Energy Efficiency of Uplink Cell-Free Massive MIMO With Transmit Power Control in Measured Propagation Channel

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Cell-free massive MIMO (CF-mMIMO) provides wireless connectivity for a large number of user equipments (UEs) using access points (APs) distributed across a wide area with high spectral efficiency (SE). The energy efficiency (EE) of the uplink is determined by (i) the transmit power control (TPC) algorithms, (ii) the numbers, configurations, and locations of the APs and the UEs, and (iii) the propagation channels between the APs and the UEs. This paper investigates all three aspects, based on extensive (~30,000 possible AP locations and 128 possible UE locations) channel measurement data at 3.5 GHz. We compare three different TPC algorithms, namely maximization of transmit power (max-power), maximization of minimum SE (max-min SE), and maximization of minimum EE (max-min EE) while guaranteeing a target SE. We also compare various antenna arrangements including fully-distributed and semi-distributed systems, where APs can be located on a regular grid or randomly, and the UEs can be placed in clusters or far apart. Overall, we show that the max-min EE TPC is highly effective in improving the uplink EE, especially when no UE within a set of served UEs is in a bad channel condition and when the BS antennas are fully-distributed.

Index Terms—Channel capacity, energy efficiency, massive MIMO, microwave propagation, power control, wide area measurements

I. INTRODUCTION

A. Motivation

Cell-free massive MIMO (CF-mMIMO), which combines various wireless communication system concepts such as mMIMO, ultra-dense networks, and cooperative multi-point (CoMP), exploits a large number of access points (APs) distributed across a wide area to reliably serve a large number of user equipments (UEs) while suppressing the inter-cell interference conventional cellular systems suffer from [1]. CF-mMIMO has significant performance advantages compared to traditional systems: the distributed nature of the antenna elements increases the reliability, which is a prerequisite for many Internet of Things (IoT) and mission-critical applications. Their distributed nature also makes them a natural fit for mobile edge computing.

Important performance metrics in CF-mMIMO systems are the energy efficiency (EE) of the (battery-powered) UEs, which is mainly determined by the information transmission in the uplink phase, i.e., UEs to APs, as well as the spectral efficiency (SE) of this process. The use of transmit power control (TPC) can, to a certain degree, trade-off EE and SE: if interference from other UEs can be cancelled, increase of transmit power improves the SE of a selected UE, but decreases the EE, because SE increases logarithmically with transmit power, while energy consumption increases in an affine way. The situation is further complicated by the fact that different UEs experience different attenuation to the various APs, and interference between the signals of different UEs can impact the SE. Hence, finding transmission algorithms, especially transmit power control (TPC) algorithms, that can maximize the EE at a target SE is very important, but nontrivial, and their performance assessment is challenging.

The performance of such algorithms is critically impacted by the propagation channels the system is operating in, as the wireless providers planning the deployment of CF-mMIMO systems require accurate and reliable statistics of the expected performance. Thus, it is important to test such TPC algorithms on realistic channel data. Such real-world data can only be obtained from extensive channel measurement campaigns. However, large measurement datasets for CF-mMIMO systems are scarce due to the complexity of setting up and operating a massive number of antennas simultaneously. To address this issue, we recently proposed that a large amount of channel data for CF-mMIMO systems can be measured using a compact channel sounder with a drone acting as a virtual array and released open-source channel data [2].

B. Related Works

Within traditional mMIMO, various power allocation methods to optimize wireless system performance have been considered. In [3], the trade-offs between the uplink SE and EE were analyzed through power models and simulations. In [4], a TPC scheme which optimizes both the SE and EE was developed. Furthermore, the ways to allocate power to both the data and pilots in order to maximize the SE was studied in [5] and an optimum number of base station (BS) antennas which can improve the downlink EE was studied in [6]. However, these works were focused on co-located massive MIMO system, where there is only one AP per cell.

