User-Centric Communications versus Cell-free Massive MIMO for 5G Cellular Networks

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***Abstract*—Recently, the so-called cell-free Massive MIMO architecture has been introduced, wherein a very large number of distributed access points (APs) simultaneously and jointly serve a much smaller number of mobile stations (MSs); each AP uses local channel estimates obtained from received uplink pilots and applies conjugate beamforming to transmit data to the users. The contribution of this work is twofold. First, the paper extends the cell-free approach to the case in which both the APs and the MSs are equipped with multiple antennas, proposing a beamfoming scheme that, relying on the channel hardening effect, does not require channel estimation at the MSs. Second, the cell-free massive approach is contrasted with a user-centric approach wherein each user is served only by the APs that are closest to it. Since far APs experience a bad SINR, it turns out that they are quite unhelpful in serving far users, and so, the user-centric approach, while requiring less backhaul overhead with respect to the cell-free approach, is shown here to achieve better performance results, in terms of achievable rate-per-user, for the vast majority of the MSs in the network.**

***Index Terms*—Cell-free Massive MIMO, user-centric channel estimation**

I. Introduction

Massive multiple-input multiple-output (MIMO), a system in which a BS with a large number of antennas simultaneously serves many users in the same time-frequency resource [1], is one of the key technologies that will be used for 5G networks [2]. Massive antenna arrays at the BS can be deployed in either co-located or distributed manner. In the co-located approach all the antennas are mounted at the BS in a compact area, while, instead, in the distributed massive MIMO architecture the service antennas are spread out over a large area. The latter approach permits to exploit macro-diversity to combat the shadow fading, and achieves a much better coverage [3]; on the other hand, the former approach is less critical in terms of backhaul requirements. Recently, the so-called cell-free (CF) massive MIMO architecture has been introduced [4], [5], for the case in which both the APs and the MSs are equipped with only one antenna. In particular, a very large number of distributed APs simultaneously and jointly serve a much smaller number of MSs; each AP uses local channel estimates obtained from received uplink pilots and applies conjugate beamforming to transmit data to the users. The APs are connected via a backhaul network to a central CPU; in order to minimize the backhaul requirements, the CPU sends to the APs the data-symbols to be transmitted to the users and receives soft-estimates of the received data-symbols from all the APs. Neither channel estimates, nor beamforming vectors are propagated through the backhaul network. Papers [4], [5] show that the CF approach provides better performance than a small-cell system in terms of 95%-likely per-user throughput. Additionally, the paper [6] has recently shown that some performance improvement can be obtained in low density networks by using downlink pilots, while the paper [7], instead, analyzes the performance improvements granted by the use of a zero-forcing precoder in the downlink, a solution however that requires centralized computations at the CPU and increased backhaul overhead. The contribution of this paper is mainly twofold:

1) We extend the CF approach to the case in which the MSs and the APs are equipped with multiple antennas. We propose a beamforming scheme that does not require channel estimation at the MSs; rather the proposed scheme exploits the channel hardening effect due to the large number of antennas in order to perform coherent data reception at the MSs. Channel inversion beamforming is proposed here as a generalization of the conjugate beamforming applied in the single-antenna case, and, again, no channel estimates and beamforming matrices are propagated through the backhaul network.
2) We contrast the CF approach with the user-centric (UC) distributed massive MIMO approach, wherein each MS is served not by all the APs in the system, but just by the ones that are in the neighbors. Indeed, intuition suggests that APs that are placed at a large distance from a MSs cannot be useful to the communication process since they mainly contribute with strongly interfered observations. The UC approach, instead, while being much simpler than the CF one and less hungry of backhaul bandwidth, is shown to provide better achievable rate-per-user to the majority of the MSs in the system.

The remainder of this paper is organized as follows. Next Section contains the description of the considered system model. Section III is devoted to the illustration of the beamforming schemes for both CF and UC approaches, while Section IV contains the numerical results. Finally, concluding remarks are given in Section V.

II. System model

We consider an area with K MSs and M APs. MSs and APs are randomly located. The M APs are connected by means of a backhaul network to a central processing unit (CPU) wherein data-decoding is performed. In keeping with the approach of [4], [5], all communications take place on the same frequency band; uplink and downlink are separated through time-division-duplex (TDD); the coherence interval is

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ISBN 978-3-8007-4394-0

thus divided into three phases: (a) uplink channel estimation, (b) downlink data transmission, and (c) uplink data transmission. In phase (a) the MSs send pilot data in order to enable channel estimation at the APs. In phase (b) APs use channel estimates to perform channel-matched beamforming and send data symbols on the downlink; while in the CF architecture APs send data to all the MSs in the system, in the UC approach APs send data only to a subset of the MSs in the system. Finally, in phase (c) MSs send uplink data symbols to the APs; while in the CF architecture all the APs participate to the decoding of the data transmitted by all the MSs, in the UC approach APs just decode the data from the nearby MSs. The procedure for the selection of the MSs to serve will be specified in the following section. No pilots are transmitted on the downlink and no channel estimation is performed at the MSs: data decoding takes place on the downlink relying on the fact that in TDD the downlink channel is the reciprocal of the uplink channel [1] and on the channel hardening effect due to many transmitting APs. In the following, we denote by $N_{\rm MS}$ and by $N_{\rm AP}$ the number of antennas at the MSs and at the APs, respectively.

