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Cell-Free Massive MIMO Energy Efficiency Improvement by Access Points Iterative Selection

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ABSTRACT

Cell-free massive multiple-input multiple-output (CF-MIMO) system has been considered a promising technology for 5G and 6G networks for its ability to handle the rise in demand effectively. With CF-MIMO, improved energy efficiency can be obtained from straightforward signal processing. One of the potential problems in CF-MIMO systems is high power consumption due to the large numbers of distributed Access Points (APs), which decrease energy efficiency. This research proposes a modified algorithm to improve overall energy efficiency by reducing total power consumption via using the APs selection technique while maintaining the system's sum of rate. The technique used for APs selection is the largest large-scale-based selection, where each user is served by a subset of APs that offer the best channel condition rather than by all of APs. Total energy efficiency has been calculated for three cases: without APs selection, fixed APs selection, and dynamic APs selection (proposed approach). The simulation result shows that the proposed approach significantly improves energy efficiency by 45% at the signal-to-noise ratio (SNR) equal to 6 dB than the case where the selection of APs is fixed due to the optimal APs selection for each user.

Keywords: Dynamic APs selection, Cell-free massive MIMO, Zero-forcing precoding, Energy efficiency.

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تحسين كفاءة الطاقة لنظام متعدد المدخلات والمخرجات الضخم الخالي من الخلايا من خلال الاختيار التكراري لنقاط الوصول

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الخلاصة

يعتبر نظام المتعدد الادخال والإخراج الضخم الخالي من الخلايا (CF–MIMO) تقنية واعدة لشبكات 5G و6G لقدرته على التعامل مع الزيادة بالطلب بشكل فعال. مع CF–MIMO، يمكن الحصول على كفاءة محسنة في استخدام الطاقة من خلال معالجة الإشارات البسيطة. تتمثل أحد المشكلات المحتملة في أنظمة CF–MIMO في ارتفاع استهلاك الطاقة بسبب الاعداد الكبيرة من نقاط الوصول الموزعة (APs)، والتي تقلل من كفاءة الطاقة. يقترح هذا البحث خوارزمية معدلة لتحسين كفاءة الطاقة الاجمالية عن طريق تقليل اجمالي استهلاك الطاقة باستخدام تقنية اختيار نقاط الوصول مع الحفاظ على مجموع معدل النظام. التقنية المستخدمة لاختيار نقاط الوصول هي أكبر اختيار واسع النطاق، حيث يتم خدمة كل مستخدم بواسطة مجموعة فرعية من نقاط الوصول التي تقدم أفضل حالة للقناة بدلا من جميع نقاط الوصول. تم حساب الكفاءة الكلية للطاقة لثلاث حالات: بدون اختيار نقاط الوصول، اختيار نقاط الوصول الثابتة، واختيار نقاط الوصول الديناميكية (النهج المقترح). تظهر نتيجة المحاكاة ان النهج المقترح يحسن بشكل كبير من كفاءة الطاقة بنسبة ٤٥٪ عند نسبة الإشارة الى الضوضاء (SNR) التي تساوي ٦ ديسيبل من الحالة التي يكون فيها اختيار نقاط الوصول ثابت بسبب الاختيار الأمثل لنقاط الوصول لكل مستخدم.

الكلمات المفتاحية: اختيار نقاط الوصول الديناميكي، النظام المتعدد الادخال والإخراج الضخم الخالي من الخلايا، ترميز القوى الصفرية، كفاءة الطاقة.

1. INTRODUCTION

Cell-free massive multiple input multiple output (CF-mMIMO) is a wireless communication technology that achieved a lot of interest in earlier studies for its efficiency in providing higher spectral efficiency and energy efficiency (EE) **(Almamori and Mohan, 2020; Kassam et al., 2023).** CF-mMIMO system is constructed by distributing many access points (APs) in the zone of coverage, where high service quality and high capacity are offered **(Chen et al., 2022; Zhou et al., 2003)**. A single or multiple antennas are presumed for each AP, and the APs are employed to facilitate the process of transmission **(Ngo, et al., 2017; Interdonato, 2020)**. The large number of APs makes the system leverage the channel hardening and favorable propagation properties **(Chen and Bjornson, 2018; Demir et al., 2021)**. CF-mMIMO can overcome the major problem of cell interference that is shown in cellular systems such as massive MIMO. CF-mMIMO is an advanced technology of massive MIMO, where high data rate in addition to good coverage with low latency are presented by massive MIMO system **(Chataut and Akl, 2020; Omer et al., 2020)**. The coverage zone in massive MIMO is formed of cells, each single cell is constructed to have massive antennas inside a base station, where the consumers within a cell are distributed around the base station **(Almamori and Mohan, 2017; Björnson et al., 2017)**. Users who are close to the

