Abstract—This paper provides an analytical performance characterization of both uplink (UL) and downlink (DL) user-centric network multiple-input multiple-output (MIMO) systems, where a cooperating BS cluster is formed for each user individually and the clusters for different users may overlap. In this model, cooperating BSs (each equipped with multiple antennas) jointly perform zero-forcing beamforming to the set of single-antenna users associated with them. As compared to a baseline network MIMO systems with disjoint BS clusters, the effect of user-centric clustering is that it improves signal strength in both UL and DL, while reducing cluster-edge interference in DL. This paper quantifies these effects by assuming that BSs and users form Poisson point processes and by further approximating both the signal and interference powers using Gamma distributions of appropriate parameters. We show that BS cooperation provides significant gain as compared to single-cell processing for both UL and DL, but the advantage of user-centric clustering over the baseline disjoint clustering system is significant for the DL cluster-edge users only. Although the analytic results are derived with the assumption of perfect channel state information and infinite backhaul between the cooperating BSs, they nevertheless provide architectural insight into the design of future cooperative cellular networks.

Index Terms—Beamforming, coordinated multi-point (CoMP), cooperative communications, interference, multi-cell, network MIMO, stochastic geometry, wireless cellular networks

I. INTRODUCTION

Inter-cell interference is the main limiting factor in the physical-layer of modern wireless cellular networks with densely deployed base-stations (BSs). Network multiple-input multiple-output (MIMO) is a promising technique for interference mitigation in which BSs jointly transmit information to and receive information from the multiple users via coherent beamforming across multiple BSs [1]. This paper aims to provide analytic modeling and performance characterization of such network MIMO systems.

Although the elimination of all inter-cell interference would in theory require cooperating BSs across the entire network, such complete cooperation is clearly impractical due to the computational complexity, delay and the capacity constraints of the backhaul, and likely not necessary as distant BSs make little impact on user’s signal strength or interference power.

Thus, practical implementations of network MIMO systems would involve only limited set of BSs forming cooperation clusters of finite sizes. A natural way to limit the cooperation size is to partition all the BSs in the network into disjoint clusters, so that BSs in each cluster jointly serve all users associated with all the BSs in the cluster. This is akin to a distributed antennas system, but in such an architecture significant inter-cluster interference still exists for cluster-edge users.

Instead of the baseline network MIMO system above, this paper focuses on a user-centric clustering strategy where a BS cooperation cluster is formed for each user individually, and clusters for different users can partially overlap. Such a clustering strategy allows the user to be always placed at the center of its cluster, so that signal strength is improved and inter-cluster interference reduced.

Although the performance advantage of user-centric clustering is intuitive, the mathematical analysis of such an architecture is a challenging task. The main goal of this paper is to provide a performance analysis of the user-centric network MIMO architecture and to compare it quantitatively with the baseline disjoint clustering in both uplink (UL) and downlink (DL). Toward this end, we assume the use of zero-forcing beamforming (ZFBB) strategy with equal power allocation across the beams, and adopt a stochastic geometry model of the BS and user locations and a Gamma distribution approximation of the direct and interfering channel strength in order to facilitate an analytic characterization of the average user rate in a user-centric network MIMO systems as a function of network parameters such as the cooperation cluster size.

Throughout the paper, we assume that perfect and instantaneous channel state information (CSI) is available at the BSs in order to facilitate analysis. The aim of this paper is to quantify the benefit of BS cooperation before CSI acquisition cost is taken into account.

A. Related Work

Network MIMO has long been advocated as being capable of treating inter-cell interference as useful signals, thereby significantly improving the throughput of wireless cellular networks [2], [3]. But the existing performance evaluation of network MIMO systems has been mostly carried out either using simplified Wyner model or by simulation; and most earlier works have focused on the optimization of transmit strategies for network MIMO systems. For example, for network MIMO systems with disjoint clustering, earlier work [4] numerically studies the throughput performance; [5], [6] present optimization strategies where users close to cluster edge are served.
with inter-cluster coordination and users close to cluster center are served only with intra-cluster BS coordination. Likewise for user-centric clustering, first proposed in [7], most existing works are based on numerical investigation and optimization strategies that select the best serving cluster of BSs for each user [8, 9, 10].

The performance analysis of network MIMO systems is a challenging task, because the cooperating BSs in a network MIMO system typically have different path-loss to the user, so traditional analytic tools for MIMO system, such as the random matrix theory [11], are not ideally suited for analyzing the network MIMO system performance, unless certain symmetry and simplifying assumptions are adopted [12].

To account for the distance dependent path-loss in wireless communication networks, stochastic geometry has emerged as a powerful tool for analyzing wireless networks with random deployment of BSs and users that are assumed to form Poisson point processes. Stochastic geometry is first applied to the analysis of cellular networks with single-cell processing in term of coverage probability for both the DL [13] and the UL [14].

The stochastic geometry analysis of coordinated multicell network is more challenging. Toward this end, most existing analyses consider the so-called noncoherent joint transmission scheme [15], [16], where multiple BSs jointly transmit data to the same user. Moreover, [17] studies the power gain in the form of coverage probability for both coherent and noncoherent joint transmission; [18] investigates the outage probability of both coordinated multi-point (CoMP) non-CoMP schemes in a 2 tier network. These papers reveal power gain from joint transmission, but the overall system does not benefit from multiuser spatial multiplexing gain. Stochastic geometry can be readily applied to the analysis of outage and coverage probabilities of these noncoherent systems, because the signal power at a user is simply the sum of powers from the cooperating BSs without the need to account for the effect of multicell beamforming.

This paper aims to provide a stochastic geometry analysis of coherent joint transmission scheme in a network MIMO system, where significant spatial multiplexing gain can be realized via multicell beamforming. The performance analysis for such a system is considerably more complicated, because of the need to model the effect of beamforming. Toward this end, [19], [20] propose a series of techniques that allow an approximate characterization of the effect of zero-forcing beamforming for multicell networks. This enables a subsequent stochastic geometry analysis of network MIMO systems to be carried out [21]. In particular, instead of a typical coverage probability analysis, [21] provides a derivation of a more useful ergodic sum rate expression for a DL network MIMO system with disjoint clustering.

This paper further extends the analysis of network MIMO system in [21] to the user-centric clustering case and to UL scenarios. The user-centric case is more complicated, because the beamforming vectors overlap with each other. The analytic performance characterizations of this paper help illustrate the benefit of user-centric clustering as compared to disjoint clustering for both UL and DL scenarios.

It should be emphasized that the user-centric scheme considered in this paper is not the only way to improve the baseline disjoint scheme with respect to the cluster-edge user performance. Intelligent scheduling algorithms can be used to partition the time, frequency and spatial resources together with interlaced clustering to achieve a similar benefit [22], [23]. For simplicity, this paper considers only the baseline disjoint clustering as the reference system for comparison. The performance analysis techniques developed in the paper would be useful for the analysis of systems developed in [22], [23], [24] as well.

The network MIMO system considered in this paper is different from yet another type of multicell cooperation scheme known as interference nulling. The interference nulling scheme realizes extra spatial dimensions at the BS to create spatial nulls at selective out-of-cell user locations, thereby eliminating selective dominant interference. This can be done without the exchange of user data between the BSs, only the CSI—but at the expense of additional BS antennas. Stochastic analysis of interference nulling scheme is somewhere easier than that of network MIMO, because the beamformed signals always come from the same BS, rather than from multiple BSs as in network MIMO. Works in this area include the analysis of outage probability [25], optimization of interference nulling range [26], and coverage probability for two-tier networks [27].