There were also numerous CF-mMIMO studies which tackled the problem of improving the EE. In order to save
energy at the APs, efforts were made to maximize the total downlink EE, with various precoding methods and operating frequencies [7–12]. Other works analyzed the downlink EE while maximizing the minimum downlink SE per UE, in the cases of hardware impairments [13], in comparison to cellular systems [14], or in relation to security [15]. For uplink, the EE was analyzed to maximize the minimum uplink SE among the UEs [16–20]. There were also efforts to optimize the power coefficients for both the uplink and downlink jointly while seeking a balance between the EE and SE [21]–[23]. In a recent conference paper [24], we suggested the max-min EE method, which optimizes the power allocation to maximize the minimum uplink EE over all UEs, at a given target SE. This algorithm improved EE for UEs with the lowest EE in comparison to the max-power and max-min SE algorithms. This is practically meaningful because all UEs want to have a sufficient lifetime on a battery charge. However, all the works mentioned above including our own [24] were based on simulated channel data achieved from statistical channel models. In [25], a CF-mMIMO testbed was developed between 16 APs and 16 UEs, but the environment was limited to indoors and the EE was not considered.

C. Contributions
To provide a more realistic assessment of TPC algorithms, and bridge the gap between the theory and practical implementation of CF-mMIMO, we apply three different TPC algorithms (max-power, max-min SE, and max-min EE) to a large number of measured propagation channel data at 3.5 GHz to analyze the trade-offs between the EE and SE for CF-mMIMO systems with varying numbers, configurations, and locations of the APs and UEs. The amount of data used for these analyses is very large, featuring ~30,000 possible AP locations and 128 possible UE locations across a 200m×200m area, providing statistical confidence of the evaluated performances in a realistic deployment setting. The current paper considers EE and SE for (i) various antenna arrangements including fully-distributed (single-antenna AP) and semi-distributed (multi-antenna AP) systems, (ii) AP distributions, where APs can be located on a regular grid or randomly, and (iii) UE distributions, i.e., the UEs can be placed in clusters, or far apart from each other. This is in contrast to the conference version of the current paper [26], where only single-antenna AP configuration and 8 UEs placed close to one another were considered for the analysis, using zero-forcing combining. We show that the max-min EE is very effective, especially when no UE within a set of served UEs is in a bad channel condition, minimum mean square error (MMSE) combining is applied, when more BS antennas are used in comparison to the number of UEs, when the BS antennas are fully-distributed evenly across the coverage area, and when the UEs are far apart in the case of distributed BS antennas.

II. SYSTEM MODEL
We consider a CF-mMIMO system (Fig. 1), where the BS is composed of L APs with N antennas each (the total number of BS antennas is hence M = LN). The APs are deployed

Fig. 1. A cell-free massive MIMO system: K UEs are served by a BS composed of a central processing unit (CPU) and M antennas. L APs, each with N antennas, are distributed across a coverage area (M = LN).
C. Channel Estimation

For channel estimation, $\tau^{(p)}$-length pilot resources from each UE are used within the coherence interval. Let $\sqrt{\tau^{(p)}\varphi_k}$ be the $\tau^{(p)}$-dimensional pilot sequence vector of UE $k$, where $\|\varphi_k\|^2 = 1$. Then, the received signal vector is written as:

$$y_m^{(p)} = \sqrt{\rho^{(p)}\tau^{(p)}} \sum_{k=1}^{K} h_{m,k} \varphi_k + z_m^{(p)}.$$  

(4)

The MMSE channel estimate can then be written as [27]:

$$h_{m,k} = \frac{\sqrt{\rho^{(p)}\tau^{(p)}} \beta_{m,k}}{\rho^{(p)}\tau^{(p)} \sum_{k'=1}^{K} \beta_{m,k'} |\varphi_k^H \varphi_{k'}|^2 + 1} \hat{y}_m^{p}.$$  

(5)

III. PERFORMANCE METRICS

To analyze the performances of different TPC algorithms in Sec. IV, we evaluate the SE and EE. We assume either maximum-ratio (MR) combining or MMSE combining on the BS side, where the weight matrices are expressed as:

$$w_k^{MR} = \hat{h}_k,$$  

(6)

$$w_k^{MMSE} = \rho q_k \left( \sum_{i=1}^{K} \rho q_i (\hat{h}_i \hat{h}_i^H + C_i) + I_{LN} \right)^{-1} \hat{h}_k,$$  

(7)

where $\hat{h}_i$ is the estimate of channel vector for UE $i$, $h_i = H(:,i)$, and $C_i = \mathbb{E}\{\hat{h}_i \hat{h}_i^H\}$ is the error correlation matrix, where the channel estimation error vector for UE $i$, $\hat{h}_i$, is defined as $\hat{h}_i = h_i - \hat{h}_i$.

