Evolution of Base Stations in Cellular Networks: Denser Deployment versus Coordination

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Abstract

Cellular systems are evolving to support high data-rate applications for the next generation network, but co-channel interference usually becomes the bottleneck for improvement. Base station cooperation has been demonstrated to increase capacity under the current network infrastructure. The main idea is to effectively form a virtual MIMO system with geographically dispersed antennas. In this work we consider another evolving direction, namely the denser base station deployment. Instead of resorting to complicated cooperation techniques, which is essentially a software approach, denser base deployment focuses on infrastructure upgrade, i.e. a hardware approach. We study how the operating regime gradually shifts from interference-limited to noise-limited with larger base density. The comparison shows that denser base deployment outperforms suboptimal cooperation schemes (zero-forcing) when the base density exceeds a certain threshold, while close-to-optimal cooperation schemes (zero-forcing dirty-paper-coding) is always superior to denser deployment.

I. INTRODUCTION

Beyond traditional voice communication, wireless networks are currently evolving to support high-speed data applications such as video streaming and internet browsing [1]. In view of scarce radio spectrum resource, channel reuse still plays an important role in improving system spectral efficiency. However, the resulting co-channel interference (CCI) usually becomes the bottleneck in cellular system design.
Recently there has been a line of work on network MIMO as an approach to combat CCI. As base stations (BS) are connected to network backbone infrastructure through high-speed wired links, they can exchange information and collaborate to form a virtual MIMO system with geographically dispersed antennas. Full cooperation, which requires measurement and distribution of channel state information, leads to a fundamental performance limit in cellular systems. Increased encoding/decoding complexity is also required. We refer to [2] as an early work on base station cooperation. [3] focuses on uplink channels and [4] deals with downlink channels. More realistic channel models are considered in [5]. See also [6] and references therein for a comprehensive literature survey.

Enabled by the remarkable advancement in chip technology, there is another approach for CCI reduction, i.e. to upgrade the network infrastructure with a denser deployment of bases. We assume the number of users to be served in a certain geographical area remains unchanged. With more and more bases, every subscriber intending to connect to the network will easily find an idle access point around him - base stations would be as dense as power sockets and lampposts. As the coverage of each cell reduces, the transmit power from either base stations or mobiles users can be scaled down. In the limiting case, the interference to co-channel cells will drop below the noise floor. As a consequence, multiple subscribers, even simultaneously active, only cause negligible interference to each other and CCI is no longer dominant as opposed to thermal noise.

Network MIMO can be considered as a software approach, i.e. an advanced signal processing technique. On the other hand, denser base deployment is a hardware approach to fundamentally upgrade network infrastructure. It is interesting to compare the two different evolving directions and we want to answer the question: what is the minimum base density required to match the performance of network MIMO?

We exploit an idealized 2-dimensional hexagon cellular array, and the criterion is to maximize the minimum rate of served users under a certain outage constraint. We demonstrate the merits of denser base deployment by showing how the operating regime evolves from interference-limited to noise-limited with more and more bases, and compare the performance gain with that of network MIMO.

The rest of the paper is organized as follows. We introduce the system model in Section II. Denser base deployment is analyzed in Section III. In Section IV we consider base cooperation
and compare the performance of two evolving directions. Conclusions are given in Section V.

II. SYSTEM MODEL

A. Topology

We consider a 2-dimensional hexagon cellular array as shown in Figure 1. Each cell is labeled with a pair of indices \((i, j)\). Base stations are located at the center of each cell. Define cell radius \((R)\) as the distance between a base and any vertex of its hexagon cell. The distance between two adjacent base stations is then \(\sqrt{3}R\). We take the cell radius to be 1 km.

To avoid boundary effect, we assume cells are arranged to tile a torus [7], i.e. the opposite sides of the rectangle area in Figure 1 are actually identified. For example, the shadowed part of cell \((1, 3)\) is outside the rectangle area but reappears on the other side.

Initially the network has 10 cells along each dimension and a total of 100 cells. This is referred to as the baseline network. Regardless of base density, the number of mobile users is always equal to the number of cells \((100)\) in the baseline network. We focus on the downlink channel from bases to mobile users.