As mentioned earlier, the proposed analysis does not include the effect of CSI estimation error and finite backhaul capacity. We refer readers to, e.g., [28], [29], [30], for a discussion on the performance of network MIMO system considering the overhead of CSI acquisition and the effect of backhaul limitation.

B. Main Contributions

The main contributions of this paper are as follows:

1) This paper provides computationally efficient user rate expressions for both UL and DL network MIMO systems under either disjoint clustering or user-centric clustering. We adopt a Poisson model for BS and user locations, and utilize techniques developed in [21] for approximating the zero-forcing (ZF) signal and interference strength.

2) This paper analytically quantifies the gain of BS cooperation as a function of the cooperation cluster size. We show that the network MIMO gain (with either disjoint or user-centric clustering) is typically larger in the DL than in the UL, due to the fact that the BSs have a much larger transmit power budget than the handsets, so DL transmission is more interference limited than UL transmission.

3) This paper shows that in term of average user rate across the network, the relative advantage of user-centric clustering over the baseline naïve disjoint clustering strategy is about 15%-20% in the UL, and smaller in the DL. In the UL, user-centric clustering essentially places every user in the center of the cluster, thus resulting in both stronger signal power and less inter-cluster interference for all UL users.
4) In the DL, user-centric clustering also brings stronger signal power to all users, but its effect on inter-cluster interference depends on user location. By removing the cluster edge, user-centric clustering reduces inter-cluster interference, hence bringing in higher throughput for the low-rate users. (For the high-rate users, user-centric clustering actually increases interference by introducing extra intra-cluster interference, but this effect is small.) The main benefit of user-centric architecture in the DL is therefore the significant improvement in low-rate user performance.

5) Finally, this paper shows that even in the limit of unrealistically large cluster sizes, the average user rate of a network MIMO system does not approach that of an isolated interference-free single cell. There is significant penalty due to ZFBF in cooperating across multiple BSs regardless of the cooperation cluster size.

C. Structure of the Paper and Notations

The remainder of the paper is organized as follows. Section II describes the system model of this paper, more specifically, it provides the setting of user-centric clustering and disjoint clustering, the ZFBF design in both schemes, and the definitions of intra-cluster and inter-cluster users. Section III gives intuitive explanation on the gain of user-centric clustering over disjoint clustering. Section IV gives the stochastic model. Section V provides the analytical result of ergodic user rate of user-centric clustering for both UL and DL using tools from stochastic geometry, which is the main mathematical contributions of this paper. Section VI provides similar analysis for disjoint clustering. Section VII makes comparison of signal and interference power between user-centric and disjoint clustering for both UL and DL based on intermediate analytical result from the previous section. Section VIII shows numeric comparison between user-centric clustering and baseline disjoint clustering. Section IX concludes the paper.

This paper uses lower-case letter \( h \) to denote scalars, boldface lower-case letter \( h \) for vectors, and bold-face upper-case letter \( H \) for matrices. We use \( I_n \) to denote an \( n \times n \) identity matrix, and use \( H^H \) to denote Hermitian transpose and \( H^+ = (H^H H)^{-1} H^H \) to denote the left pseudo-inverse of a matrix \( H \). Upper-case letters such as \( K, M \) represent scalar constants. The expectation of a random variable is denoted as \( E[\cdot] \); the \( l_2 \) norm of a vector is denoted as \( || \cdot ||_2 \).

II. SYSTEM MODEL

Consider a wireless cellular network in which each BS is equipped with \( M \) antennas and each user is equipped with a single antenna. The users are associated with the closest BS by distance. We assume that the user density is much larger than the BS density, so that each BS has many associated users. Among all its associated users, each BS schedules \( K < M \) users in each time slot. The ratio \( K/M \) is called the loading factor. We assume round-robin scheduling for simplicity. We assume flat-fading channels with full frequency reuse, i.e., transmissions from neighboring cells cause mutual interference to each other.

This paper aims to analyze the performance of network MIMO systems in which each user is jointly served by a cooperative cluster of BSs. In the disjoint clustering scheme, the set of BSs are partitioned into disjoint clusters; each user is served by the cluster of BSs to which its associated BS belongs. In user-centric clustering, each scheduled user forms an individually chosen cluster of serving BSs; the clusters for different users can partially overlap. Fig. 1 illustrates the disjoint and user-centric clustering topologies.

Let \( \Theta_i \) denote the cooperative cluster of serving BSs for user \( i \). Let \( B_i \) be the cluster size, i.e., \( B_i = |\Theta_i| \). Recall that each BS in \( \Theta_i \) schedules \( K \) of its associated users. We denote the set of all users scheduled by the BSs in user \( i \)'s serving cluster as \( \Omega_i \), so that \( |\Omega_i| = K B_i \). In the rest of the paper, user \( i \) is called the typical user. The other \( K B_i - 1 \) users in \( \Omega_i \) are called intra-cluster users of user \( i \). All the rest of the scheduled users in the network are termed inter-cluster users.

This paper assumes the use of ZFBF in both UL and DL, in which a beamformer for the typical user \( i \) is designed across its serving BSs in \( \Theta_i \) to null interference from/to all intra-cluster users. ZFBF is easy to implement; it performs well at high SNR. Further, the ZF assumption significantly simplifies the analysis, because the signal and the interference can be analyzed separately under ZFBF.

Below, we describe the ZFBF design in both UL and DL. The same design procedure applies to both disjoint and user-centric clustering—the only difference being the choice of cooperative BS cluster \( \Theta_i \) for each user \( i \). Throughout this paper, perfect channel state information (CSI) is assumed to be available for the purpose of beamformer design.

A. Uplink ZFBF

In uplink ZFBF, the message from the typical user \( i \) is jointly decoded across the BSs in \( \Theta_i \), while interference from
all intra-cluster users in $\Omega_i$ is nulled. Let $y_i \in \mathbb{C}^{MB_i}$ be the received signal across all the serving BSs of user $i$:

$$y_i = \sum_j h_{ij}x_j + z$$

$$= h_{i\text{signal}}x_i + \sum_{m: m \neq i, m \in \Omega_i} h_{im}x_m + \sum_{j \in \Omega_i \setminus \{i\}} h_{ij}x_j + z$$

where $h_{ij}^H = [\cdots g_{ij}^H \cdots] b \in \Theta_i$ denotes the collective vector channel between user $j$ and the set of serving BSs of user $i$, and $g_{ij} \in \mathbb{C}^H$ denotes the channel between user $j$ and BS $b$. Here, $x_j$ is the transmit signal of user $j$ with power normalized to 1, i.e., $\mathbb{E}[x_j^2] = 1$. Finally, $z \sim \mathcal{C}\mathcal{N}(0, \sigma_n^2 I_{MB_i})$ is the background noise at the BSs including thermal noise and other possible sources of interference and scaled to account for transmit power normalization.

The ZF receive beamformer for user $i$ is designed to be orthogonal to the transmission from the $KB_i - 1$ intra-cluster users, so that the interference from these users is completely eliminated. In particular, the normalized ZF receive beamformer for user $i$ is chosen to be the following:

$$w_i = \frac{(I_{MB_i} - H_{-i} H_{-i}^H) h_{ii}}{\| (I_{MB_i} - H_{-i} H_{-i}^H) h_{ii} \|_2},$$

where $H_{-i} = [\cdots h_{ij} \cdots]_{j \neq i, j \in \Omega_i}$ denotes the channel matrix between the serving BSs of user $i$ and its $KB_i - 1$ intra-cluster users. It is easy to see that the row space of the matrix $(I_{MB_i} - H_{-i} H_{-i}^H)$ is the left null space of $H_{-i}$. By projecting the direct channel $h_{ii}$ onto the left null space of $H_{-i}$, the signal power is maximized while the required orthogonality is guaranteed.