The MR has the advantage over MMSE for its simplicity, as it can even be implemented locally per AP. The MMSE in contrast, has to be implemented centrally after collecting the channel data from all APs due to the matrix inversion process. Yet, the MMSE can cancel out the interference from other UEs, providing better performance at the cost of its complexity. It has been shown in the seminal paper of Marzetta [28] that in the limit of very large arrays, the MR performance converges to that of MMSE; though experimental investigations with co-located arrays with 64 antennas have shown significant performance differences [29]. As we will see in Sec. V, there also are significant performance differences between MR and MMSE in our (distributed) mMIMO arrays, even when the number of antennas is large.

A. Spectral Efficiency

The SE of UE $k$ is:

$$S_k = \log_2 \left( 1 + \frac{\rho q_k |w_k^H \hat{h}_k|^2}{\rho \sum_{k' \neq k} \sum_{i=1}^{K} q_{k'} |w_{k'}^H \hat{h}_{k'}|^2 + \|w_k\|^2 \|Z_k\|} \right).$$  

(8)

where $Z_k = \rho \sum_{i=1}^{K} q_i C_i$.

B. Energy Efficiency

Based on [30], the power consumption of UE $k$ is:

$$P_k = \bar{P} q_k + P_U,$$  

(9)

where $\bar{P}$ is the maximum transmit power and $P_U$ is the required power to run circuit components at each UE. The EE of UE $k$ is then defined as:

$$E_k = \frac{\text{Bandwidth} \cdot S_k}{P_k}.$$  

(10)

IV. TRANSMIT POWER CONTROL ALGORITHMS

In this work, we consider three different types of uplink TPC algorithms: max-power, max-min SE, and max-min EE.

A. Max-Power Method

Max-power is the most simplistic method: each UE transmits with the maximum allowed power ($q_k = 1$). It is not strictly a TPC method, but we use it as the baseline to be compared with other TPC algorithms.

B. Max-Min Spectral Efficiency Method

Max-min SE is one of the most commonly used TPC methods in the CF-mMIMO literature, and aims to maximize the minimum SE among all UEs. The optimization problem is:

$$\min_{\{q_k\}} \max_{k=1,\ldots,K} S_k$$  

subject to $0 \leq q_k \leq 1, k = 1, \ldots, K$.

Since the SE is a logarithmic function increasing monotonically with the signal-to-interference-plus-noise ratio (SINR), the problem (11) can be reformulated as:

$$\max_{\{q_k\}} t$$  

subject to $t \leq \text{SINR}_k, k = 1, \ldots, K$  

$0 \leq q_k \leq 1, k = 1, \ldots, K$.

As proved in [31], the problem (12) can be formulated as a standard geometric programming problem, and can be solved by a software solver such as CVX for MATLAB [32], [33].

C. Max-Min Energy Efficiency Method

To improve the EE at a given SE, [24] proposed the max-min EE TPC method. Similar to the max-min SE, the optimization problem of the max-min EE method can be written as:

$$\min_{\{P_k\}} \max_{k=1,\ldots,K} \frac{\text{Bandwidth} \cdot S_k}{P_k}$$  

subject to $S_k \geq S^{(i)}_k, k = 1, \ldots, K$  

$0 \leq q_k \leq 1, k = 1, \ldots, K$.
where $S^{(t)}$ is the required minimum (target) SE for UEs to ensure a certain quality of service.