A. Channel model

We denote by the $(N_{\rm AP} \times N_{\rm MS})$-dimensional matrix $\mathbf{G}_{k,m}$ the channel between the k-th MS and the m-th AP. We have

$$\mathbf{G}_{k,m} = \beta_{k,m}^{1/2} \mathbf{H}_{k,m} \ , \tag{1}$$

with $\beta_{k,m}$ a scalar coefficient modeling the channel shadowing effects and $\mathbf{H}_{k,m}$ an $(N_{\rm AP} \times N_{\rm MS})$-dimensional matrix whose entries are i.i.d $\mathcal{CN}(0,1)$ RVs. For the path loss and the shadow fading correlation models we use the ones reported in [5]. The large scale coefficient $\beta_{k,m}$ in (1) models the path loss and shadow fading, according to

$$\beta_{k,m} = 10^{\frac{\text{PL}_{k,m}}{10}} 10^{\frac{\sigma_{\rm sh} z_{k,m}}{10}}, \tag{2}$$

where $\text{PL}_{k,m}$ represents the path loss (expressed in dB) from the k-th MS to the m-th AP, and $10^{\frac{\sigma_{\rm sh} z_{k,m}}{10}}$ represents the shadow fading with standard deviation $\sigma_{\rm sh}$, while $z_{k,m}$ will be specified later. For the path loss we use the following three slope path loss model [9]:

$$\text{PL}_{k,m} = \begin{cases} -L - 35\log_{10}(d_{k,m}), & \text{if } d_{k,m} > d_1 \\ -L - 10\log_{10}\left(d_1^{1.5} d_{k,m}^2\right), & \text{if } d_0 < d_{k,m} \leq d_1 \\ -L - 10\log_{10}\left(d_1^{1.5} d_0^2\right), & \text{if } d_{k,m} < d_0 \end{cases} , \tag{3}$$

where $d_{k,m}$ denotes the distance between the m-th AP and the k-th user, L is

$$\begin{aligned} L = 46.3 + 33.9\log_{10}(f) - 13.82\log_{10}(h_{\rm AP}) - \\ [1.11\log_{10}(f) - 0.7]\, h_{\rm MS} + 1.56\log_{10}(f) - 0.8, \end{aligned} \tag{4}$$

f is the carrier frequency in MHz, $h_{\rm AP}$ and $h_{\rm MS}$ denotes the AP and MS antenna heights, respectively. In real-world scenarios, transmitters and receivers that are in close vicinity of each other may be surrounded by common obstacles, and hence, the shadow fading RVs are correlated; for the shadow fading coefficient we thus use a model with two components [10]

$$z_{k,m} = \sqrt{\delta} a_m + \sqrt{1-\delta} b_k, \quad m = 1, \ldots, M, \ k = 1, \ldots, K, \tag{5}$$

where $a_m \sim \mathcal{N}(0,1)$ and $b_k \sim \mathcal{N}(0,1)$ are independent RVs, and δ, $0 \leq \delta \leq 1$ is a parameter. The covariance functions of a_m and b_k are given by:

$$E\left[a_m a_{m'}\right] = 2^{-\frac{d_{\rm AP(m,m')}}{d_{\rm decorr}}} \quad E\left[b_k b_{k'}\right] = 2^{-\frac{d_{\rm MS(k,k')}}{d_{\rm decorr}}}, \tag{6}$$

where $d_{\rm AP(m,m')}$ is the geographical distance between the m-th and m'-th APs, $d_{\rm MS(k,k')}$ is the geographical distance between the k-th and the k'-th MSs. The parameter $d_{\rm decorr}$ is a decorrelation distance which depends on the environment, typically this value is in the range 20-200 m.

III. The communication protocol for the CF and UC approaches

As already discussed, the communication procedure is made of three different phases, (a) uplink training, (b) downlink data transmission, and (c) uplink data transmission. The overall duration of these three phases must not exceed the channel coherence time, thus implying that these three phases must be sequentially repeated with a frequency larger than the channel Doppler spread.