The signal-to-interference-and-noise ratio (SINR) of user $i$ can now be stated as follows:

$$\gamma_i = \frac{|w_i^H h_{ii}|^2}{\sum_{j \notin \Omega_i} |w_i^H h_{ij}|^2 + \sigma_n^2}.$$  

### III. User-Centric vs. Disjoint Clustering

The main objective of this paper is to provide a performance analysis of the user-centric network MIMO scheme in order to quantify its advantage as compared to baseline disjoint clustering. Toward this end, we first give some intuitive comparison of the signal and interference powers under the different clustering strategies, then provide a statistical model of network MIMO system in the next section.

#### A. Signal Power

In user-centric clustering, each user is always at the center of its serving BSs. Since the channel strength is a function of the distance, the signal power in the user-centric case is equivalent to that of a cluster-center user in disjoint clustering, and much larger than that of a cluster-edge user. Thus on average, user-centric clustering has an advantage in term of signal power as compared to disjoint clustering. This holds for both UL and DL.

#### B. UL Interference Power

In the UL, ZFBF receiver is designed to null interference from all intra-cluster users for both user-centric and disjoint clustering; in fact, the received vector of interference at the serving BSs in the two cases are the same. However, the interference powers in the user-centric and the disjoint clustering cases are not identical, because the interference power is the inner product of the interference vector and the receive beamformer, and the beamformers for the user-centric and disjoint cases are different. Nevertheless, this effect is relatively minor. Overall, since UL user-centric clustering gives stronger signal power and about the same amount of interference for all users, we expect uniform improvement in UL user rate as compared to disjoint clustering.

#### C. DL Interference Power

In the DL, the transmit ZF beamformer for the typical user is designed to be orthogonal to the channels to all its intra-cluster users. Thus, the transmission to the typical user only interferes with its inter-cluster users. Conversely, the interference at the
typical user comes only from transmission to the users for whom the typical user is an inter-cluster user. This observation gives distinct interference characteristics for disjoint and user-centric clustering.

Under baseline disjoint clustering, since all users within the cluster are served by the same set of BSs, the interference at any of the users comes only from BSs outside of the cluster. In particular, cluster-edge users see strong interference, while cluster-center users see less interference.

Under user-centric clustering, the serving BSs of the typical user can overlap with the serving BSs of the interfering users. Thus, the interference at the typical user can come from not only BSs outside of its serving cluster, but also from within the user’s own serving cluster of BSs. As a consequence, a typical user in user-centric clustering sees more interference than the cluster-center users in disjoint clustering; but it sees less interference than cluster-edge users in disjoint clustering. Putting it another way, as compared to baseline disjoint clustering, user-centric clustering reduces interference for cluster-edge users at the expense of cluster-center users.

To summarize, DL user-centric clustering improves the cluster-edge user rate in baseline disjoint clustering, because it both improves the signal power and reduces interference. However, the effect of user-centric clustering for cluster-center users is not so clear cut, as both signal and interference powers are increased.

IV. STOCHASTIC NETWORK MODEL

In order to provide an analytic performance characterization of network MIMO systems, this paper proposes a statistical model of cellular networks accounting for both the random geographic locations of the BSs and the users, as well as the random fluctuation of the channels, i.e., fading.

The channel from BS $b$ to user $i$ is modeled as $g_{bi} = \sqrt{\beta_{bi}}f_{bi} \in \mathbb{C}^{M \times 1}$. The distance-dependent path-loss component is modeled as $\beta_{bi} = (1 + r_{bi}/d_0)^{-\alpha}$, where $r_{bi}$ is the distance between the BS $b$ and user $i$, $d_0$ is a reference distance, and $\alpha$ is the path-loss exponent. The Rayleigh fading component is modeled as $f_{bi} \sim \mathcal{CN}(0, I_M)$.

We use tools from stochastic geometry to account for the path-loss and use a Gamma distribution approximation to analyze the overall performance. To facilitate the analysis, we make the following further assumptions:

1) The BSs are randomly placed over a two-dimensional (2D) plane as a homogenous Poisson Point Process (PPP) with a fixed intensity $\lambda_b$, denoted as $\Phi_b$. The PPP model allows us to derive expressions of system performance by averaging over the random BS locations using tools from stochastic geometry. The PPP model also accounts for the randomness of BS deployment in practice. The validity of the PPP model for performance analysis of cellular networks have been discussed in the literature (see e.g., [13]).

2) The users are also randomly placed in the 2D plane as a PPP. In our model, the users are associated with the closest BS; each BS schedules $K$ active users from the set of associated users. Technically the active users no longer form a PPP. But to enable the averaging over user locations, we further approximate that the active users form a PPP, $\Phi_u$, with intensity $\lambda_u = K\lambda_b$.

3) In user-centric clustering, each user chooses its BS cooperation cluster based on the distance between the BSs and the users. In particular, the user $i$’s BS cooperation cluster $\Theta_i = \Phi_b \cap \mathcal{B}_{x_i}(R)$, where $\mathcal{B}_{x_i}(R)$ denotes a unit circle of radius $R$ centered at user $i$ whose location is denoted as $x_u$.

4) In baseline disjoint clustering, we partition the 2D plane using a hexagonal lattice; the BSs located within each hexagon form a cluster. In the analysis of disjoint clustering, the hexagon shape is further approximated by a circular disk of equal area.

5) ZFBF is used in both uplink and downlink to serve the target user, while cancelling interference from and to the $KB - 1$ users scheduled by the $B_i$ BSs in the cooperating cluster. Nulling the interference for these intra-cluster users is intuitively a good design since they are in close proximity to the typical user. We do not perform power control in either uplink or downlink. In the uplink, all users transmit at a fixed power; in the downlink, each downlink beam transmits at a fixed power. This power allocation model does not guarantee per-BS power constraint, but accounting for per-BS power would make analysis much more complicated.

6) In computing interference for the typical user at the origin in the user-centric clustering case as well as for any user in disjoint clustering, we further assume that the interfering users are simply all users located outside of a circular area of radius $R$. This is an approximation, e.g., in the downlink it assumes that the users for whom the target user is its inter-cluster user are exactly ones further than distance $R$. The approximation is accurate when the cluster size is much larger than the coverage size of each BS. With this approximation, in the uplink, the interfering users are located outside of $\Phi_u \cap \mathcal{B}_{o}(R)$. In the downlink, the interfering signals are the beamformed signals from the serving cluster of BSs for users outside of $\Phi_u \cap \mathcal{B}_{o}(R)$. Note that the serving cluster can overlap with the serving BSs of the typical user.

Note that in the BS clustering scheme described above, the number of BSs in the cooperating cluster is not a constant, but a Poisson random variable. The later simulation part of the paper examines the effect of having random rather than fixed number of cooperating BSs in the cluster.

These modeling assumptions are made for the purpose of deriving efficiently computable achievable rate expressions for network MIMO systems. These assumptions have been used in [21] for deriving the ergodic rate of the DL network MIMO system with disjoint clustering. This paper extends the analysis to the UL and in particular to the user-centric cases.