![10 x 10 2-dimensional hexagon cellular array](image)

Fig. 1. 10 x 10 2-dimensional hexagon cellular array
B. Denser Base Deployment

While keeping the number of users and the rectangle area fixed, we increase base density by deploying \(10N\) bases along each dimension, where \(N\) is an integer. The total number of bases in the densely-deployed network is \(100N^2\). For example, when \(N = 2\) we add one additional base in the middle of every pair of adjacent bases. In the following we use \(N\) to differentiate networks with various base densities. The location of the base in cell \((i, j)\) is

\[
x = \begin{cases} 
\sqrt{3}(i - 1)R/N, & j \text{ odd} \\
\sqrt{3}(i - 0.5)R/N, & j \text{ even}
\end{cases}
\]

\[
y = 1.5(j - 1)R/N,
\]

where \(1 \leq i, j \leq 10N\).

With the number of base stations increased, each BS only needs to cover a smaller area. To maintain the angle of elevation from a cell vertex to the top of base antenna, we assume the base antenna height \(h_t\) changes to

\[h_t = h_{t0}/N\]

where \(h_{t0} = 20\) m is the transmit antenna height in the base-line network \((N = 1)\). The receive antenna height \(h_r = 6\) m is fixed. The transmit power from bases also scales down. It will be explained after we introduce the propagation model.

C. Propagation Models

We assume both mobile users and bases are equipped with single omni-directional antenna. The maximum transmit power from any base is \(P_{t1} = 10\) W in the baseline network. The noise power is \(N_0 = 6.5 \times 10^{-14}\) W [7]. Next we need to model two important effects on propagation resulting from denser base deployment:

- As cell coverage reduces, mobile users are more likely to be close to the base station. It is well-known that propagation characteristics of wireless channels are usually different for near field and far field.
- In the baseline network, the base antenna is mounted higher than the mobile antenna, which is an *above-cluster* scenario. Reducing base antenna height may create a *below-cluster* situation and the difference between these two has been noticed [8].
In view of these we consider three different models.

**Short-range model** (SR) is applicable when a mobile user has a line-of-sight (LOS) path to the base. It consists of free space path loss and Rayleigh fading.

\[
\frac{P_r}{P_t} = \left(\frac{\lambda}{4\pi d}\right)^2 \cdot G \cdot g,
\]

(1)

where \(P_t\) and \(P_r\) are transmit and receive power, respectively. \(\lambda\) is the carrier wavelength. For a 2 GHz system, \(\lambda = 0.15\) m. \(d\) is the distance between a mobile and a base. \(G\), the constant antenna gain, is taken to be 10.3 dB. \(g\) is exponentially distributed with mean 1, which models the Rayleigh fading effect.

**Long-range macrocell model** (Hata) [9] applies to far-field users and the above-cluster scenario. Besides path loss and Rayleigh fading, the shadowing effect is also included:\(^1\)

\[
10 \log_{10} \left(\frac{P_r}{P_t}\right) = -L + G_{dB} + \psi + 10 \log_{10}(g),
\]

(2)

where \(\psi \) [dB] is a Gaussian random variable with mean 0 and standard deviation 8 dB, which characterizes the shadowing effect. \(G_{dB}\) and \(g\) are defined similarly as in the SR model. \(L\) [dB] is the path loss component [9],

\[
L = 69.55 + 26.16 \log(f_c) - 13.82 \log(h_t) - a(h_r) + 10\gamma \log(d),
\]

where

\[
\gamma = 4.49 - 0.655 \log_{10}(h_t),
\]

\[
a(h_r) = 3.2[\log_{10}(11.75h_r)]^2 - 4.97.
\]

The units are \(d\) [km], \(f_c\) [MHz], \(h_t\) [m] and \(h_r\) [m].

**Long-range microcell model** (HXB) is an empirical model proposed by Har, Xia and Bertoni [8] for the below-cluster scenario. It also includes path loss, shadowing and Rayleigh fading similar to (2). The difference is in the path loss component

\[
L = 31.68 + 35.16 \log(f_c)
\]

\[
-4.16 \log(f_c) \cdot \text{sign}(\Delta h) \cdot \log (1 + |\Delta h|)
\]

\[
+ [39.46 - 4.13 \cdot \text{sign}(\Delta h) \cdot \log (1 + |\Delta h|)] \cdot \log(d).
\]

\(^1\)The logarithm is this paper is all base 10.
where $\Delta h$ is the base antenna height $h_t$ relative to the cluster height $h_r$, i.e. $\Delta h = h_t - h_r$.

There are two distances where propagation characteristics change.

- **Cutoff distance** $d_c$, assuming equal to twice the distance between two adjacent base stations $d_c = 2\sqrt{3}R$. It does not change with BS density $N$. Because of the curvature of the earth, channel strength beyond $d_c$ is simply set to be 0 [7].