To make the problem easier to handle, replace $q_k$ in the denominator with an auxiliary variable $\nu$:

$$\text{maximize} \quad \min_{\{q_k, \nu\}} \quad \text{Bandwidth} \cdot S_k$$
$$\text{subject to} \quad S_k \geq S^{(t)}, k = 1, \ldots, K$$
$$0 \leq q_k \leq 1, k = 1, \ldots, K$$
$$q_k \leq \nu, k = 1, \ldots, K$$
$$\nu^* \leq \nu \leq 1,$$

where $\nu^*$ is the slack variable and given as the maximum $q_k$ that achieves the target SE, obtained by solving the following optimization problem:

$$\text{minimize} \quad \max_{\{q_k\}} \quad q_k$$
$$\text{subject to} \quad S_k \geq S^{(t)}, k = 1, \ldots, K$$
$$0 \leq q_k \leq 1, k = 1, \ldots, K.$$

which is explained further in [24]. The optimization problem is hence summarized as:

1) Finding the optimal value of $\nu$ to maximize the minimum EE using a hill climbing algorithm.
2) Optimizing $q_k$ to minimize the maximum transmit power when the target SE is reached.

When solving the EE-maximization problem, $\nu$ is always the maximum value of $q_k$ while $\nu^*$ is the maximum value of $q_k$ that achieves the required SE. Therefore, the actual EE, which is calculated by using the optimized $q_k$, becomes higher than is calculated within the optimization problem because the actual denominator of EE for those UEs also becomes smaller ($Pq_k + P_U \leq \nu P + P_U$).

V. CHANNEL MEASUREMENT

A. CHANNEL SOUNDER

We acquired our channel data with a measurement setup (“channel sounдер”) that includes a transmitter (TX) on a drone [34] and a receiver (RX) on the ground (Fig. 2). The TX, which sends out a known waveform, acts as a virtual array with a single omnidirectional antenna being moved by the drone along a trajectory of different possible AP locations, while the RX remains stationary at one location. The RX, which records the received waveforms for later postprocessing, is connected via an RF switch to eight physically separated omnidirectional antennas and thus records the channels for 8 UEs during each measurement run. Note that while our setup measures the downlink channel, the resulting channel measurements can still be used for uplink performance evaluations, since propagation channels are reciprocal.

The signal is a 46 MHz OFDM-like sounding waveform with 2301 subcarriers (20 kHz subcarrier spacing) at 3.5 GHz. As the TX moves along a trajectory at 1 m/s speed, it continuously transmits the waveform at 27 dBm while the RX constantly captures the channel data between the TX antenna and 8 RX antennas every 50 ms through switching. Therefore, $1 \times 8 \times 2301$ channel matrix may be captured at every 5 cm of drone movement. The characteristics of the drone sounnder and the channel measurement principle for CF-mMIMO systems are further discussed in [2], [34].

The measured channel may show correlation in the fading at the different antenna elements, in particular when they are closely spaced together. However, due to the measurement principle of our sounnder, phase coherence of the measurements between closely located points could not be achieved. This is partly due to the oscillator drift during the time that it takes the drone to move between locations, the potential positioning error, and the vibrations. Consequently, it is difficult to consider a correlation model for the linear array with closely spaced antenna elements. In order to resolve this issue, we have decided to separate each antennas by at least four wavelengths during evaluations, even for the cases of co-located scenarios and semi-distributed scenarios. This achieves greater diversity of the antenna arrays (which is beneficial for deployment), and ensures that the signals have uncorrelated phases at the antenna elements both in theory and in the measurements.

B. CHANNEL MEASUREMENT SETTING

The channel measurements were conducted at the southwest side of the University of Southern California (USC) University