A. Uplink training

During this phase the MSs send uplink training pilots in order to permit channel estimation at the APs. This phase is the same for both the UC and CF approaches. We denote by τ_c the length (in samples) of the channel coherence time, and by τ_p the length (in samples) of the uplink training phase. Of course we must ensure that $\tau_p < \tau_c$. Denote by $\mathbf{\Phi}_k \in \mathcal{C}^{N_{\rm MS} \times \tau_p}$ the pilot sequence sent by the k-th MS, and assume that $\|\mathbf{\Phi}_k\|_F^2 = 1$. The signal received at the m-th AP in the n-th signaling time is represented by the following $N_{\rm AP}$-dimensional vector:

$$\mathbf{y}_m(n) = \sum_{k=1}^{K} \sqrt{p_k} \mathbf{G}_{k,m} \mathbf{\Phi}_k(:,n) + \mathbf{w}_m(n) \ , \tag{7}$$

with $\sqrt{p_k}$ the user k transmit power during the training phase. Collecting all the observable vectors $\mathbf{y}_m(n)$, for $n = 1, \ldots, \tau_p$ into the $(N_{\rm AP} \times \tau_p)$-dimensional matrix $\mathbf{Y}_m$, it is easy to show that:

$$\mathbf{Y}_m = \sum_{k=1}^{K} \sqrt{p_k} \mathbf{G}_{k,m} \mathbf{\Phi}_k + \mathbf{W}_m \ . \tag{8}$$

In the above equation the matrix $\mathbf{W}_m$ is $(N_{\rm AP} \times \tau_p)$-dimensional and contains the thermal noise contribution and out-of-cell interference at the m-th AP; its entries are assumed to be i.i.d. $\mathcal{CN}(0, \sigma_w^2)$ RVs. Based on the observable matrix $\mathbf{Y}_m$, the m-th AP performs estimation of the channel matrices $\{\mathbf{G}_{k,m}\}_{k=1}^K$. We assume here simple pilot-matched (PM) single-user channel estimation for the sake of simplicity (more sophisticated channel estimation schemes might however be

[1] According to [5], the channel reciprocity is also ensured by perfect hardware chain calibration, whose feasibility has been recently shown in [8].

ISBN 978-3-8007-4394-0

considered) and we assume knowledge of MSs transmit powers $\{p_k\}_{k=1}^K$. The estimate, $\widehat{\mathbf{G}}_{k,m}$ say, of the channel matrix $\mathbf{G}_{k,m}$ is obtained as

$$\widehat{\mathbf{G}}_{k,m} = \frac{1}{\sqrt{p_k}} \mathbf{Y}_m \mathbf{\Phi}_k^H = \mathbf{G}_{k,m} \mathbf{\Phi}_k \mathbf{\Phi}_k^H + \sum_{j=1, j \neq k}^{K} \sqrt{\frac{p_j}{p_k}} \mathbf{G}_{j,m} \mathbf{\Phi}_j \mathbf{\Phi}_k^H + \frac{1}{\sqrt{p_k}} \mathbf{W}_m \mathbf{\Phi}_k^H \ . \quad (9)$$

Estimation (9) must be made in all the APs (i.e., for all the values of $m = 1, \ldots, M$) for all the values of $k = 1, \ldots, K$. If the rows of the matrices $\mathbf{\Phi}_1, \ldots, \mathbf{\Phi}_K$ are pairwisely orthogonal (i.e. $\mathbf{\Phi}_k \mathbf{\Phi}_j = \mathbf{I}_{N_{\mathrm{MS}}} \delta_{i,k}$, for all i, k), then Eq. (9) simplifies to

$$\widehat{\mathbf{G}}_{k,m} = \frac{1}{\sqrt{p_k}} \mathbf{Y}_m \mathbf{\Phi}_k^H = \mathbf{G}_{k,m} + \frac{1}{\sqrt{p_k}} \mathbf{W}_m \mathbf{\Phi}_k^H \ , \quad (10)$$

and thermal noise is the only disturbance impairing the channel estimate. A necessary condition for this to happen is however $\tau_p \geq K N_{\mathrm{MS}}$, a relation that usually is not verified in practical scenarios due to the fact that τ_p must be a fraction of the channel coherence length. As a consequence, almost orthogonal pilot sequences are usually employed. In this paper, we assume that the pilot sequences assigned to each user are mutually orthogonal, so that $\mathbf{\Phi}_k \mathbf{\Phi}_k^H = \mathbf{I}_{N_{\mathrm{MS}}}$, while, instead, pilot sequences from different users are non-orthogonal. As a consequence, Eq. (9) is actually expressed as:

$$\widehat{\mathbf{G}}_{k,m} = \mathbf{G}_{k,m} + \sum_{j=1, j \neq k}^{K} \sqrt{\frac{p_j}{p_k}} \mathbf{G}_{j,m} \mathbf{\Phi}_j \mathbf{\Phi}_k^H + \frac{1}{\sqrt{p_k}} \mathbf{W}_m \mathbf{\Phi}_k^H \ , \quad (11)$$

which clearly shows that the channel estimate is degraded not only by noise, but also by the pilots from the other users, an effect which is well-known to be named pilot contamination.