V. STOCHASTIC ANALYSIS OF ERGODIC USER RATE FOR USER-CENTRIC NETWORK MIMO

In a stochastic model of the user-centric network MIMO system with uniformly random deployment of BSs and users,
the users are all essentially statistically identical. In this section, we focus on a typical user indexed as user 1, centered at the origin. We first derive distributions of signal and interference powers for a given realization of BS and user locations. We then obtain an ergodic rate expression by averaging over the BS and user location PPPs. The techniques used here are due to [21], where the DL disjoint case is analyzed. The analysis here accounts for the different channel topology and interference characteristics of user-centric cooperation.

A. Analysis of Uplink

1) Signal Strength: The channel strength of the intended signal for the typical user is:

$$\|h_{11}\|^2 = \sum_{b \in \Theta_1} g_{1b}^H g_{1b} = \sum_{b \in \Theta_1} \beta_{b1} f_{b1}^H f_{b1} \sim \sum_{b \in \Theta_1} \Gamma(M, \beta_{b1}).$$

Since the entries of the MIMO channels are Gaussian distributed, the overall magnitude of the channel between the typical user and its set of cooperating BSs is a sum of Gamma random variables with different scale parameters depending on the distances between the user and the BSs. We proceed to approximate the above distribution into a form amenable to stochastic geometry analysis. The series of approximations below are developed in part in the analysis in [19], [20], [21].

The analysis first uses a technique pioneered in [19] for approximating the sum of Gamma distributions as a single Gamma distribution with shape and scale parameters determined by matching the first and second moments.

Lemma 1: Let $Y_i \sim \Gamma(k_i, \theta_i), i = 1 \cdots n$ be independent Gamma distributed with different shape and scale parameters $k_i$ and $\theta_i$, respectively. Consider $Y = \sum_i Y_i$, then $Y$ has the same first and second moments as a Gamma random variable $\Gamma(k, \theta)$ with shape and scale parameters

$$k = \frac{\sum_{i=1}^n k_i \theta_i^2}{\sum_{i=1}^n k_i \theta_i^2}, \quad \theta = \frac{\sum_{i=1}^n k_i \theta_i^2}{\sum_{i=1}^n k_i \theta_i^2}.$$

For the channel $\|h_{11}\|^2$ in (7), this approximation leads to $\|h_{11}\|^2 \sim \Gamma(k_1, \theta_1)$ with

$$k_1 = M \frac{\left(\sum_{b \in \Theta_1} \beta_{b1}\right)^2}{\sum_{b \in \Theta_1} \beta_{b1}^2}, \quad \theta_1 = \frac{\sum_{b \in \Theta_1} \beta_{b1}^2}{\sum_{b \in \Theta_1} \beta_{b1}^2}.$$

To obtain signal power, we need to further project the channel vector onto the beamforming vector. The exact signal power distribution resulting from such a projection is not easy to characterize. Instead, we adopt a second approximation by drawing a parallel with the following fact on the projection of an isotropic channel vector to a lower dimensional space (although our actual channel is not isotropic).

If a channel vector $h \in \mathbb{C}^N$ were isotropic in the $N$-dimensional space such that $\|h\|^2 \sim \Gamma(N, \theta)$, then the projection of $h$ onto a $P$-dimensional subspace results in a Gamma distribution $\Gamma(P, \theta)$. In other words, the shape parameter is scaled by $P/N$, while the scale parameter is kept the same.

To obtain an approximate signal power distribution after the projection, we apply the same scaling of the shape parameter even when the channel is non-isotropic. This same approximation technique is also used in [20], [21]. Specifically in our case, $\|h_{11}\|^2 \sim \Gamma(k_1, \theta_1)$. To project the channel vector onto the ZF beamforming vector, we note that the receive beam of the user lies in the null space of the subspace spanned by the $KB_1 - 1$ interfering channel vectors. Therefore, the shape parameter for the signal power after projection must be scaled by $MB_1 - KB_1$. The signal power distribution can therefore be approximated as:

$$\nu_{11}^{(UL)} = |w_1^H h_{11}|^2 \sim \Gamma\left(\frac{MB_1 - KB_1 + 1}{MB_1} k_1, \theta_1\right).$$

Recall that the number of BSs in the cluster $B_1$ is a Poisson random variable with mean $\bar{B} = \lambda_0 \pi R^2$. To make the analysis tractable, we replace $B_1$ by its mean $\bar{B}$ as a further approximation.

Finally, the distribution above has parameters that depend on the BS location. To facilitate a stochastic geometry analysis, we decompose the above signal distribution as a linear combination of independent Gamma distributions. Using again the technique of matching the first and second moments matching, the signal power can now be approximated as follows [21]:

$$\nu_{11}^{(UL)} = |w_1^H h_{11}|^2 \approx \sum_{b \in \Theta_1} \beta_{b1} G_{b1}^{(\pi)}$$

where $G_{b1}^{(\pi)}$ are i.i.d. random variables distributed as $\Gamma(\pi, 1)$, where $\pi = MB_1 - KB_1 + 1$. Here, we also use the fact that if $X \sim \Gamma(\kappa, \theta)$, then $cX \sim \Gamma(\kappa, c\theta)$ for any positive $c$.

2) Interference Strength: As intra-cluster interference is eliminated with ZF receiver, the residual interference only comes from inter-cluster users. In deriving the distribution of aggregate interference, we first investigate the interference from a single user $j$, then sum up the interference over all interfering users.

Similar to the analysis of [20], the interfering channel strength can also be approximated as a Gamma random variable using the moment matching technique as follows:

$$\|h_{1j}\|^2 = \sum_{b \in \Theta_j} g_{1j}^H g_{1j} \sim \sum_{b \in \Theta_j} \Gamma(M, \beta_{bj}) \sim \Gamma(k_{1j}, \theta_{1j}),$$

where

$$k_{1j} = M \frac{\left(\sum_{b \in \Theta_j} \beta_{bj}\right)^2}{\sum_{b \in \Theta_j} \beta_{bj}^2}, \quad \theta_{1j} = \frac{\sum_{b \in \Theta_j} \beta_{bj}^2}{\sum_{b \in \Theta_j} \beta_{bj}^2}.$$

To project the interference signal onto the receive beamformer $w_1$, (which is a one-dimensional subspace independent of the interfering channel vector $h_{1j}$ of dimension $MB_1$), we again approximate the channel vector as isotropic. The projection then results in the scaling of the shape parameter of the interference as $\frac{k_{1j}}{MB_1}$. Finally, we replace $B_1$ by its mean $\bar{B}$, then decompose the interference into linear combination of independent Gamma distributions again using the moment matching technique as:

$$\nu_{1j}^{(UL)} = |w_1^H h_{1j}|^2 \approx \sum_{b \in \Theta_j} \beta_{bj} G_{bj}^{(\pi)},$$

where $G_{bj}^{(\pi)}$ are i.i.d. $\Gamma\left(\frac{1}{\bar{B}}, 1\right)$ distributed.
The aggregate residual interference is the sum of interference from all interfering users:

\[ \nu_1^{(UL)} = \sum_{j \notin \Omega_1} v_{ij} \approx \sum_{j \notin \Omega_1} \sum_{b \in \Theta_1} \beta_{bj} G_{bj}^{(UL)}. \]  

(15)