- **Transition distance** $d_t$. Each base is associated with a specific transition distance, randomly chosen from $30 \sim 70$ m, where the propagation changes from short-range to long-range models. This is to model the location of an possible obstacle that blocks a user’s LOS path.

In summary, the channel strength is determined as follows

- $d < d_t$, SR model;
- $d_t < d < d_c$
  - $h_t > h_r$, base antenna above cluster, Hata model;
  - $h_t < h_r$, base antenna below cluster, HXB model;
- $d > d_c$, channel strength 0.

Finally as mentioned before, we need to determine the transmit power scaling rule. The criterion is to maintain the received power at cell vertices, assuming no random shadowing and fading effect. More specifically, we can compute the path loss $L_1$ at distance $R$ for the baseline network according to (2). When increasing base density to $N$, we recompute the path loss $L_N$ at distance $R/N$ from (2) or (3), depending on whether $h_t > h_r$ or not. The transmit power is then scaled by

$$10 \log \left[ \frac{P_{tN}}{P_{t1}} \right] = L_N - L_1.$$  \hspace{1cm} (3)

**D. Network Population**

Regardless of the base density $N$, the network always serve the same number of users. One by one, each user is randomly placed into the network and assigned to the base with the strongest propagation path. If the BS is already serving another user, think of the current user as being referred to another orthogonal subchannel and simply discard it. The process is repeated until 100 users are placed into the network.

Figure 2 shows an example of base deployment and user association. Circles mark the location of users, and a line connects each user to its serving base, marked by a star. Triangles mark
idle base stations which do not serve any user and are consequently shut down. Because of the random shadowing and fading effect, it can be seen that users are not always associated with the nearest base. Instead the assignment depends more on propagation strength.

![Base deployment and user association, N = 2](image)

Fig. 2. Base deployment and user association, \( N = 2 \)

III. Denser Base Station Deployment

In this section we study the performance of denser base deployment. We assume single base transmission to avoid complicated signal processing, and the focus is on the benefit from an infrastructure upgrade.

A. Open Loop: Full Power Transmission

In the downlink of a cellular system, mobile users generally have to estimate the channel strength to facilitate decoding. If there is no feedback link between the mobile user and the base, the channel state information (CSI) is not accessible at the transmitter. We call this an open loop scenario.

Without CSI, base stations simply transmit at full power and a constant rate. Each mobile user achieves a certain received SINR, depending on the random signal and interference level. For example, consider a user served by BS \( i \) and the received SINR is

\[
\beta(i) = \frac{|h(i)|^2}{\sum_{j \neq i} |h(j)|^2 + N_0/P_tN}.
\]
where $h(i)$ is the channel gain from base $i$ to the user, and $h(j), j \neq i$ is the channel gain from interfering base $j$ to the user. Note that the summation over interfering bases only include these active bases but not the idle ones. Moreover, among these active bases, many of them are further away from the user than the cutoff distance $d_c$, so the corresponding channel strength is 0. In other words, although there are $100N^2$ bases in the network, for any specific user only a few of them will cause significant interference.

Assuming all active bases transmit at full power, we compute the received SINR for each user according to (4). We then plot in Figure 3 the empirical cumulative distribution function (cdf) $F(\beta)$, defined as the percentage of users having received SINR not exceeding $\beta$. It is immediately observed that the empirical cdf curve shifts to the right as we increase the base density $N$, which implies that more users have relative high SINR’s. In particular we gauge the system performance by the minimum served rate with 10% user outage, which also increases with the base density $N$.

![Empirical cdf of received SINR, open loop](image)

**Fig. 3.** Empirical cdf of received SINR, open loop

### B. Operating Regime Shift

The benefit of denser base deployment as observed in Figure 3 comes from an operating regime shift from interference-limited to noise-limited. To serve the same number of users with an increasing number of bases, there will be more and more idle bases. These idle bases create a guard area to spatially separate the active bases. For any active base, although there are
more bases around it when increasing base density, the number of active interfering bases stays approximately the same. Since the transmit power scales down with increasing base density, the interference will gradually drop below the noise level.