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4The initial value of $\nu$ is set to $\nu^*$. The step size for each iteration is set to 0.1, and $\nu$ approaches 1. If the obtained minimum EE is smaller that that of the previous point, the step size will be divided by 2 and the sign will be inverted, i.e., the point will turn back with a smaller step. The iteration will end if the step size becomes smaller than $10^{-4}$.
5While (15) is a non-convex problem, the constraint $S^{(r)} - S_k \leq 0$ can be transformed into a polynomial function, and geometric programming can find the global optimal solution for (15).
6We emphasize that we are not considering a drone-based wireless system, but we are only obtaining the channel data for CF-mMIMO systems using the drone channel sounnder for system analysis in Sec. VI.
7The separations of the eight antennas per RX site are limited to 15m by the RF cables connecting the antennas to the switch.
8We do not compensate for the carrier frequency and sampling rate offsets, and assume they are parts of the channels. In fact, we consider the channel coefficients at each subcarrier as a particular channel realization of a single frequency (3.5 GHz flat channel).
The channel environment may show some variations during the repeated flights along the trajectory, and the path of the drone may not exactly overlap for different RX sites due to elongated measurement time. Please refer [2] for a discussion and measures taken to minimize the impact of such variations.

In our analysis, we can obtain 2301 different realizations of $H$ from the measurement campaign between $M$ BS antennas chosen from the trajectory and $K$ UEs chosen from 128 possible locations, since our analysis focuses on frequency-flat channels. Hence, the channel coefficients at 2301 subcarriers are regarded as particular realizations of a 3.5 GHz flat channel. If we define each frequency index as $i$, then $\beta_{m,k} = \frac{1}{F} \sum_{i=1}^{F} h_{m,k}(i)^2$ is the average large-scale fading with $F$ the total number of frequency indices ($F = 2301$). Calibration and time invariance of the sounder characteristics over the duration of the measurements were tested, and some frequency points (less than 10% of the total acquired data) exhibiting excessive calibration errors were discarded.

The channel environment may show some variations during the repeated flights along the trajectory, and the path of the drone may not exactly overlap for different RX sites due to elongated measurement time. Please refer [2] for a discussion and measures taken to minimize the impact of such variations.

In order to show some propagation characteristics from the channel measurement campaigns, Fig. 4 shows the path losses between the drone flying across the TX trajectory (with starting and end positions given in Fig. 3), which are about 30,000 potential AP antenna locations, and 128 UE antennas distributed across 16 RX sites. The SNR of the measurement varied, and was as high as 50 dB: we could measure path loss between about 70 dB to 120 dB after compensating for the hardware calibration. It shows that the path losses for most of the UEs close to each other, either within a single RX site (in groups of 8 UE antennas) or RX sites close to one another, have similar values, while the path losses change drastically if the UE antennas are far from one another.

### E. Comparison With Rayleigh Model

Fig. 5 shows the raw measurement data compared with Rayleigh model that uses a standard $\alpha$-$\beta$ path loss law plus log-normal shadowing. Specifically, we compared with the cases when A) the path loss (in dB) is $L(d) = 30.5 + 36.7 \log_{10}(d)$ where $d$ is the distance between an AP and a UE (in meters) and shadowing standard deviation value is 4 dB ($\sigma_{sdw}^2 = 4$ dB) as suggested from [1] and B) an “adjusted model” that obtains the path loss law and shadowing obtained from direct fitting of all our measurement data: $L(d) = 68.3568 + 52.3 \log_{10}(d/25)$ and $\sigma_{sdw}^2 = 9$ dB. 25m breakpoint from the adjusted model comes from the minimum distance between the TX and the RX during the measurement.

The gap is shown not only between the measurement data and the existing model, but also in between the measurement data and the adjusted model. This comes from a fundamental model mismatch, i.e., the structure of the popular $\alpha$-$\beta$ plus log-normal shadowing model does not fit completely to the structure of the measured data. In particular, the adjusted model can achieve an unrealistically low path loss (< 60 dB) due to high variance in shadowing, which can dominate.
the system performance in MIMO scenarios if some of the channels between a UE and APs are channels with unusually low path loss. Development of a more detailed channel model for distributed MIMO that can explain all the observed features of path loss and correlation is a subject for future work.

VI. PERFORMANCE EVALUATIONS

Performances of the TPC algorithms in Sec. [IV] are evaluated and compared by applying them to the channel data obtained from the measurement campaigns described in Sec. VI using various setup parameters. We assume MMSE combining unless MR is mentioned specifically. We fix 20 MHz of bandwidth, 290K noise temperature, and 7 dB noise figure for all simulations. For the transmit power ($P_t$) and the circuit power ($P_c$), 0.2W [36] and 0.1W [6] are assumed. For the max-min EE TPC algorithm, we consider low target SE to maximize the EE unless stated otherwise.