3) Ergodic Rate: The ergodic rate of the typical user in the UL user-centric network MIMO system can now be derived using tools from stochastic geometry by using the signal and interference power distributions (11) and (15) with further approximations that the cooperation cluster for the typical user is \( \Theta_1 = \Phi_b \cap B_o(R) \) and the interfering users are located in \( \Phi_u \setminus B_o(R) \). The achievable rate of the user is computed as \( \log(1 + \text{SINR}) \). By utilizing the following expression of the log function in term of integral [31] Lemma 1

\[ \ln(1 + x) = \int_0^\infty \frac{e^{-sz}}{z}(1 - e^{-xz})dz, \]  

(16)

the ergodic rate averaged over the distributions of \( \Phi_b \) and \( \Phi_u \), can be obtained as follows [31]:

\[ \bar{C}_U = \int_0^\infty \frac{e^{-s\sigma^2}}{s} L_{\zeta_1^{(UL)}}(s) \left( 1 - L_{\zeta_1^{(UL)}}(s) \right) ds, \]  

(17)

where \( L_{\zeta_1^{(UL)}}(s) \), \( L_{\zeta_1^{(UL)}}(s) \) are respectively the Laplace transforms of signal and interference power distributions arising from Poisson distributed antenna ports in disjoint regions, as expressed in (19) below and in (19) at the top of the next page:

\[ L_{\zeta_1^{(UL)}}(s) = E_{h,\Phi_b} \left[ \exp \left( -s\zeta_1^{(UL)} \right) \right] \]

\[ = E_{h,\Phi_b} \left[ \prod_{x_b \in \Phi_b \cap B_o(R)} \exp \left( -s\beta_{x_b,u} G_{x_b,u}^{(UL)} \right) \right] \]

(a) \[ = \mathbb{E}_{\Phi_b} \left[ \prod_{x_b \in \Phi_b \cap B_o(R)} \mathbb{E}_h \left[ \exp \left( -s\beta_{x_b,u} G_{x_b,u}^{(UL)} \right) \right] \right] \]

(b) \[ = \mathbb{E}_{\Phi_b} \left[ \prod_{x_b \in \Phi_b \cap B_o(R)} \left( 1 + s\beta_{x_b,u} \right)^{-\infty} \right] \]

(c) \[ = \exp \left( -\lambda_b \int_{x \in B_o(R)} \left( 1 - (1 + s\beta_{x,u})^{-\infty} \right) dx \right) \]

\[ = \exp \left( -2\pi \lambda_b \int_0^R \left( 1 - \left( 1 + s \left( 1 + \frac{r}{d_0} \right)^{-\alpha} \right)^{-\infty} \right) dr \right). \]  

(18)

where (a) comes from the independence of fading and BS location, (b) is based on the Laplace transform of Gamma random variables, (c) follows from the probability generating functional (p.g.fl.) of a PPP [32]. Here, we use \( \beta_{x,u} \) to denote the path-loss component between a BS located at \( x_b \) and the typical user located at the origin, \( \beta_{x,u} = (1 + \frac{|x_b - x_u|}{d_0})^{-\alpha} \). Likewise, \( e_{x,u}^{(\infty)} \) denotes the i.i.d. random variable with \( \Gamma(\infty,1) \) distribution.

In (19), the integration is over the 2D plane outside of the disk \( B_o(R) \) as illustrated in Fig. (a). The integral involves the hypergeometric function \( _2F_1(\cdot) \). Again, (a) comes from the independence of fading, BS and user location; (b) is based on the Laplace transform of Gamma random variables; (c) and (d) follow from the probability generating functional (p.g.fl.) of a PPP [32]. Here, \( \beta_{x,u} = (1 + \frac{|x_b - x_u|}{d_0})^{-\alpha} \), \( G_{x_b,u}^{(UL)} \) are i.i.d. \( \Gamma(\infty,1) \) distributed.

Note that we have made an implicit assumption that the signal power and interference power distributions are independent. Although strictly speaking correlation between signal and interference power distribution exists, since both depend on the BS and user locations, the effect of such an approximation is expected to be minor.

B. Analysis of Downlink

Examining the SINR expressions (3) and (6), it is clear that the signal component of the typical user has the same form in DL as in UL. Thus, the signal distribution in DL is the same as that in UL i.e., as in (11).

\[ \zeta_1^{(DL)} = \sum_{b \in \Theta_1} \beta_{b1} G_{b1}^{(p)}. \]  

(20)

The analysis of the interference is more complicated, but it turns out that the UL and DL interference distributions have approximately the same expression. Consider a user \( j \) for whom the typical user is its inter-cluster user. A careful observation reveals that the DL interference that is received...
by the typical user and is due to the transmission to user $j$, i.e.,
\[ \nu_{1j}^{(DL)} = | h_{j}^H w_{j} |^2 \approx \sum_{b \in \Theta_{j}} \beta_{b1} G_{b1}^{(\Phi)} \] (21)

has the same form as the corresponding UL interference generated by user $j$ and received at the typical user’s cooperating BS cluster, so it has the same approximate distribution as $\nu_1^{(UL)}$ in the uplink case.

The reason for this equivalence of UL and DL interference is illustrated in Fig. [3]. The UL interference from user $j$ to the serving BSs of the typical user in the UL is the projection of the UL vector channel onto the typical user’s receive beamformer. The DL interference at the typical user due to user $j$’s transmission is the projection of the DL vector channel onto user $j$’s transmit beamformer. The UL and DL vector channels have the same statistical distribution because of the symmetry of the channels and uplink-downlink reciprocity. The two channels involve the same path-loss component between a user and a neighboring user’s serving BSs as illustrated in Fig. [3]. The UL and DL beamforming vectors also have the same distribution. Therefore, the overall UL and DL interference distributions are the same.

The aggregate interference of the typical user in DL is the summation of interference from all the BSs serving the interfering users:
\[ \nu_1^{(DL)} = \sum_{j: 1 \not\in \Omega_{j}} \nu_{1j}^{(DL)} = \sum_{j: 1 \not\in \Omega_{j}} \sum_{b \in \Theta_{j}} \beta_{b1} G_{b1}^{(\Phi)}. \] (22)

When the user and BS locations are distributed as PPPs, and if we assume that the interfering users are simply ones outside of the circle with radius $R$, the aggregate DL interference at the typical user due to the transmission for all DL interfering users must also have the same distribution as the aggregate UL interference received by the typical user’s serving BSs due to the transmissions by all UL interfering users.

Finally, as both the signal and interference in the UL and DL have the same distributions, so must their Laplace transforms. Consequently, the ergodic rate of the typical user in DL must have the same expression as the ergodic rate of the typical user in UL, as obtained by plugging (18) and (19) into (17).

The only difference is that the normalized background noise variance $\sigma_n^2$ in UL should be replaced by $\sigma_d^2$ in DL, accounting for the difference in transmit power budgets in the UL and DL.

VI. STOCHASTIC ANALYSIS OF DISJOINT CLUSTERING

One of the goals of this paper is to compare user-centric clustering with baseline disjoint clustering. Toward this end, we derive in this section a stochastic analysis of disjoint clustering. In our model of baseline disjoint clustering, the
network is partitioned into hexagonal regions; BSs within the hexagon form cooperative clusters. The hexagon is further approximated as a circle with the same area to facilitate analysis. To make comparison with user-centric clustering, we set the cluster radius \( R \) to be the same in both cases.