B. Downlink data transmission

After that each AP has obtained estimates of the channel matrix from all the MSs in the system, the downlink data transmission phase begins. The APs treat the channel estimates as the true channels, and channel inversion beamforming is performed to transmit data to the MSs. The objective of this beamforming scheme is to ensure that the MSs will be able to receive data with no information on the channel state. Denoting by P_k the multiplexing order (i.e., the number of simultaneous data-streams) for user k, and by $\mathbf{x}_k^{\mathrm{DL}}(n)$ the P_k-dimensional unit-norm vector containing the k-th user data symbols to be sent in the n-th sample time, and letting $\mathbf{L}_k = \mathbf{I}_{P_k} \otimes \mathbf{1}_{N_{\mathrm{MS}}/P_k}$, the downlink precoder at the m-th AP for the k-th MS is expressed as

$$\mathbf{Q}_{k,m}^{\mathrm{DL}} = \widehat{\mathbf{G}}_{k,m} \left(\widehat{\mathbf{G}}_{k,m}^H \widehat{\mathbf{G}}_{k,m} \right)^{-1} \mathbf{L}_k \ . \quad (12)$$

1) CF massive MIMO architecture: In the CF architecture all the APs communicate with all the MSs in the systems, so the signal transmitted by the m-th AP in the n-th interval is the following N_{AP}-dimensional vector

$$\mathbf{s}_m^{\mathrm{cf}}(n) = \sum_{k=1}^{K} \sqrt{\eta_{k,m}^{\mathrm{DL,cf}}} \mathbf{Q}_{k,m}^{\mathrm{DL}} \mathbf{x}_k^{\mathrm{DL}}(n) \ , \quad (13)$$

with $\eta_{k,m}^{\mathrm{DL,cf}}$ a scalar coefficient ruling the power transmitted by the m-th AP for the k-th MS. In this paper we simply assume that each AP uniformly divides its power among all the MSs in the system, i.e. we have that

$$\eta_{k,m}^{\mathrm{DL,cf}} = \frac{P_T^{\mathrm{DL}}}{K \mathrm{tr} \left(\mathbf{Q}_{k,m}^{\mathrm{DL}} \mathbf{Q}_{k,m}^{\mathrm{DL\,H}} \right)} \ , \quad (14)$$

with P_T^{DL} the power transmitted by each APs[2]. The generic k-th MS receives signal contributions from all the APs; the observable vector is expressed as

$$\begin{aligned} \mathbf{r}_k^{\mathrm{cf}}(n) &= \sum_{m=1}^{M} \mathbf{G}_{k,m}^H \mathbf{s}_m^{\mathrm{cf}}(n) + \mathbf{z}_k(n) \\ &= \sum_{m=1}^{M} \sqrt{\eta_{k,m}^{\mathrm{DL,cf}}} \mathbf{G}_{k,m}^H \mathbf{Q}_{k,m}^{\mathrm{DL}} \mathbf{x}_k^{\mathrm{DL}}(n) + \\ & \sum_{m=1}^{M} \sum_{j=1, j \neq k}^{K} \sqrt{\eta_{j,m}^{\mathrm{DL,cf}}} \mathbf{G}_{k,m}^H \mathbf{Q}_{j,m}^{\mathrm{DL}} \mathbf{x}_j^{\mathrm{DL}}(n) + \mathbf{z}_k(n) \ . \end{aligned} \quad (15)$$

In (15), the N_{MS}-dimensional vector $\mathbf{z}_k(n)$, modelled as i.i.d. $\mathcal{CN}(0, \sigma_z^2)$ RVs, represents the thermal noise and out-of-cluster interference at the k-th MS. Based on the observation of the vector $\mathbf{r}_k^{\mathrm{cf}}(n)$, a soft estimate of the data symbols $\mathbf{x}_k^{\mathrm{DL}}(n)$ is obtained at the k-th MS as

$$\widehat{\mathbf{x}}_k^{\mathrm{DL,cf}}(n) = \mathbf{L}_k^H \mathbf{r}_k^{\mathrm{cf}}(n) \ . \quad (16)$$

Note that no channel estimation is performed at the MSs; the beamformers $\mathbf{L}_k$ have a fixed structure independent of the channel realization, so that the entries of the observation vector are partitioned in P_k groups and a coherent sum is made within each group.

2) UC massive MIMO architecture: In the user-centric approach, we assume that the APs communicate only with the closest MSs. In order to define a measure for the closeness of the MSs, several procedures can be conceived. One possible strategy is that each AP computes the average Frobenius norm of the estimated channels for all the MSs, i.e.:

$$\bar{\mathbf{G}}_m = \frac{1}{K} \sum_{k=1}^{K} \| \widehat{\mathbf{G}}_{k,m} \|_F , \quad (17)$$

and will serve only the APs whose channel has a Frobenius norm larger than the computed average value. Another possible approach is that each AP sorts these estimates in descending Frobenius norm order and serves only the N MSs with the strongest channel, with N a proper design parameter. In this paper we will present numerical results using this latter strategy. We denote by $\mathcal{K}(m)$ the set of MSs served by the m-th AP. Given the sets $\mathcal{K}(m)$, for all $m = 1, \ldots, M$, we can define the set $\mathcal{M}(k)$ of the APs that communicate with the k-th user:

$$\mathcal{M}(k) = \{ m : \ k \in \mathcal{K}(m) \} \quad (18)$$

[2]The extension to the case in which APs transmit with different power levels is straightforward. Additionally, the use of more sophisticated power control laws is certainly an interesting generalization that will be considered in the future.