A. Comparing Different Energy Efficiency Algorithms

First, we compare different types of TPC algorithms and evaluate their trade-offs. For this comparison, fully-distributed 512 single-antenna APs ($M = L = 512$) and 8 single-antenna UEs ($K = 8$) are chosen randomly from 30,000 and 128 possible locations respectively.

Cumulative distribution functions (CDFs) in Fig. 6 show that the SE generally ranks in the order of max-power, max-min SE, and max-min EE algorithm (with target SE $<6$ bits/s/Hz), while the EE ranks conversely, so that there is a clear trade-off between the SE and EE. It must be noted that the performance of the max-min EE algorithm can differ significantly depending on the target SE parameter. For example, if we compare the min max EE plots with two different target SE values (20 and $<6$ bits/s/Hz) on Fig. 6, the median of the SE is greater for 20 bits/s/Hz target SE by about 4.8 bits/s/Hz, while the median of the EE is 1.3 Gbit/J less than that of $<6$ bits/s/Hz target SE. Both the SE and EE plots for the max-min EE approach with 20 bits/s/Hz target SE overlap on the plots of the max-power algorithm.

The max-min EE hence is a very flexible algorithm where the target SE acts as an adjustable parameter modifying the system performances depending on the SE or EE requirements. However, the disadvantage of the max-min EE algorithm is its runtime, requiring high computing power to be used in real time [13]. The max-min SE meanwhile provides the middle ground performance between the max-min EE with target SE $<6$ bits/s/Hz and max-power.

B. Impacts of Serving Indoor UEs From Outdoor APs

It is noteworthy that for the max-min EE and max-min SE algorithms, a small step-like behavior in the CDF occurs near the 20-30% level. This occurs because there is a 23% probability that the randomly chosen set of UEs involves at least one indoor UE (associated with 4 antennas located indoors at RX5 site on Fig. 3) also corresponding to UE37 to UE40 in Fig. 4, which has a poor channel quality, impacting the TPC algorithm for all other UEs in the same set (remember that the TPC algorithm maximizes the minimum EE performance). Likewise, for the max-power, there are about 3 percent UEs with very low SE, which comes from the 4/128 probability of selecting an indoor UE.

Fig. 7 shows the case with 64 single-antenna APs and 4 UEs, where the max-min EE algorithm with $<6$ bits/s/Hz target SE is applied. While the horizontal tail and the stepping
Fig. 7. CDFs of spectral and energy efficiency for max-min EE, when 64 single-antenna APs serve 4 UEs selected from different environments.

behavior at the lower end of the CDF in the case when we randomly select UEs are not as evident as in the case of $K = 8$ from Fig. 6 (due to 12% of selecting at least one indoor UE from the measurement data), such characteristics still remain. These characteristics are removed and the CDF is smoother if we only select outdoor UEs. In contrast, if only the 4 indoor UEs are served, the performance for both the SE and EE are very poor. This shows that the performance of TPC algorithms can be heavily affected by the UEs with poor channel qualities.

C. MMSE vs. MR: Varying the Number of BS Antennas

Fig. 8 shows results for a larger number of UEs ($K = 64$), which creates a more challenging scenario. We still assume the fully-distributed scenario, and the number of BS antennas (single-antenna APs) varies from 64 to 512 ($M = L = 64, 128, 256, 512$), but consider only the max-power and max-min EE algorithms. Both the MMSE and MR are compared, by looking at the median (50% likely) and lower-end (95% likely) values of the CDFs per scenario.

In the max-power case on Fig. 8a and Fig. 8b both the SE and EE increase with the number of BS antennas, for both MMSE and MR. The increase is the largest when moving from $M = 64$ to $M = 128$ for the MMSE because the MMSE, although much better than MR, is not as effective when $M = K$, since this usually leads to an ill-conditioned channel matrix and therefore excessive noise enhancement 35. Comparing the MR against the MMSE, the MR has much worse performance due to its inability to cancel interference. Performance is increased slightly as $M$ increases, but remains far below the MMSE performance. This indicates that even extremely large arrays ($M = 512$) do not provide the theoretically predicted similar performance between the MMSE and MR combining.