We follow the same methodology for analysis as in the previous section. In fact, the analysis of DL disjoint clustering has already been carried out in [21]; the main contribution of this section is the corresponding UL analysis. For both UL and DL, the main difference between disjoint and user-centric clustering is that the serving BSs are no longer symmetrically centered around the user. Thus, the analysis needs to be modified in two respects. First, the computation of achievable rate for a user depends on its location; it requires a careful analysis of the distribution of the channel strengths from the serving BSs. Second, because the rates are location dependent, average rate is no longer necessarily an adequate measure. Cluster-edge performance is of equal, if not more, importance.

We use \( C_D (d) \) to denote the ergodic rate of a user whose distance to the cluster center is \( d \). The average user rate under disjoint clustering can be derived as

\[
C_D = \int_0^R f (d) C_D (d) \, dd, \tag{23}
\]

where \( f (d) \) is the probability density function of the distance \( d \) of the given user. Assume that users are uniformly distributed within the circle with radius \( R \), then \( f (d) = \frac{2d}{\pi R^2} \). It remains to find \( C_D (d) \) in both UL and DL.

### A. Ergodic Rate of Location-Specific User in the UL

Without loss of generality, we consider the ergodic rate of a location-specific user, user \( i \), in the cluster centered at the origin, located at \( x_0 \) with distance \( |x_0| = d \) from the origin. In the UL, the signal power depends on the distance between the user and its serving BSs. Using the same idea as in the user-centric case, the signal power can be approximated as a summation of Gamma random variables over the locations of its serving BSs as follows:

\[
\zeta_i^{(UL)} = \sum_{x_k \in \Phi_b \cap B_x (R)} \beta_{x_k, x_0} \xi(x_k, x_0)^{\alpha}. \tag{24}
\]

The derivation of the above result is similar to the analysis of signal power in the user-centric case in [11]; the key difference is that user-location specific distances need to be accounted for.

As far as interference is concerned, it is not difficult to see that the UL interference for the user-centric and the disjoint clustering cases have identical distributions, i.e., as expressed in [13].

Thus, the ergodic rate of a location-specific user can be derived as follows [31],

\[
C_D (d) = \int_0^\infty e^{-s \sigma^2} \mathbb{E}_{h, \Phi_b} \left[ \exp \left( -s \zeta_i^{(UL)} \right) \right] \, ds, \tag{25}
\]

where \( L_{\zeta_i^{(UL)}} (s) = \mathbb{E}_{h, \Phi_b} \left[ \exp \left( -s \zeta_i^{(UL)} \right) \right] \) is the Laplace transform of the signal distribution as

\[
L_{\zeta_i^{(UL)}} (s) = \mathbb{E}_{h, \Phi_b} \left[ \prod_{x_k \in \Phi_b \cap B_x (R)} \exp \left( -s \beta x_k, x_0 G(x_k, x_0)^{\alpha} \right) \right], \tag{26}
\]

\[
L_{\zeta_i^{(DL)}} (s) = \mathbb{E}_{h, \Phi_b} \left[ \prod_{x_k \in \Phi_b \cap B_x (R)} \exp \left( -s \beta x_k, x_0 G(x_k, x_0) \right) \right]. \tag{27}
\]

The difference between this interference expression and the interference distribution in the other cases, i.e., [13], reflects the different interfering paths in this disjoint DL case. A detailed derivation of this result is available in [21]. The Laplace transform of the distribution in [27] can be expressed as follows:

\[
L_{\zeta_i^{(DL)}} (s) = \mathbb{E}_{h, \Phi_b} \left[ \exp \left( -s \nu_i^{(DL)} \right) \right] \tag{28}
\]

where \( \nu_i^{(DL)} = \sum_{x_k \in \Phi_b \cap B_x (R)} \beta_{x_k, x_0} G^{(K)}(x_k, x_0) \) is i.i.d. distributed as \( \Gamma (K, 1) \).

We see that the interference is the summation of the path-loss component from all the out-of-cluster BSs to the location-specific user, multiplied by a Gamma random variable of shape parameter \( K \). The difference between this interference expression and the interference distribution in the other three cases, i.e., [13], reflects the different interfering paths in this disjoint DL case. A detailed derivation of this result is available in [21].
Finally, the ergodic rate of the location-specific user is obtained by substituting $L_{\xi_i}^{(UL)}(s)$ and $L_{\epsilon_i}^{(UL)}(s)$ in (25) with (26) and (28).

### VII. Analytic Comparison of User-Centric and Baseline Disjoint Clustering

The analytic results on the signal and interference distribution derived in the previous section are summarized in Table I. These analytic results illustrate the advantage of user-centric clustering as compared to disjoint clustering.

For the received signal power distribution, we see that in both the user-centric and disjoint clustering, the received signal power is a linear combination of Gamma random distributions of the same parameter, but the coefficients of linear combination differ. This is due to the fact that the user is located at the center of the cluster in the user-centric case, so its serving BSs are located symmetrically around the user, while in the disjoint case the analysis of path-losses from the serving BSs is a function of the user location’s distance $d$ from the cluster center. Thus, user-centric clustering has benefit in term of signal power. This applies to both UL and DL, (in fact UL and DL powers have the same distribution).

For the interference power distribution, first we see that the UL user-centric and disjoint cases have the same distribution. For the DL, although the DL interference in the user-centric case has a different form as in UL, its distribution actually turns out to be identical. The only case where the interference distribution is different is the DL disjoint case. Here, the Gamma random variable has a different shape parameter. Interestingly, the coefficients of linear combination in the DL disjoint case involves only BSs outside of the cluster, while in the DL user-centric case it involves BSs inside the cluster as well. In fact, the DL interference is improved in the user-centric case as compared to the disjoint case for cluster-edge users (where $d$ is large), but is worsened for cluster-center users (where $d$ is small).

As consequence, user-centric clustering is expected to outperform disjoint clustering uniformly in the UL, but in the DL, the main advantage of user-centric clustering is for cluster-edge users.

|                  | Signal Distribution                                                                 | Interference Distribution                                                                 |
|------------------|-------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| User-centric     | $\sum_{x_b \in \Phi_b \cap B_o(R)} \beta_{x_b,0} G_{x_b,0}^{(w)}$                  | $\sum_{x_u \in \Phi_u \cap B_o(R)} \sum_{x_b \in \Phi_b \cap B_o(R)} \beta_{x_b,0} G_{x_b,u}^{(w)}$ |
| Downlink         | $\sum_{x_b \in \Phi_b \cap B_o(R)} \beta_{x_b,0} x_b G_{x_b,0}^{(w)}$              | $\sum_{x_u \in \Phi_u \cap B_o(R)} \sum_{x_b \in \Phi_b \cap B_o(R)} \beta_{x_b,0} x_b G_{x_b,u}^{(w)}$ |
| Disjoint         | $\sum_{x_b \in \Phi_b \cap B_o(R)} \beta_{x_b,0} G_{x_b,0}^{(w)}$                  | $\sum_{x_u \in \Phi_u \cap B_o(R)} \sum_{x_b \in \Phi_b \cap B_o(R)} \beta_{x_b,0} G_{x_b,u}^{(w)}$ |

#### Table I

The signal and interference distributions in the UL and DL under user-centric and disjoint clustering.