ISBN 978-3-8007-4394-0

So, in this case, the signal transmitted by the m-th AP in the n-th interval is the following $N_{\rm AP}$-dimensional vector

$$\mathbf{s}_m^{\rm uc}(n) = \sum_{k\in\mathcal{K}(m)} \sqrt{\eta_{k,m}^{\rm DL,uc}} \mathbf{Q}_{k,m}^{\rm DL}\mathbf{x}_k^{\rm DL}(n) \;, \qquad (19)$$

with $\eta_{k,m}^{\rm DL,uc}$, again, a scalar coefficient ruling the power transmitted by the m-th AP. Assuming uniform power allocation, we have

$$\eta_{k,m}^{\rm DL,uc} = \begin{cases} \dfrac{P_T^{\rm DL}}{|\mathcal{K}(m)| \text{tr}\left(\mathbf{Q}_{k,m}^{\rm DL}\mathbf{Q}_{k,m}^{\rm DL\,H}\right)} & \text{if } \; k\in\mathcal{K}(m) \\ 0 & \text{otherwise} \end{cases} \qquad (20)$$

The generic k-th MS receives signal contributions from all the APs; the observable vector is expressed as

$$\begin{aligned} \mathbf{r}_k^{\rm uc}(n) &= \sum_{m=1}^{M} \mathbf{G}_{k,m}^H \mathbf{s}_m^{\rm uc}(n) + \mathbf{z}_k(n) \\ &= \sum_{m\in\mathcal{M}(k)} \sqrt{\eta_{k,m}^{\rm DL,uc}} \mathbf{G}_{k,m}^H \mathbf{Q}_{k,m}^{\rm DL}\mathbf{x}_k^{\rm DL}(n) + \\ & \sum_{j=1,j\neq k}^{K} \sum_{m\in\mathcal{M}(j)} \sqrt{\eta_{j,m}^{\rm DL,uc}} \mathbf{G}_{k,m}^H \mathbf{Q}_{j,m}^{\rm DL}\mathbf{x}_j^{\rm DL}(n) + \mathbf{z}_k(n) \;. \end{aligned} \qquad (21)$$

In (21), the $N_{\rm MS}$-dimensional vector $\mathbf{z}_k(n)$ represents the thermal noise and out-of-cluster interference at the k-th MS, and is modeled as i.i.d. $\mathcal{CN}(0,\sigma_z^2)$ RVs. Based on the observation of the vector $\mathbf{r}_k^{\rm uc}(n)$, a soft estimate of the data symbols $\mathbf{x}_k^{\rm DL}(n)$ is obtained at the k-th MS as

$$\widehat{\mathbf{x}}_k^{\rm DL,uc}(n) = \mathbf{L}_k^H \mathbf{r}_k^{\rm uc}(n) \;. \qquad (22)$$

C. Uplink data transmission

The final phase of the communication protocol consists of the uplink data transmission. Since the MSs do not perform channel estimation, they just send their data symbols using the already defined trivial beamformer $\mathbf{L}_k$. Basically, this corresponds to partition the MS antennas in as many disjoint subsets as the multiplexing order, and to use all the antennas in each same subset to transmit the same data symbol. We denote by $\mathbf{x}_k^{\rm UL}(n)$ the P_k-dimensional data vector to be transmitted by the k-th user in the n-th sample time. The signal received at the m-th AP in the n-th time sample is an $N_{\rm AP}$-dimensional vector expressed as

$$\bar{\mathbf{y}}_m(n) = \sum_{k=1}^{K} \sqrt{\eta_k^{\rm UL}} \mathbf{G}_{k,m}\mathbf{L}_k\mathbf{x}_k^{\rm UL}(n) + \mathbf{w}_m(n) \;, \qquad (23)$$

with $\eta_k^{\rm UL} = \dfrac{P_{T,k}^{\rm UL}}{N_{\rm MS}}$, and $P_{T,k}^{\rm UL}$ is the uplink transmit power of the k-th MS.

1) CF massive MIMO architecture: In the case of CF MIMO, all the APs participate to the decoding of the data sent by all the MSs. The m-th AP, thus, forms, for each $k = 1,\ldots,K$, the following statistics

$$\begin{aligned} \widetilde{\mathbf{y}}_{m,k}(n) &= \left(\mathbf{L}_k^H \widehat{\mathbf{G}}_{k,m}^H \widehat{\mathbf{G}}_{k,m}\mathbf{L}_k\right)^{-1} \mathbf{L}_k^H \widehat{\mathbf{G}}_{k,m}^H \bar{\mathbf{y}}_m(n) \\ &= \widetilde{\mathbf{G}}_{k,m}\bar{\mathbf{y}}_m(n), \end{aligned} \qquad (24)$$

