tag{3}$$

Although the problem in (3) is a difficult one in general, the advantage of this particular MCA scheme lies in the possibility of doing offline optimization of the function $\mathrm{P}(g)$. Once determined, this function can be used by each individual AP to determine if it will be active or not. This can be demonstarted with a simple binary access probability distribution.

3.4. Binary Access Probability Distribution

To see how the framework given above can offer increased capacity, we look at the case where the probability of access has a binary distribution:

$$\mathrm{P}(g) \begin{cases} 1 & \text{if } g \geq T \\ 0 & \text{if } g < T. \end{cases} \quad ,$$

for some threshold T. When $T = 0$ the probability of access is 1, independent of the channel gain g, which means that all cells are turned on. Then the expectation of a cell being turned on becomes a function of T,

$$F(T) = \int_T^\infty f_G^{(U)}(g)\ \mathrm{d}\, g = 1 - F_G^{(U)}(T)$$

and

$$F'(T) = -f_G^{(U)}(T).$$

We then find the optimal threshold T, i.e. the maximum of $\mathrm{E}[\mathcal{C}(T)]$, by looking at the derivative of $\mathrm{E}[\mathcal{C}(T)]$.

First we note that the noise-plus-interference-term as well as the kernel of the network capacity integral become functions of T, i.e.

$$I(T) = N_0 + G_I(N-1)F(T)P_{\max},$$

and

$$h(\tilde{g}, T) = \log_2\left(1 + \frac{\tilde{g}P_{\max}}{I(T)}\right) f_G^{(U)}(\tilde{g}),$$

respectively. Using a binary distribution for $\mathrm{P}(g)$ the expression for the network capacity becomes

$$\mathrm{E}[\mathcal{C}(T)] = \int_T^\infty h(\tilde{g}, T)\ \mathrm{d}\,\tilde{g}.$$

The derivative of the network capacity with respect to T is then (by the Leibniz' Integral Rule)

$$\begin{aligned}\frac{\partial}{\partial T}\left\{\mathrm{E}[\mathcal{C}(T)]\right\} &= \frac{\partial}{\partial T}\left[\int_T^\infty h(\tilde{g}, T)\ \mathrm{d}\,\tilde{g}\right] \\ &= \int_T^\infty \frac{\partial}{\partial T}\left[h(\tilde{g}, T)\right]\ \mathrm{d}\,\tilde{g} - h(T, T).\end{aligned}$$

The derivative of $h(\tilde{g}, T)$ with respect to T is

$$\begin{aligned}\frac{\partial}{\partial T}\left[h(\tilde{g}, T)\right] &= \frac{\partial}{\partial T}\left[\log_2\left(1 + \frac{\tilde{g}P_{\max}}{I(T)}\right) f_G^{(U)}(\tilde{g})\right] \\ &= \frac{G_I(N-1) f_G^{(U)}(T) P_{\max}^2 \tilde{g} f_G^{(U)}(\tilde{g})}{\ln 2 \cdot I(T)(I(T) + \tilde{g}P_{\max})},\end{aligned}$$

which gives

$$\begin{aligned}\frac{\partial}{\partial T}\left\{\mathrm{E}[\mathcal{C}(T)]\right\} &= \frac{G_I(N-1) f_G^{(U)}(T) P_{\max}^2}{\ln 2 \cdot I(T)} \\ &\cdot \int_T^\infty \frac{\tilde{g} f_G^{(U)}(\tilde{g})}{I(T) + \tilde{g}P_{\max}}\ \mathrm{d}\,\tilde{g} - h(T, T).\end{aligned} \tag{4}$$

The optimal threshold can now be found through a simple gradient search, by starting with an initial value T_0 and itertively improving the estimate by following the search direction

$$s_k = -\frac{\partial}{\partial T_k}\left\{\mathrm{E}[\mathcal{C}(T_k)]\right\}$$

until $|\,\mathrm{E}[\mathcal{C}(T_{k+1})] - \mathrm{E}[\mathcal{C}(T_k)]|$ is sufficiently small.

3.5. Fairness Issues

It is known that resource allocation in wireless networks give rise to an interesting trade-off between fairness and network capacity performance. As we focus here on network capacity maximization schemes, it is expected here as well that fairness issues will arise. Some cells might experience long periods of silence due to prolonged detrimental fading conditions or poor user distribution. It is beyond the scope of this paper to investigate detailed solutions to this problem. However, we draw the reader's attention to the fact that solutions, akin to the single-cell scheduling scenario giving various levels of fairness-capacity trade-off, can be used in the multi-cell context, e.g. use of proportional-fair type measures [9]. Hence we may cite using a capacity measure for each cell that is normalized by the throughput of the cell (in this case the thresold is applied to the capacity measure rather than the channel gain). Another practical solution consists in using multiple orthogonal units of spectral resource rather than a single one. In this case, a cell that is kept silent for one code, frequency, or time slot may be active on another slot. However, investigations of the fairness-capacity trade-off are left for another companion paper.