![Fig. 4. A stochastic model of cellular networks where the BSs and the users are distributed as a Poisson process.](image)

**VIII. Numerical Comparison of User-Centric and Baseline Disjoint Clustering**

This section provides numerical results to validate the analysis developed in this paper. We consider a stochastic deployment of BSs in a cellular network as shown in Fig. 4. Each BS is equipped with 4 antennas and schedules 2 single-antenna users (in a round-robin fashion) within its Voronoi cell, i.e., $M = 4$, $K = 2$, with loading factor 0.5. The power of the transmit beam for each user in the DL is set to be 40 dBm over 20MHz bandwidth. The transmit power of each user in UL is 23dBm over 20MHz. Power spectrum density of the background noise is set to -174dBm/Hz; a noise figure of 9dB and an SINR gap of 3dB are included. We use a path-loss model of $128.1 + 37.6 \log(d)$ in dB, where $d$ is expressed in km. This corresponds to a path-loss exponent of 3.76 with reference distance $d_0$ approximately equal to 0.3920m.

**A. Signal and Interference Power Distributions**

We first validate the qualitative comparison of signal and interference power by plotting their distributions for both UL and DL for a fixed scenario with average cluster size of 6 BSs. Fig. 5 shows the signal power distributions of the user-centric vs. disjoint clustering from simulation. The signal power in DL...
Fig. 5. Comparison of UL and DL signal power: User-centric vs. disjoint clustering

Fig. 6. Comparison of UL and DL interference power: User-centric vs. disjoint clustering

is larger than UL due to the larger DL transmission power. The benefit of user-centric clustering is clearly shown, especially for the cluster edge users.

Fig. 6 shows that interference power distributions in user-centric clustering as compared to disjoint clustering. We see that the two cases are nearly identical in the UL. In the DL, the interference power in the user-centric case is smaller than the disjoint case for cluster-edge users (i.e., users with strong interference), but stronger for cluster-center users (i.e., users with weak interference). This agrees with the analytic comparison. User-centric clustering improves the cluster-edge user performance at slight expense of cluster-center users.

B. Ergodic Rate

Next we investigate the ergodic rate of the typical user in both UL and DL as a function of cluster size. Figs. 7 and 8 show respectively the UL and DL ergodic user rates evaluated from the analytical expressions as well as obtained from system-level simulation for both user-centric and disjoint clustering cases. The horizontal axis is the average number of serving BSs in the typical user’s cluster, i.e., \( \bar{B} \), which is a measure of cluster size. Recall that the analytic expressions developed in this paper are based on a fixed cooperation cluster radius \( R \). As BSs are modeled as PPP, the number of BSs within the cluster is a Poisson random variable. Practical implementation of network MIMO system would likely have fixed number of BSs in the cooperation cluster. For numerical comparison, we thus include both the simulation results with Poisson number of BSs as well as the case with fixed number of exactly \( \bar{B} \) BSs in the cooperation cluster. Finally, the single-cell processing baseline case is also included, where BSs do not cooperate and each user is served by its nearest BS.

First, we observe that the analytical results for the ergodic sum rate match with the simulation within an error of about 5%, which is remarkable given the number of approximations involved in modeling both the signal and interference. We also see that the Poisson assumption gives reasonable ergodic rate estimates as compared to the case where the number of BSs in the cluster is fixed. The cases with fixed number of BSs vs. Poisson number of BSs are expected to converge when \( \bar{B} \) is large. The simulations show that even at small \( \bar{B} \), the two are fairly close.

We make the following observations on the ergodic rate performance of user-centric network MIMO systems:

- The ergodic rate increases as the cluster size grows for both UL and DL and for both user-centric and disjoint clustering cases. But larger cluster benefits in DL more than UL. This is because DL transmit power is larger, so it is more interference limited than UL. Consequently, interference mitigation brings more improvement to the DL.

- User-centric clustering achieves higher ergodic rate than disjoint clustering for both UL and DL. The benefit of user-centric cluster in UL is about 15-20%, and in DL only about 5%. The main advantage of user-centric clustering is the enhanced signal power, because user-centric clustering puts every user at the center of the BS cooperation cluster. Also, as compared to disjoint clustering, user-centric cooperation reduces interference uniformly for the UL. But in DL, user-centric clustering reduces interference for cluster-edge users only, and may actually increase interference for cluster-center users. Thus, in term of average rate, the benefit of user-centric clustering mainly occurs in the UL.

C. Distribution of Rates

Although user-centric clustering brings in more average rate improvement in the UL, it does provide significant improvement to cluster-edge performance in DL. This is evident from the simulation results of the cumulative distribution function (CDF) shown in Figs. 9 and 10.

In the CDF curve for the UL case shown in Fig. 9, we see that the user-centric CDF curves are always to the right of
the disjoint CDF curves. This is consistent with our analysis: user-centric clustering improves the performance of every user regardless of the location.

In the CDF curve for the DL case shown in Fig. 10, we see that the performance of low-rate users (corresponding to the cluster-edge users in the disjoint clustering case) is significantly improved, while the performance of high-rate users is actually reduced under user-centric clustering. This also confirms our analysis: user-centric clustering improves signal power and reduces inter-cluster interference for cluster-edge users, while creating additional intra-cluster interference for cluster-center users.

It should be noted that the improvement for cluster-edge users for DL user-centric clustering is significant. The 10-percentile user rate performance is improved by a factor of three or more at $\bar{B} = 10$. Given the importance of low-rate user performance to the cellular service providers, this provides strong justification for the user-centric architecture.

D. Asymptotic Performance

To obtain a better understanding of the role of BS cooperation, Figs. 11 and 12 plot the analytic ergodic rate expression for user-centric and disjoint clustering in the limit as the number of BSs in the cluster goes to infinity. (For large cluster size, simulation would not have been computationally feasible to do.) The results show:

- BS cooperation brings more improvement in the DL as compared to UL as compared to single-cell processing. Cluster size of $\bar{B} = 10$ achieves 20% gain in UL and 40% in DL. Cluster size of $\bar{B} = 100$ achieves 60% gain
in UL and 150% in DL. The difference is due to the fact that DL is more interference limited than UL.

- User-centric clustering always outperforms disjoint clustering in the UL, but the gap between the two narrows at large cluster size. In the DL, user-centric clustering does not have a significant benefit in term of ergodic rate as compared to disjoint clustering; (the main advantage of DL user-centric clustering is for cluster-edge performance.)
- Even as cluster size goes to infinity (which is clearly not realistic, given the amount of backhaul signalling that would require), the analytic performance of network MIMO system with either user-centric or disjoint clustering derived in this paper does not approach that of an isolated cell. Thus, there is significant signalling cost to BS cooperation (at least with ZFBF), even before additional overhead, e.g., CSI acquisition cost, is taken into account.

IX. Conclusion

This paper analyzes the system performance of network MIMO system with zero-forcing beamforming across multiple BSs, with either user-centric and disjoint BS clustering, for both DL and UL. Using tools from stochastic geometry and by approximating the channel and interference power distributions, we derive tractable analytical expressions of ergodic rate and reveal the benefit of cooperation in different cases. This paper shows that as compared to the baseline naïve disjoint clustering strategy, user-centric clustering brings advantage to cluster-edge users in DL network MIMO systems, while improving user rates uniformly in the UL. The analytic techniques developed in this paper provide useful insight to the design of future cooperative wireless cellular communication networks.