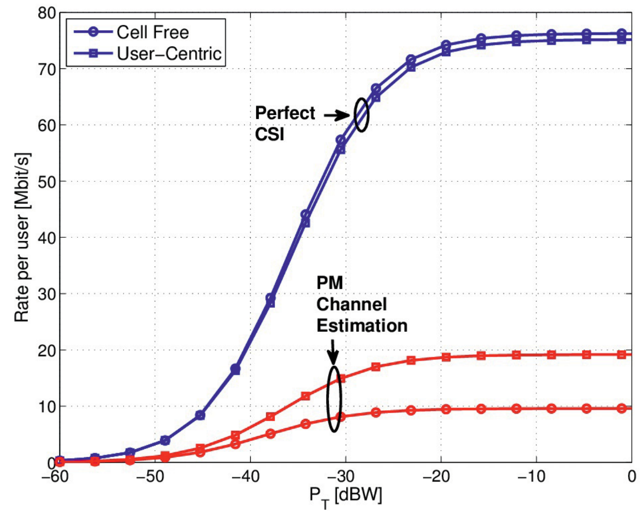

Figure 1. Average achievable rate per user in the downlink versus the transmit power P_T. .

where we have defined $\widetilde{\mathbf{G}}_{k,m}$ as the following $P_k \times N_{\rm AP}$-dimensional matrix:

$$\widetilde{\mathbf{G}}_{k,m} = \left(\mathbf{L}_k^H \widehat{\mathbf{G}}_{k,m}^H \widehat{\mathbf{G}}_{k,m}\mathbf{L}_k\right)^{-1} \mathbf{L}_k^H \widehat{\mathbf{G}}_{k,m}^H \;. \qquad (25)$$

The vectors $\widetilde{\mathbf{y}}_{m,k}(n)$, for all $k = 1,\ldots,K$, are then sent to the CPU via the backhaul link; the CPU, finally, forms the following soft estimates of the data vectors transmitted by the users:

$$\widehat{\mathbf{x}}_k^{\rm UL,cf}(n) = \sum_{m=1}^{M} \widetilde{\mathbf{y}}_{m,k}(n) \;, \quad k = 1,\ldots,K \;. \qquad (26)$$

Note that only the soft estimates $\widetilde{\mathbf{y}}_{m,k}(n)$ are to be transmitted from the APs to the CPU, while channel estimates transmission is not required.

2) UC massive MIMO architecture: In this case, the signal transmitted by the k-th MS is decoded only by the APs in the set $\mathcal{M}(k)$. Otherwise stated, the m-th AP computes the statistics $\widetilde{\mathbf{y}}_{m,k}(n)$ only for the MSs in $\mathcal{K}(m)$. Accordingly, the CPU is able to perform the following soft estimates for the data sent by the K MSs in the system:

$$\widehat{\mathbf{x}}_k^{\rm UL,uc}(n) = \sum_{m\in\mathcal{M}(k)} \widetilde{\mathbf{y}}_{m,k}(n) \;, \quad k = 1,\ldots,K \;. \qquad (27)$$

Notice that in this case the backhaul overhed is reduced with respect to the CF case since each AP has to send only the soft estimates of the data received by its associated MSs.

IV. Numerical results

We will consider as performance measure the achievable rate per user, measured in bit/s. It is easy to show that in all the previously considered cases the soft estimate of the data-symbol of interest in the n-th time epoch can be written as

$$\widehat{\mathbf{x}}_k(n) = \mathbf{A}_{k,k}\mathbf{x}_k(n) + \sum_{j=1,j\neq k}^{K} \mathbf{A}_{k,j}\mathbf{x}_j(n) + \mathbf{z}_k(n) \;, \qquad (28)$$

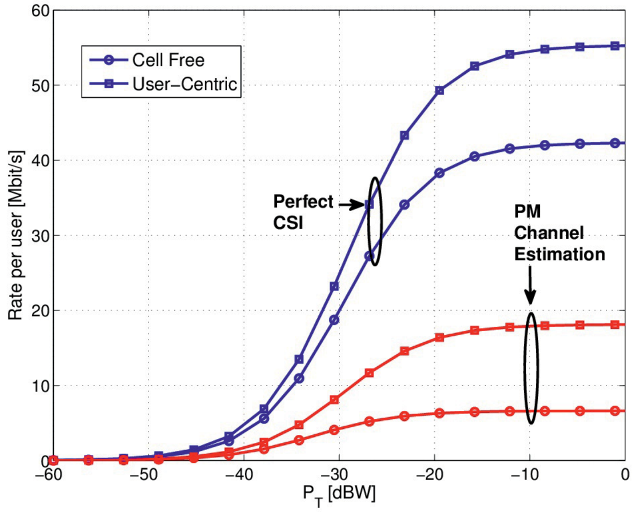

Figure 2. Average achievable rate per user in the uplink versus the transmit power P_T. .