The results for the max-min EE are shown on Fig. 8c and 8d. Compared to the max-power, the EE increases much faster with the number of BS antennas when MMSE is used. For MR combining, in contrast, the max-min EE algorithm has close or better performance to the max-power algorithm for both the SE and EE. This is because the MR performance is dominated by interference, and the max-min EE algorithm controls the power coefficients of the UEs, which can result in both the interference mitigation and the energy reduction. However, the performance of MR is still much worse than the MMSE. In terms of the total system EE, this indicates a trade-off in the energy consumption of the UE, and the energy consumption at the receiving BS, since MMSE requires more energy both for the more complicated processing, and the backhauling of the received data to a central processing location. However, the details of this optimization will depend significantly on the specific processing, backhauling hardware, and the relative importance the network operator assigns to UE and infrastructure energy consumption.

D. MMSE vs. MR: Varying the Number of UEs

We compare how both the SE and EE changes if the number of BS antennas is fixed and the number of UEs increases. We consider only the fully-distributed case with $M = L = 64$ and $K = 8, 16, 32, 64$. Again, for the TPC algorithms, the max-power and max-min EE are used, and both MMSE and MR processing are analyzed. The medians (50% likely) and lower-ends (90% likely) of the CDFs are shown in Fig. 9.

We first look at the max-power algorithm. Looking at MMSE, the performance decreases slowly with increasing $K$, except for the case when $M = K = 64$, where the decrease is sharp due to difficulty of cancelling interference. Meanwhile, the performance also decreases for MR, as the interference from other UEs increases with the number of UEs. We also see that the SE performance gap between MMSE and MR remains very large even when we have many more APs than UEs: $M = 64$ and $K = 8$.

Now we look at the max-min EE algorithm. Compared with the max-power method, the EE increased at the cost of SE for the MMSE, but both the SE and EE values are equal or greater for the MR. This again is because each UE does not transmit at the full power, so the reduction in interference helps the SE while also improving the EE. Another difference to the max-power is that the 50% likely performance of the MMSE decreases more sharply with the number of UEs, even when $M > K$. In summary, the performances of both max-power and max-min EE decrease with the number of UEs, the MMSE is much more effective than MR despite its complexity, and the max-min EE algorithm is again shown to be effective in improving the EE, especially when the number of UEs is much less than the number of BS antennas.
Fig. 8. Spectral and energy efficiency of the fully-distributed scenario when the number of UEs is fixed at 64 ($K = 64$) and the number of BS antennas (APs) varies from 64 to 512 ($M = L = 64, 128, 256, 512$) - two TPC algorithms (max-power and max-min EE) are compared.

Fig. 9. Spectral and energy efficiency of the fully-distributed scenario when the number of BS antenna is fixed at 64 ($M = L = 64$) and the number of UEs varies from 8 to 64 ($K = 8, 16, 32, 64$) - two TPC algorithms (max-power and max-min EE) are compared.
E. Comparing Different Number of APs

We fix the total number of BS antennas ($M = 64$) and vary the number of APs ($L$) to find the best way to deploy the APs among fully-distributed ($L = M$), semi-distributed ($1 < L < M$), and co-located ($L = 1$) cases, similar to the evaluations for indoor scenarios in [37]. The number of UEs is fixed at 8 ($K = 8$). We compare the max-power and max-min EE TPC algorithm when $L = 1, 4, 16, 64$.\footnote{For the semi-distributed and co-located cases, we select consecutive spatial points of the drone which are separated by at least 43cm, which is about $5\lambda$ at 3.5 GHz carrier frequency.}

The results in Fig. [10] show that for the max-power algorithm, fully-distributed ($L = 64$) deployment has the best SE and EE for about 80% of the UEs, while the co-located case ($L = 1$) has the best peak performance. This contrasts with our previous results from [37], where the semi-distributed performance was very close to fully-distributed in a smaller indoor environment with fewer BS antennas ($M = 8$). The CDFs are also steeper when there are more APs ($L$). This makes sense because distributing more APs across areas allows UEs to have at least one good channel between all BS antennas and a UE. In contrast, a UE is likely to experience a bad channel with all BS antennas in the co-located case when the single AP is strongly shadowed from the UE; yet this case can also result in the highest performance if it has good channels to all antennas of the AP.