boundary of the cell are facing the boundary effects, where inter-cell interference represents it. To overcome such an issue, instead of taking the antennas together, we spread them out over the coverage area, which means that the user in a particular area will be surrounded by antennas and there is no cell in a network like that, and here is where the term "cell-free" comes from **(Björnson and Sanguinetti, 2015; Obakhena et al., 2021)**.
In the traditional form of the CF-MIMO system, the user is fed by all APs but it is not practical to implement a network like that because we cannot let the user base increase significantly **(Ngo et al., 2018)**. To solve such a problem, the user must not be served by all APs but by a subset of APs, which offer the optimal channel condition **(Buzzi and D'Andrea, 2017; Bjornson and Sanguinetti, 2020; Ammar et al., 2021)**. Choosing the right APs for each user lowers the amount of power used for backhaul and therefore increases overall energy efficiency **(Sheikh, 2022)**. There are many ways to choose the set of APs that serve each user. **(Buzzi and D'Andrea, 2017)** employed a user-centric technique for selecting APs, whereby the user is served by a small number of APs, and it demonstrated that with straightforward estimation schemes, the user-centric strategy works better than the traditional CF strategy, but APs continue to serve several users at once. **(Ngo et al., 2017)** studied CF-MIMO and a small cell system, and they demonstrated that the CF system had higher throughput than the small cell system. They concentrated on max-min power control to ensure better service quality to all users, but the user is served by all APs, which is impractical. In **(Ngo et al., 2018)** the authors proposed two APs selection methods: received power-based selection and the largest large-scale fading-based selection. The two techniques are utilized to reduce backhaul power usage and raise the system's overall energy efficiency. They selected the APs based on the outcomes of the power allocation optimization, which complicated the APs selection due to the difficulty of the optimization process. In **(Dao and Kim, 2020)** the authors proposed a technique to connect each user by certain APs according to channel gain and channel quality, which both depend on large-scale fading coefficients. The scheme that they used should apply only when the number of users is much higher than the number of APs. In **(Vu et al., 2020)** the authors proposed a joint design for both power allocation and APs selection. They assumed a fixed pattern to select the APs for all users which has reduced the backhaul power consumption as compared to the case where all APs are activated and large-scale-based selection. However, the user cannot take advantage of all the good available APs. In **(Palhares et al., 2020)** the authors presented iterative APs selection, MMSE precoding, and three power allocation strategies for downlink CF-MIMO with varied performances and they revealed that the suggested strategy performs better than existing approaches and can lower cost but the pattern of choosing APs is fixed.
In this paper, CF massive MIMO is considered with Zero-forcing precoding and uniform power allocation in downlink transmission and dynamic APs selection based on the largest large-scale selection technique to reduce total power consumption while satisfying the spectral efficiency constraint for each user, also this paper examines the impact of changing selected APs on the overall energy efficiency.

2. THE SYSTEM MODEL

In this study, a CF-MIMO system with randomly placed single antenna M_APs supporting single antenna K-users. There must be many more APs overall than there are users overall **(Ngo et al., 2017)** to enhance throughput. Each AP is connected to a central processing unit

(CPU) by backhaul links as shown in **Fig. 1**, sometimes referred to as the fronthaul links in some studies, to provide users with consistent uplink and downlink service.