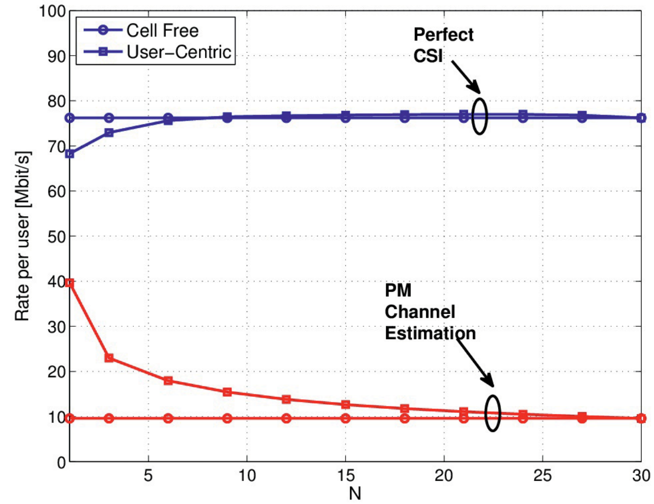

Figure 3. Average achievable rate per user in the downlink versus N.

where $\mathbf{x}_k(n)$ is the unit-energy data-symbol vector of interest, $\mathbf{x}_j(n)$, with $j \neq k$, are the unit-energy interfering vector data-symbols, the quantities $\mathbf{A}_{\cdot,\cdot}$ are suitable matrices, and, finally $\mathbf{z}_k(n)$ is the additive disturbance modeled as i.i.d. $\mathcal{CN}(0, \sigma_z^2)$. Based on (28), the k-th user achievable rate is expressed as [11]

$$\mathcal{R}_k = W \log_2 \det \left[\mathbf{I} + \mathbf{R}_k^{-1} \mathbf{A}_{k,k} \mathbf{A}_{k,k}^H \right] \ , \qquad (29)$$

with

$$\mathbf{R}_k = \sigma_z^2 \mathbf{I} + \sum_{j=1, j\neq k}^{K} \mathbf{A}_{k,j} \mathbf{A}_{k,j}^H \ . \qquad (30)$$

the covariance matrix of the interfering terms. The plots to be commented in the following are thus obtained by using expression (29).

In our simulation setup, we consider a communication bandwidth of $W = 20$ MHz centered over the carrier frequency $f_0 = 1.9$ GHz. The antenna height at the AP is 15 m and at the MS is 1.65 m. The standard deviation of the shadow fading is $\sigma_{\text{sh}} = 8$ dB, the parameters for the three slope path loss model in (3) are $d_1 = 50$ m and $d_0 = 10$ m, the parameter δ in (5) is 0.5 and the correlation distance in (6) is $d_{\text{decorr}} = 100$ m. The additive thermal noise is assumed to have a power spectral density of -174 dBm/Hz, while the front-end receiver at the AP and at the MS is assumed to have a noise figure of 3 dB. The shown results come from an average over 500 random scenario realizations with independent MSs and APs locations and channels. We quantitatively study and compare the performances of the CF and UC massive MIMO architectures. We consider $M = 100$ APs and $K = 30$ MSs; we assume $N_{\text{AP}} = 4$, $N_{\text{MS}} = 2$ and $P_k = 2$, $\forall k = 1, \dots, K$. We consider that all the APs transmit the same power in downlink and all the MSs transmit the same power in uplink

In Figs. 1 and 2 we report the average rate per user versus the downlink and uplink transmit power, respectively, for the UC and CF approach, both for the case of PM channel estimation and of perfect channel state information (CSI).

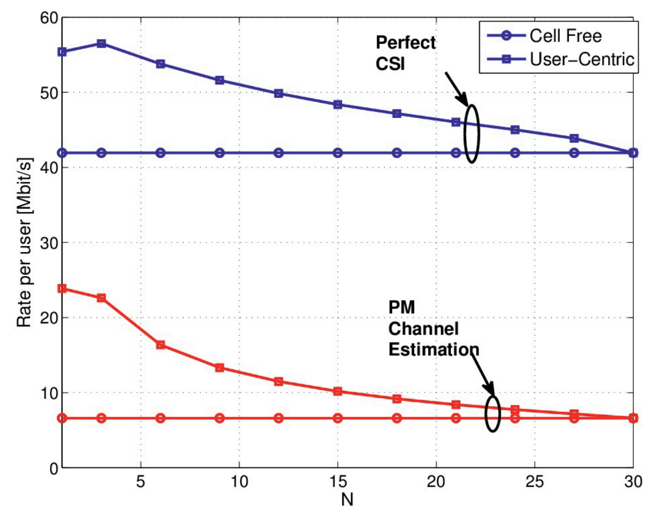

Figure 4. Average achievable rate per user in the uplink versus N.

For channel estimation, we use maximum-length-sequences (pseudo-noise) pilots of length $\tau_p = 16$ and uplink transmit power for channel estimation $p_k = 100$ mW, $\forall k = 1, \dots, K$. For the UC approach, it is assumed that each AP serves the $N = 5$ MSs with the highest Frobenius norm channel. Results show that for the case of perfect CSI, the CF approach is very slightly superior to the UC approach in the downlink, while in the uplink the UC approach achieves better performance. For PM channel estimation, instead, the UC approach always outperforms the CF architecture. Intuitively, this behavior can be justified by noticing that APs will receive far MSs' signals with a very low SINR, thus implying that they will perform a very noisy channel estimate for those users, so that their participation to both the decoding phase in the uplink and to the beamforming phase in the downlink ultimately endangers the system achievable rate. The UC architecture, instead, just relies on the APs that can guarantee a reasonable SINR, so that they can positively take part to the data communication