Even for the max-min EE, the fully-distributed case still performs the best. All cases resulted in better EE in comparison to max-power at the cost of SE, and more performance gap in EE could be made with more APs ($L$). In summary, more APs usually provides the better SE and EE, and the max-min EE is especially more useful when there are more APs.

F. Comparing Different UE Concentrations

In order to determine how the performance differs depending on possible clustering of the UEs, we compare the cases when 8 UEs ($K = 8$) are randomly distributed versus when 8 UEs are concentrated to a single RX site from Sec. [V-B] (at most 15m distance between the UEs). We fix the number of BS antennas to 64, and the BS antennas are either co-located ($L = 1$) or fully-distributed ($L = 64$). We again compare max-power and max-min EE TPC algorithms by observing the CDFs for SE and EE shown on Fig. [11].

For the max-power case, we notice that the performance is better when the UEs are distributed across different sites when the BS antennas are fully-distributed because the geometric separation translates to an easier separation in the angle domain. At the same time, different sets of BS antenna are dominant for different UEs, creating an almost-block-diagonal structure of the H matrix that is advantageous for the condition number and thus reduces noise enhancement. Meanwhile, the co-located scenario shows that the performances are similar for both the distributed UEs and concentrated UEs, as it has both the advantage of ability to separate the UEs as well as the disadvantage of higher chance of shadowing.
Fig. 11. CDFs of spectral and energy efficiency for co-located ($L = 1$), and fully-distributed ($L = 64$) scenarios, when the UEs are either concentrated to one site versus when the UEs are distributed to different sites - two TPC algorithms (max-power and max-min EE) are compared.

Fig. 12. CDFs of spectral and energy efficiency when for semi-distributed ($L = 4$) and fully-distributed ($L = 64$) scenarios, when the APs are located either randomly versus evenly across the coverage area - two TPC algorithms (max-power and max-min EE) are compared.
In contrast, the max-min EE algorithm interestingly shows that for the co-located scenario, further increase in the EE can be achieved when the UEs are concentrated than when UEs are distributed. The uniformity of the channels works in favor for co-located BS when assigning the transmit power coefficients for the max-min EE. For the fully-distributed UEs, concentrated UEs still perform little worse than the distributed UEs.

G. Comparing Different AP Locations

Until now, all the APs were selected at a random from all possible locations. We compare such random placement of the APs to the regular placement of the APs, i.e., dividing up the coverage area to $L$ different grid areas, and selecting an AP per grid area.

Fig. 12 shows the case where $M = 64$ and the number of APs varies ($L = 4, 64$) when there are 8 UEs ($K = 8$). The max-power case shows that the evenly spaced APs provide similar performance as the randomly spaced APs. In contrast, the max-min EE case shows that the evenly distributed APs generally provides a larger increase in performance than randomly distributed APs. Overall, spacing the APs evenly per area is recommended, especially if the max-min EE algorithm is used, but strict planning of the deployment may not be necessary.

VII. CONCLUSION

For CF-mMIMO, evaluating the trade-offs between the SE and EE for different types of TPC algorithms is very important for a large number of battery-powered UEs which the system serves. Our work shows that the max-min EE algorithm can be very effective in comparison to the max-power or max-min SE algorithm in terms of improving EE, based on the channel data obtained from extensive measurement campaigns. The analysis showed that the algorithm is more effective when no UE within a set of served UEs is in a bad channel condition, MMSE combining is applied, when the number of UEs are much less than the number of BS antennas, when the BS antennas are fully-distributed with even spacing, and when the UEs are distributed in the case of distributed BS antennas. Overall, the max-min EE is expected to improve the EE for future CF-mMIMO systems, when very high SEs from the UEs are not required.

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