The following simple example gives us a rough idea when the regime shift occurs. We temporarily ignore the random shadowing and fading, and focus on path loss in the propagation models outlined in Section II-C. We also include only the first tier of 6 interfering bases, located at a distance \( d = \sqrt{3}R/N \) from the center base, where \( N \) is the base density. The total interference is approximately

\[
P_I(N) = 6P_{tN} \frac{N^2}{N^2} \cdot 10^{-\frac{L_N(d)+G_{dm}}{10}},
\]

where \( P_{tN} \) is the transmit power calculated from (3), \( L_N(d) \) is the path loss at \( d = \sqrt{3}R/N \) determined by (2) or (3), depending on the relative height between the base and mobile antenna height. The factor \( 1/N^2 \) is to account for the fact that 100 users are served by \( 100N^2 \) bases, so each base has a probability \( 1/N^2 \) to be active. Straightforward calculation shows that the interference power \( P_I(N) \) decreases with \( N \) and reaches the noise floor \( N_0 \) when \( N = 8 \).

We then consider the more realistic system described in Section II. Namely we incorporate the random propagation effect, random user locations, interfering bases out of the first tier and etc. In Figure 4 for different base density \( N \) we plot the minimum received SINR (4) with 10% users allowed in outage. In (4) the denominator consists of both interference and noise. If one of them is set to 0 we obtain the signal-to-noise ratio (SNR) and the signal-to-interference ratio (SIR), respectively. The minimum received SNR (SIR) with 10% user outage is also shown in Figure 4. We observe that for small \( N \leq 4 \) the combined SINR coincides with SIR with noise playing a negligible role. However when \( N \geq 7 \) noise becomes the dominant factor. The regime shift occurs around \( N = 7 \) for the more practical system, and we see a much simplified example (5) actually gives a good estimation.

C. Close loop: Power Control

In the open loop scenario described in Section III-A, base stations do not have knowledge about the channel strength, so simply transmit at full power and a constant rate. Approximately 10% of the users will have relatively weak channels that can not support the rate and these users will fall into outage. The drawback of open loop approach is centered around two issues:
outage users actually do not require any rate but their serving bases still transmit at full power and cause interference to other users; some non-outage users have relatively strong channels to support higher rate but this advantage is not exploited.

In a system where feedback paths exist between users and bases, which is called a close loop scenario, we can shut down those bases serving the outage users to eliminate unnecessary interference. Furthermore, for those non-outage users with strong channels, we can reduce the transmit power as long as the target rate can still be supported. The objective is also to reduce their interference to others.

In summary we want to maximize the minimum served rate subject to a certain outage constraint. Some outage-user selection criterion and a brute-force iterative search procedure were proposed in [7] [5]. Here we propose another scheme based on Perron-Frobenius theorem and binary search, which is computationally more efficient.

It is well-known that [10] for a nonnegative irreducible matrix $F$, the eigenvalue with the largest norm is positive and is defined to be the Perron-Frobenius eigenvalue $\rho_F$. Moreover we have the following result

**Lemma III.1** [10] If $\rho_F < 1$, then $P^* = (I - F)^{-1}u$ is the Pareto optimal solution to the componentwise inequality

$$ (I - F)P \geq u \quad \text{with} \quad P \geq 0, \quad (6) $$
i.e. if $P$ is any other solution to (6), then $P \geq P^*$ componentwise.

Here $I$ is the identity matrix, $u \geq 0$ is a given vector with nonnegative components.

We start with a system of $K$ users. Denote the channel power gain matrix as $M_{K \times K}$, where $m_{ij}$ is the channel power gain from base $j$ to user $i$. Note that idle bases are shut down and not included in $M$. We separate the channel gain matrix into $M = D + A$, where $D$ contains the diagonal elements and $A$ contains the off-diagonal elements. To support a constant SINR $\beta$ for each user, we need

$$m_{ii}P_i \geq \beta \left( N_0 + \sum_{j \neq i} m_{ij}P_j \right), \forall i.$$  

Denote $P = [P_1, \cdots, P_K]^T$ as the power vector. (7) can be written in matrix form

$$(I - \beta D^{-1}A)P \geq \beta N_0D^{-1}1 \quad \text{with} \quad 0 \leq P \leq P_{tN}1,$$  

where 1 is the vector with all ones. Note that we also have the maximum transmit power constraint $P_{tN}$ for each base. From Lemma III.1 we conclude that $0 \leq \beta < \rho_F^{-1}(D^{-1}A)$. Through a simple binary search we can easily identify the maximum $\beta$ such that the Pareto optimal solution

$$\beta N_0(I - \beta D^{-1}A)^{-1}D^{-1}1$$

satisfies the transmit power constraint.