REFERENCES

[1] M. K. Karakayali, G. J. Foschini, and R. Valenzuela, “Network coordination for spectrally efficient communications in cellular systems,” IEEE Wireless Commun., vol. 13, no. 4, pp. 56–61, Aug. 2006.
[2] O. Somekh, B. M. Zaidel, and S. Shamai, “Sum rate characterization of joint multiple cell-site processing,” IEEE Trans. Inf. Theory, vol. 53, no. 12, pp. 4473–4497, 2007.
[3] S. Jing, D. N. Tse, J. B. Soriaga, J. Hou, J. E. Smee, and R. Padovani, “Multicell downlink capacity with coordinated processing,” EURASIP J. Wireless Commun. and Netw., vol. 2008, p. 18, 2008.
[4] H. Huang, M. Trivellato, A. Hotrinen, M. Shafi, P. J. Smith, and R. Valenzuela, “Increasing downlink cellular throughput with limited network MIMO coordination,” IEEE Trans. Wireless Commun., vol. 8, no. 6, pp. 2983–2989, 2009.
[5] J. Zhang, R. Chen, J. G. Andrews, A. Ghosh, and R. W. Heath Jr, “Networked MIMO with clustered linear precoding,” IEEE Trans. Wireless Commun., vol. 8, no. 4, pp. 1910–1921, Apr. 2009.
[6] Z. Jiang, S. Zhou, and Z. Niu, “Capacity bounds of downlink network MIMO systems with inter-cluster interference,” in IEEE Global Commun. Conf. (GLOBECOM), 2012, pp. 4612–4617.
[7] A. Papadogiannis, D. Gesbert, and E. Hardouin, “A dynamic clustering approach in wireless networks with multi-cell cooperative processing,” in IEEE Int. Conf. Commun. (ICC), 2008, pp. 4033–4037.
[8] C. T. Ng and H. Huang, “Linear precoding in cooperative MIMO cellular networks with limited coordination clusters,” IEEE J. Sel. Areas Commun., vol. 28, no. 9, pp. 1446–1454, Dec. 2010.
[9] B. Dai and W. Yu, “Sparse beamforming and user-centric clustering for downlink cloud radio access network,” IEEE Access, vol. 2, pp. 1326–1339, Nov. 2014.
[10] D. Su and C. Yang, “User-centric downlink cooperative transmission with orthogonal beamforming based limited feedback,” IEEE Trans. Commun., vol. PP, no. 99, pp. 1–1, 2015.
[11] A. M. Tulino and S. Verdú, “Random matrix theory and wireless communications,” Foundations Trends Commun. Inf. Theory, vol. 1, no. 1, pp. 1–182, 2004.
[12] H. Hub, A. M. Tulino, and G. Caire, “Network MIMO with linear zero-forcing beamforming: Large system analysis, impact of channel estimation, and reduced-complexity scheduling,” IEEE Trans. Inf. Theory, vol. 58, no. 5, pp. 2911–2934, 2012.
[13] J. G. Andrews, F. Baccelli, and R. K. Ganti, “A tractable approach to coverage and rate in cellular networks,” IEEE Trans. Commun., vol. 59, no. 11, pp. 3122–3134, Nov. 2011.
[14] T. D. Novlan, H. S. Dhillon, and J. G. Andrews, “Analytical modeling of uplink cellular networks,” IEEE Trans. Wireless Commun., vol. 12, no. 6, pp. 2669–2679, June 2013.
[15] R. Tanbourgi, S. Singh, J. G. Andrews, and F. K. Jondral, “A tractable model for noncoherent joint-transmission base station cooperation,” IEEE Trans. Wireless Commun., vol. 13, no. 8, pp. 4959–4973, 2014.
[16] V. Garcia, Y. Zhou, and J. Shi, “Coordinated multipoint transmission in dense cellular networks with user-centric adaptive clustering,” IEEE Trans. Wireless Commun., vol. 13, no. 8, pp. 4297–4308, 2014.
[17] G. Nigam, P. Minero, and M. Haenggi, “Coordinated multipoint joint transmission in heterogeneous networks,” IEEE Trans. Commun., vol. 62, no. 11, pp. 4134–4146, Nov. 2014.

[18] A. H. Sakr and E. Hossain, “Location-aware cross-tier coordinated multipoint transmission in two-tier cellular networks,” IEEE Trans. Wireless Commun., vol. 13, no. 11, pp. 6311–6325, 2014.

[19] R. W. Heath Jr, T. Wu, Y. H. Kwon, and A. C. Soong, “Multiuser MIMO in distributed antenna systems with out-of-cell interference,” IEEE Trans. Signal Process., vol. 59, no. 10, pp. 4885–4899, Oct. 2011.

[20] N. Seifi, R. W. Heath Jr, M. Coldrey, and T. Svensson, “Adaptive multicell 3d beamforming in multi-antenna cellular networks,” IEEE Trans. Veh. Technol., vol. 65, no. 8, pp. 6217–6231, Aug. 2016.

[21] K. Hosseini, W. Yu, and R. S. Adve, “A stochastic analysis of network MIMO systems,” IEEE Trans. Signal Process., vol. 64, no. 16, pp. 4113–4126, Aug. 2016.

[22] G. Caire, S. A. Ramprashad, H. C. Papadopoulos, C. Pepin, and C. E. W. Sundberg, “Multiuser MIMO downlink with limited inter-cell cooperation: Approximate interference alignment in time, frequency and space,” in Allerton Conf. Commun., Control, Computing, Sep. 2008, pp. 730–737.

[23] H. Huh, G. Caire, H. C. Papadopoulos, and S. A. Ramprashad, “Achieving “massive MIMO” spectral efficiency with a not-so-large number of antennas,” IEEE Trans. Wireless Commun., vol. 11, no. 9, pp. 3226–3239, Sep. 2012.

[24] V. V. Ratnam, A. F. Molisch, and G. Caire, “Capacity analysis of interlaced clustering in a distributed antenna system with/without CSIT,” IEEE Trans. Wireless Commun., vol. 15, no. 4, pp. 2629–2641, Apr. 2016.

[25] K. Huang and J. G. Andrews, “An analytical framework for multicell cooperation via stochastic geometry and large deviations,” IEEE Trans. Inf. Theory, vol. 59, no. 4, pp. 2501–2516, 2013.

[26] C. Li, J. Zhang, M. Haenggi, and K. B. Letaief, “User-centric intercell interference nulling for downlink small cell networks,” IEEE Trans. Commun., vol. 63, no. 4, pp. 1419–1431, Apr. 2015.

[27] Y. Cui, Y. Wu, D. Jiang, and B. Clerckx, “User-centric interference nulling in downlink multi-antenna heterogeneous networks,” IEEE Trans. Wireless Commun., vol. 15, no. 11, pp. 7484–7500, Aug. 2016.

[28] G. Caire, S. A. Ramprashad, and H. C. Papadopoulos, “Rethinking network MIMO: Cost of CSIT, performance analysis, and architecture comparisons,” in Information Theory and Applications Workshop (ITA), 2010, pp. 1–10.

[29] Q. Zhang, C. Yang, and A. F. Molisch, “Downlink base station cooperative transmission under limited-capacity backhaul,” IEEE Trans. Wireless Commun., vol. 12, no. 8, pp. 3746–3759, 2013.

[30] A. Lozano, R. W. Heath, and J. G. Andrews, “Fundamental limits of cooperation,” IEEE Trans. Inf. Theory, vol. 59, no. 9, pp. 5213–5226, Sep. 2013.

[31] Y. Lin and W. Yu, “Downlink spectral efficiency of distributed antenna systems under a stochastic model,” IEEE Trans. Wireless Commun., vol. 13, no. 12, pp. 6891–6902, Dec. 2014.

[32] M. Haenggi, Stochastic geometry for wireless networks. Cambridge University Press, 2012.

[33] C. Zhu and W. Yu, “Stochastic analysis of user-centric network MIMO,” in IEEE Int. Workshop Signal Processing Advances Wireless Commun. (SPAWC), 2016.