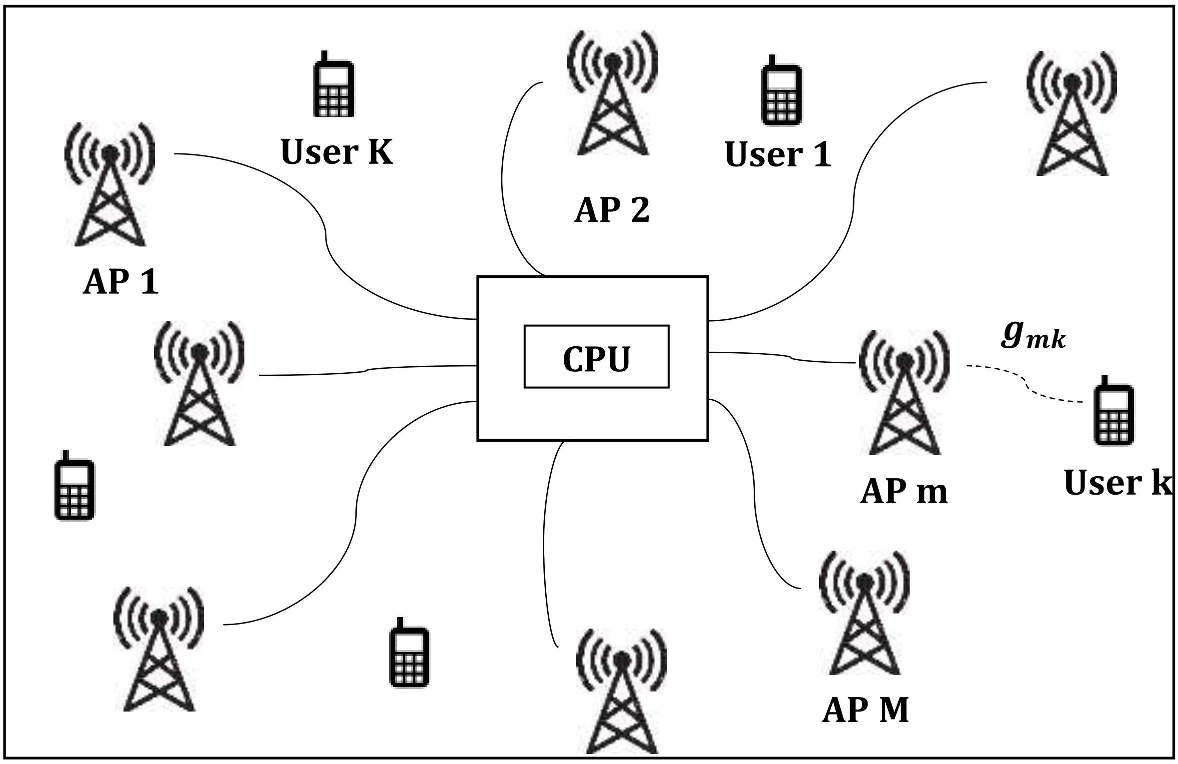

Figure 1. Cell-free massive MIMO network

Notation: Transpose, complex conjugates, and Hermitian are expressed as $(\,.\,)^T, (\,.\,)^*,$ and $(\,.\,)^H$ respectively. The expectation value is represented as $E\{.\}$. Euclidean norm is expressed as $\|\,.\,\|$. Circularly symmetric complex Gaussian distribution is expressed as $\mathcal{CN}\,(\,0, \sigma^2)$, which has a mean equal to zero and variance σ^2. Real valued Gaussian distribution is stated as $\mathcal{N}(\,0, \sigma^2)$ with a mean equal to zero and variance σ^2 **(Ngo et al., 2018)**.

The channel coefficient g_{mk} between the k user and the m AP is provided by the equation as in **(Ngo et al., 2017)**

$$g_{m,k} = \sqrt{\beta_{m,k}}\, h_{m,k} \tag{1}$$

where $h_{m,k} \sim \mathcal{CN}(0,1)$ is the small-scale fading, which is considered to be Rayleigh fading, where the elements of it are identified as independent and identically distributed (i.i.d.) random variables (RVs) that stay constant throughout a coherence interval and are independent over various coherence intervals, and $\beta_{m,k}$ is the large-scale fading that includes path loss and shadowing effects. The large-scale fading remains constant during a variety of coherence intervals and it is expressed as follows **(Ngo et al., 2017)**

$$\beta_{m,k} = PL_{mk}\,.\,10^{\frac{\sigma_{sh}\, z_{mk}}{10}} \tag{2}$$

where $z_{mk} \sim \mathcal{N}(0,1)$ is described the shadow fading, σ_{sh} is defined as the standard deviation, and $\mathrm{PL}_{m,k}$ is the three-slop path loss model formulated in dB **(Ngo et al., 2018)**,

$$\mathrm{PL}_{m,k} = \begin{cases} -L - 35\log_{10}(d_{m,k}), \text{ if } d_{m,k} > d_1 \\ -L - 15\log_{10}(d_1) - 20\log_{10}(d_{m,k}) \\ \text{if } d_0 < d_{m,k} \le d_1 \\ -L - 15\log_{10}(d_1) - 20\log_{10}(d_0), \text{ if } d_{m,k} \le d_0 \end{cases} \tag{3}$$

where $d_{m,k}$ identifies the distance between both the m-AP and k-UE, d_1 and d_0 are the breakpoints of the three-slope model, and L is expressed as follows

$$L \triangleq 46.3 + 33.9\log_{10}(f) - 13.82\log_{10}(h_{AP}) - (1.1\log_{10}(f) - 0.7)h_U + (1.56\log_{10}(f) - 0.8) \tag{4}$$