4. SIMULATIONS

The performance evaluation is based on Monte Carlo simulations running over $100\,000$ random channel realizations. A hexagonal cellular system (cfr. Figure 2) functioning at 1800 MHz is considered, consisting of $N = 19$ cells of 1 Km. radius. Each cell schedules users at random for each frame, an approximation to round-robin scheduling, where all users are randomly placed according to a uniform distribution. Channel gains for *both inter-cell and intra-cell* AP-UT links are based on a COST-231 path loss model [7] including log-normal shadowing plus fast-fading. Log-normal shadowing is a zero mean Gaussian distributed random variable in dB with a standard deviation of 10 dB. Fast-fading is modeled by i.i.d. $\mathcal{CN}(0, 1)$ random variables and $P_{MAX} = 1\,\mathrm{W}$. The network capacity is shown in Figure 3.

To calculate the optimal threshold we use the gradient search outlined at the end of Section 3.4. This yields an estimated optimal threshold of $T = 7.56$. The estimate for the threshold is somewhat off from the true optimal value due to the two approxmiation factors mention earlier, namely the interference ideal assumption and the interchange of the expectation operator and the logarithm. An additional source of errors is if the analytical model for the fading statistics differ from the realistic channel model (distance based pathloss including log-normal shadowing plus fast-fading).

A natural scheme for comparison of the network capacity is keeping all cells on. This corresponds to having a threshold of $T = 0$. We see that compared to having $T = 0$ there is an improvement in the network capacity of $19.6\,\%$. Using this

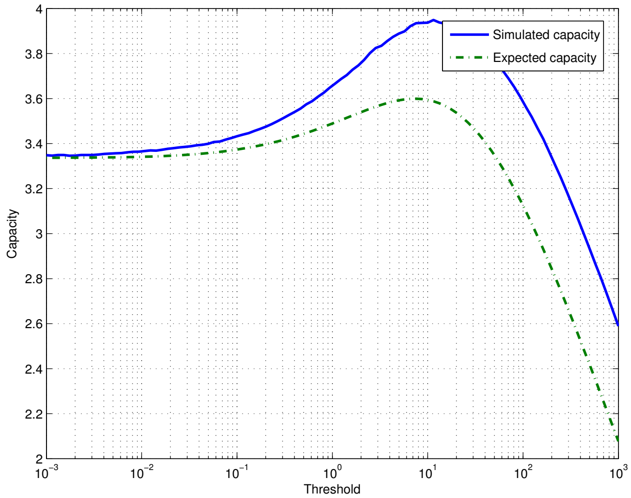

Fig. 3. Network capacity vs. threshold for a network with $N = 19$ cells. The optimal gain is observed for a threshold $T \approx 7.5$, confirming the benefit of the proposed MCA scheme compared to having all cells active.

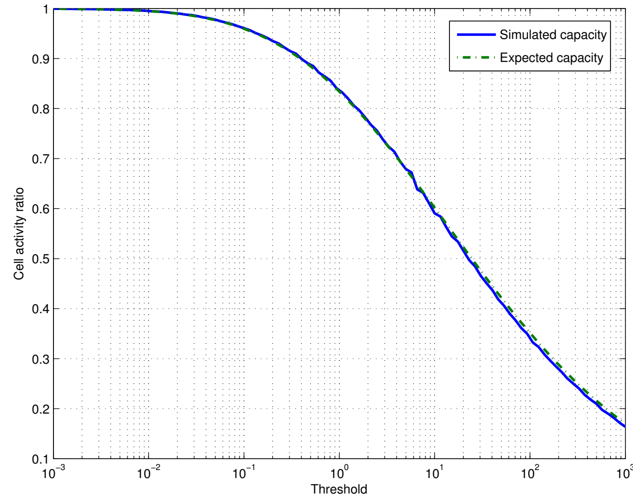

Fig. 4. The ratio of active cells in the network expressed as cell activity ratio for $N = 19$ cells.

threshold there is only a $0.1\,\%$ loss in capacity compared to using the optimal threshold, using measurements from the realistic network. Thus, there is a potential gain in the network capacity of $19.7\,\%$ compared to keeping all the cells active.

The cell activity ratio corresponding to the network capacity in Figure 3 is shown in Figure 4. We see that the optimal threshold corresponds to an average cell activity ratio of 0.63.

5. CONCLUSION

In this work we have presented a framework for a fully decentralized multi-cell access scheme based on a random access mechanism. Each cell is given a credit and access is granted with a given probability dependent on this credit. The expected network capacity of the scheme was found, given the fading statistics. Furthermore, the case where the probability of access has a binary distribution was demonstrated through Monte Carlo simulations. The simulation parameters were equivalent of those used in realistic wireless networks. Significant gains in the network capacity was observed compared to keeping all cells on.

6. REFERENCES

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