There are two schemes for outage user selection. The one-shot close loop scheme directly eliminates 10% of users with the worst SINR, assuming full power transmission from each base. It then considers a system of only 90 users. The iterative close loop scheme starts with a system of 100 users. The user that causes the power constraint to be active is declared outage and the corresponding base shut down. We then repeatedly apply the process to the updated system, eliminate one user at a time, till the outage constraint is satisfied.

In Figure 5 we compare the performance of both open and close loop schemes. For the open loop scheme, we plot the minimum received SINR subject to 10% user outage. For close loop schemes, we plot the equal received SINR. The noise-only upper bound is also shown in Figure 5 for illustration purpose. It is interesting to see the one-shot close loop scheme generally achieves a SINR about 3 dB higher than the open loop scheme. There is a further gain about $1 \sim 2$ dB if we exploit the more delicate iterative close loop scheme. For $N \geq 7$, the iterative scheme actually approaches the noise-only upper bound.
Two other curves, namely network MIMO with zero-forcing (ZF) and zero-forcing dirty-paper-coding (ZF-DPC), are also plotted in Figure 5. These curves will be explained in the next section.

IV. NETWORK MIMO: BASE STATION COOPERATION

We have considered denser base deployment in Section III, which upgrades the network infrastructure and is essentially a hardware approach. An alternative software approach maintains the current network structure, but improves system performance through base station cooperation.

With full base cooperation, the downlink in a cellular system becomes effectively an MIMO broadcast channel. In a recent result [11], the capacity region is shown to be achievable under dirty paper coding (DPC) together with optimization of input covariance matrices. However, the optimal DPC scheme is computationally intensive and many suboptimal but more practical schemes are also explored. In the following we briefly outline two schemes, ZF and ZF-DPC. The ZF scheme is attractive because of its relative simplicity. The ZF-DPC scheme, although suboptimal in general [11], has been demonstrated to capture most of the benefit of base cooperation and is close to optimal. These two schemes are then compared with the denser base deployment. We refer readers to [5] for the motivation and more details.
A. Base Cooperation: Zero Forcing

We consider the baseline network with $K = 100$ bases and 100 users. Denote $\tilde{H}_{K \times K}$ as the channel gain matrix. Note that the propagation model in Section II-C actually gives the channel power gain and the corresponding power gain matrix is denoted as $M$ in Section III-C. Here we take the square root and convert it to channel magnitude gain. There is also a random phase factor from Rayleigh fading, so overall the channel gain from base $j$ to mobile $i$ is

$$h_{ij} = \sqrt{m_{ij}} e^{\sqrt{-1} \theta_{ij}},$$

where $m_{ij}$ is the power gain and $\theta_{ij}$ are i.i.d. uniformly distributed on $[0, 2\pi]$. The $i$th row $\tilde{h}_i^T$ of $\tilde{H}$ is the gain vector from all bases to mobile $i$.

To implement a ZF scheme with $q = 10\%$ user outage, we first eliminate $qK$ users of the smallest channel gain norms $|\tilde{h}_i|$, and shut down the corresponding bases. The remaining channel gain matrix $H$ is of size $(1-q)K \times (1-q)K$. The transmitted signals from base stations are

$$X = [w_1 \cdots w_{(1-q)K}] \cdot [x_1 \cdots x_{(1-q)K}]^T = Wx,$$

where $x_i \sim \mathcal{N}(0, P_i)$ and $w_i$ is the pre-coding weight vector. ZF scheme requires $HW = I$, or equivalently $h_i^T w_j = 0$ for any $i \neq j$, which implies that users do not cause interference to each other. The received signal is

$$y = HX + n = HWx + n = x + n,$$

where $n$ is the noise vector with i.i.d. components of mean 0 and variance $N_0$.

The objective is to maximize the minimum received SINR,

$$\max \min_i P_i / N_0,$$

subject to the per-base power constraint

$$V \cdot P \leq P_t 1$$

where $v_{ji} = |w_{ji}|^2$, $P = [P_1 \cdots P_{qK}]^T$ and $P_t$ is the maximum transmit power from each base. The solution is seen to be $P_i = P_{ZF}$ for all $i$ and

$$P_{ZF} = \frac{P_t}{\max_j \sum_i v_{ji}}.$$
B. Base Cooperation: Zero Forcing Dirty Paper Coding

To eliminate interference in the ZF scheme, the weight vector \( w_i \) for user \( i \) is constrained to be orthogonal to channel vectors \( h_j \) for all \( j \neq i \). In ZF-DPC, we first assign an order to the users, for example \( \{1, 2, \cdots, N\} \). Next we only require the weight vector \( w_j \) to be orthogonal to \( h_i \) for \( i < j \), which ensures user \( j \) causes no interference to \( i \). Furthermore, we encode users’ information through DPC, which has the desirable property that user \( i \) does not see \( j \) as an interferer for \( i > j \). Overall the interference among users are perfectly removed.