ISBN 978-3-8007-4394-0

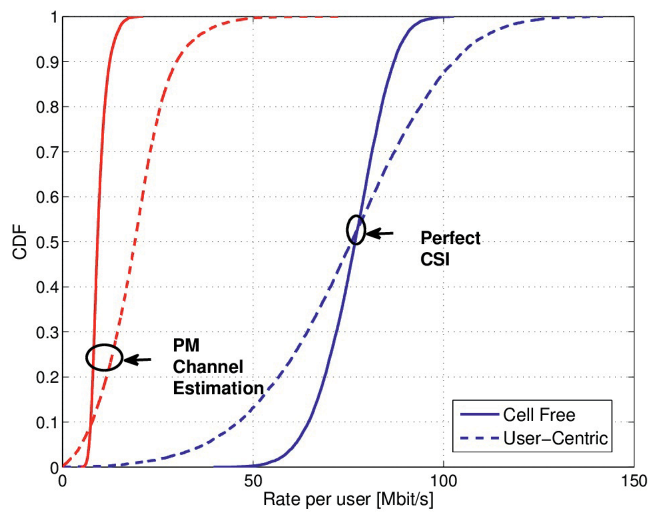

Figure 5. Average achievable rate per user CDF in the downlink.

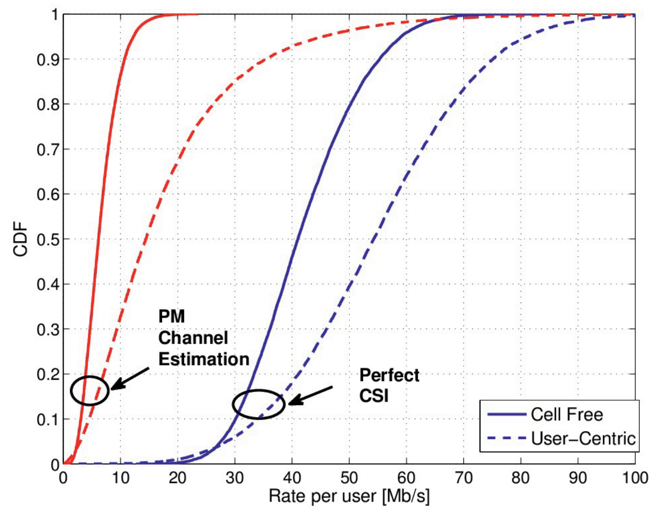

Figure 6. Average achievable rate per user CDF in the uplink .

process. Figures 3 and 4 basically confirm this result. Here, the average rate-per-user is reported versus N, the number of MSs that each AP serves in the UC architecture. Results refer to the same scenario as the one considered in Figs. 1 and 2; we assume here $P_T^{\rm DL} = 200$ mW and $P_{T,k}^{\rm UL} = 100$ mW, and the results show that it is convenient to keep N in the order of few units in order to maximize the benefits of the UC approach. While previous figures have reported the average rate-per-user, Figs. 5 and 6 focus on the rate distribution across the users, for the downlink and uplink, respectively, assuming again an uplink transmit power of 100 mW, a downlink transmit power of 200 mW, and using the value $N = 5$ in the UC approach. Focusing on the rate distribution across users, we find that the UC approach provides much better performance than the CF architecture to the vast majority of the MSs in the system. As an example, focusing on the case of PM channel estimation, the downlink 95%-likely per-user rate is 4.91 (6.95) Mbit/s for the UC (CF) approach, i.e. the loss of the UC approach is about 29%; on the other hand, the UC approach outperforms the CF approach by 5% in terms of 90%-likely per-user rate, and by 106% (19 Mbit/s versus 9.2 Mbit/s) in terms of median-rate. For the uplink, instead, again considering PM channel estimation, we see from Fig. 6 the UC approach greatly outperforms the CF approach in terms of 95%-likely per-user rate (2.97 Mbit/s versus 2.5 Mbit/s, +19% gain), of 90%-likely per-user rate (4.5 Mbit/s versus 3.1 Mbit/s, +45% gain), and of median rate (14.4 Mbit/s versus 6.1 Mbit/s, +136% gain).

V. Conclusion

The paper has focused on the recently introduced CF massive MIMO architecture. First of all, we have extended the CF approach to the case in which both the APs and the MSs are equipped with multiple antennas, and have proposed the use of a channel-inverting beamforming scheme that does require no channel estimation at the MSs. Then, we have contrasted the CF architecture with the UC approach wherein each AP only decodes a pre-assigned number of MSs. Results have shown that the UC approach generally outperforms the CF one, especially on the uplink. Detailed performance results in terms of per-user percentile rates have been given. This work can be extended by providing some analytical comparison between the CF and the UC approach, as well as by introducing suitable power allocation strategies to maximize either the system throughput or the system energy efficiency. These topics form the object of current research.

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ISBN 978-3-8007-4394-0