We use the same notation here as in the ZF scheme. In ZF-DPC, similarly we first eliminate \( qK \) users of the smallest channel gain norms \( |\hat{h}_i| \), and shut down the corresponding bases. The resulting channel gain matrix is denoted as \( H \) with rows \( h_i^T \).

We then assign an order to the remaining \( (1 - q)K \) users. Note that for user \( j \) the weight vector \( w_j \) is orthogonal to channel vectors \( \{h_1, \cdots, h_{j-1}\} \), so the effective channel \( \hat{h}_j \) of user \( j \) is \( h_j \) projected away from the subspace spanned by \( \{h_1, \cdots, h_{j-1}\} \). The effective channel \( \hat{h}_j \) generally shrinks with expanding subspaces. In view of fairness, users with small effective channel norms are placed in front of the encoding list.

We adopt the following rule to determine a heuristic encoding order: without loss of generality assume users \( (1 - q)K + 1 \) to \( K \) are declared outage,

1) Initialize \( k = 1 \), candidate pool \( S = \{1, \cdots, (1 - q)K\} \);
2) Project \( h_i \), \( i \in S \) away from the subspace spanned by \( [h_{\pi(1)}, \cdots, h_{\pi(k-1)}] \) to get \( \hat{h}_i \). Select among \( \hat{h}_i \)'s the one with the smallest norm to be user \( \pi(k) \);
3) \( k \to k + 1 \), \( S \to S - \{\pi(k)\} \);
4) End if \( S \) empty, otherwise go to Step 2.

The ZF-DPC scheme encodes information of each user in the order \( \pi(1) \) to \( \pi((1 - q)K) \). For simplicity in the following we drop the notation \( \pi \) of permutation.

After outage user selection and non-outage user reordering, we perform a QR decomposition \( H = LQ \) such that \( L \) is lower triangular and \( QQ^\dagger = I \). We take the pre-coding matrix to be \( W = Q^\dagger \), so the received signal is

\[
y = HX + n = LQQ^\dagger x + n = Lx + n.
\]

Our objective is to maximize the minimum SINR subject to per base power constraint, i.e.

\[
\max_{i} \min_{i} |L_{ii}|^2 P_i / N_0
\]
subject to per-base power constraint which is still in the form of (9) with $V$ and $W$ properly defined. The solution is shown to be $P_i = \frac{P_{\text{ZFDPC}}}{|L_{ii}|^2}$ for all $i$ and

$$P_{\text{ZFDPC}} = \frac{P_t}{\max_j \sum_i |w_{ji}|^2 |L_{ii}|^2}.$$ 

C. Performance Comparison

To evaluate the performance of network MIMO, we randomly sample 25 baseline networks, each with 100 bases and 100 users. The above ZF and ZF-DPC schemes are then applied to these networks to maximize the minimum SINR subject to 10% user outage. Finally we average the achievable SINR over these 25 networks, and the results are plotted in Figure 5 to compare with denser base deployment.

ZF is in general a suboptimal cooperation scheme, but it has certain appeal from a practical standpoint because of simple implementation. To match the performance of ZF, it is observed that we have to increase base density along each dimension by a factor approximately between 4 and 6, and the exact value depending on whether we exploit an open or close loop scheme, and also on the user elimination procedures.

ZF-DPC, on the other hand, is a close-to-optimal cooperation scheme but highly complicated to implement. If the complexity of ZF-DPC is still within the affordable range, then it is preferred over the denser base deployment approach.

V. Conclusion

We study another evolving direction of cellular networks, namely denser base station deployment, based on a 2-dimensional hexagon cellular array. We propose a propagation model to characterize the difference between far-field and near-field users, and the difference between base-above-cluster and base-below-cluster scenarios. We show how the operating regime shifts from interference-limited to noise-limited as increasing the base density. To gauge the performance our criterion is to maximize the minimum achievable SINR subject to a certain user outage constraint. The benefit of denser base deployment is then compared with that of base cooperation. It is observed that denser base deployment outperforms suboptimal cooperation schemes (ZF) when the base density exceeds a certain threshold, while close-to-optimal cooperation schemes (ZF-DPC) is always superior to denser base deployment.
REFERENCES