where f is the carrier frequency, h_{AP} is the size of the height related to AP, and h_{U} is the size of the height related to the user. The assumption is that all APs and users operate in time division duplex (TDD) mode to take advantage of channel reciprocity **(Lin et al., 2022)**. The propagation channels' frequency and time variations are represented by using a block fading model **(Demir et al., 2021),** in which the time-frequency grid is split into coherence blocks. The coherence block's length is represented by τ_c, which is separated into three phases as follows **(Demir et al., 2021)**

$$\tau_c = \tau_p + \tau_u + \tau_d \tag{5}$$

where τ_p is the uplink training, τ_u is the uplink payload data transmission, and τ_d is the downlink payload data transmission. It should be noted that the block-fading model approximates the actual multi-carrier modulation model being used in orthogonal frequency division multiplexing (OFDM) **(Al-Haddad, 2014; Zheng et al., 2022)**.

2.1 Uplink Training and Channel Estimation

When users have access to the network, they are given pilots that are used for channel estimation **(Abdul Majed and Omran, 2020)**. The pilot sequence $\varphi_k, k = 1, \dots, K$, achieved by each user must be orthogonal to other pilot sequences, this operation is called the pilot assignment **(Buzzi et al., 2021; Imoize et al., 2022)**. In this paper the pilot assignment that has been used is random and all the pilot sequences are orthogonal to each other, which means the number of pilots is equal to the number of users ($\tau_p = K$), where $\varphi_k^H \varphi_i = 0$ for $k \ne i$ and $\|\varphi_k\|^2 = 1$. In some cases, $\tau_p < K$ and we can only estimate τ_p orthogonal sequence signals, consequently, some of the users are forced to re-use the pilots and that is what is called pilot contamination, where the pilot sequence is shared by several users **(Al-Hubaishi et al., 2020)**. In this work, the impacts of pilot contamination are ignored.
At first, all users send their pilot sequences to the APs to obtain channel state information (CSI). The equation below receives by m-th AP

$$Y_m = \sqrt{\tau_p \rho_p} \sum_{k=1}^{K} g_{mk} \varphi_k^H + W_m \tag{6}$$

where τ_p is the pilot length, ρ_p is the pilot power (normalized by the noise power) and W_m is the additive noise where the components of it are identified as (i.i.d.) $\mathcal{CN}(0,1)$ RVs. Secondly, the channel estimation of g_{mk} that can be done at the CPU (centralized operation). The minimum mean square error (MMS) estimator is used for the channel estimation process, which lessens the mean square error between the estimated channel and the real channel **(Idan and Al-Haddad, 2023)**. MMSE is used to estimate g_{mk} by the CPU is expressed in **(Nguyen et al., 2017)** such as:

$$\hat{g}_{mk} \sim \mathcal{CN}\left(0, \frac{\rho_p \tau_p \beta_{mk}^2}{1+\rho_p \tau_p \beta_{mk}}\right) \tag{7}$$

The channel estimation error of g_{mk} denotes by (Nguyen et al., 2017)

$$\tilde{g}_{mk} \sim \mathcal{CN}\left(0, \beta_{mk} - \frac{\rho_p \tau_p \beta_{mk}^2}{1+\rho_p \tau_p \beta_{mk}}\right) \tag{8}$$

where $\hat{g}_{mk}$ and $\tilde{g}_{mk}$ are independent of each other.

2.2 Precoding and Downlink Payload Data Transmission

After the achieving of CSI, the CPU uses zero-forcing (ZF) precoding to beamform signals to the users, where the impact of inter-user interference will be avoided with ZF precoding **(Nguyen et al., 2017; Tripathi et al., 2018)**. The signal transmitted from m-AP to all users is provided by:

$$x_m = \sqrt{\rho_d} \sum_{k=1}^{K} \sqrt{\eta_k}\, \mathrm{a}_{\mathrm{mk}}\, s_k \tag{9}$$

where ρ_d is the downlink power (normalized by the noise power), η_k, $k = 1, \dots, K$ is the power control coefficient and the total power control coefficients must be chosen according to the following constraint:

$$E\{\|x_m\|^2\} \leq \rho_d \tag{10}$$

where this constraint must be satisfied at every AP, a_{mk} is the mk element of the matrix A that identifies the pseudo-inverse matrix, which ZF precoding is often characterized by **(Nayebi et al., 2015)** as:

$$A = \hat{G}^*\left(\hat{G}^T \hat{G}^*\right)^{-1} \tag{11}$$

where $[\,\hat{G}\,]_{mk} = \hat{g}_{mk}$ is the channel estimation, and s_k is the symbol designed for k-th user, $E\,\{|s_k|^2\} = 1$.
The precoding matrix F that forms at the CPU can be expressed as:

$$F = A\,P \tag{12}$$

where P is a diagonal matrix with $\sqrt{\eta_1}, \dots, \sqrt{\eta_K}$ on its diagonal. The k-user receives the signal **(Nayebi et al., 2017)**

$$y_k = \sqrt{\rho_d}\, g_k^T F\, s + w_k = \sqrt{\rho_d}\,(\,\hat{g}_k + \tilde{g}_k)^T\; \hat{G}^*\left(\hat{G}^T \hat{G}^*\right)^{-1} P\, s + w_k$$
$$= \sqrt{\rho_d\, \eta_k}\, s_k + \sqrt{\rho_d}\, \hat{G}^*\left(\hat{G}^T \hat{G}^*\right)^{-1} (\,\tilde{g}_k\,)^T P\, s + w_k \tag{13}$$

where the first part, in the last line of Eq. (13), is the desired signal, the second part is the channel estimation error where $s = (s_1, \dots, s_K)^T$, and the last part $w_k\, \mathcal{CN}(0,1)$ is the additive noise. The achievable spectral efficiency of the k-user is given by **(Nguyen et al., 2017)**

$$SE_k = \left(1 - \frac{\tau_p}{\tau_c}\right)\log_2(1 + \frac{\rho_d\,\eta_k}{1+\rho_d\sum_{i=1}^{K}\eta_i\gamma_{ki}}) \quad (14)$$

where γ_{ki} is the i-th element of the vector below **(Nayebi et al., 2017)**

$$\gamma_k = diag\left\{E\left(\left(\left(\hat{G}^T\,\hat{G}^*\right)^{-1}\hat{G}^T E\,(\tilde{g}_k^*\tilde{g}_k^T)\,\hat{G}^*\left(\hat{G}^T\,\hat{G}^*\right)^{-1}\right)\right)\right\} \quad (15)$$

The following term $E\,(\tilde{g}_k^*\tilde{g}_k^T)$ represents a diagonal matrix including the variance of Eq. (8) on its m-th diagonal component. The summation of spectral efficiency for all users is:

$$SE = \sum_{k=1}^{K} SE_k \quad (16)$$

The power constraint in Eq. (10) can be rewritten as:

$$\sum_{k=1}^{K}\theta_{mk}\,\eta_k \leq 1\,,\; m = 1, \dots, M \quad (17)$$

where θ_{mk} is the k-th element of θ_m expressed by **(Nayebi et al., 2017)**

$$\theta_m = diag\left\{E\left(\left(\left(\hat{G}^T\,\hat{G}^*\right)^{-1}\hat{g}_{[m]}\hat{g}_{[m]}^H\left(\hat{G}^T\,\hat{G}^*\right)^{-1}\right)\right)\right\} \quad (18)$$

The operation of allocating power to the users in this work is considered uniform for clarity, where each AP transmits with full power as follows **(Nayebi et al., 2017)**

$$\sum_{k=1}^{K}\theta_{mk}\,\eta_k = 1 \quad (19)$$

So the power control coefficient is defined as **(Nayebi et al., 2017)**

$$\eta_k = \frac{1}{\sum_{k=1}^{K}\theta_{mk}},\; k = 1, \dots, K \quad (20)$$

3. TOTAL POWER CONSUMPTION AND ENERGY EFFICIENCY

The total power consumed throughout the operation of the uplink and downlink transmission is formulated as **(Ngo et al., 2018)**

$$P_{total} = \sum_{m=1}^{M} P_m + \sum_{m=1}^{M} P_{bh\,,m} \quad (21)$$

where the first part P_m is the amount of power that is used at the m-th AP by the amplifier, transceiver chains, and the operation of signal processing. It can be formulated as follows **(Nguyen et al., 2017)**

$$P_m = \alpha_m\,\rho_d\,N_0(\sum_{i=1}^{K}\theta_{mi}\,\eta_i) + P_{tc,m} \quad (22)$$

where α_m is the power amplifier efficiency with range $0 < \alpha_m \leq 1$, N_0 is the noise power, and $P_{tc,m}$ is the internal power needed to operate the converters, mixers, and filters connected with each antenna of the m-th AP's circuits.

The second part $P_{\mathrm{bh},m}$ is the amount of power used by the backhaul link between the CPU and each AP and it can be formulated as follows **(Ngo et al., 2018)**

$$P_{bh,m} = P_{0,m} + B \cdot SE \cdot P_{bt,m} \tag{23}$$

where $P_{0,m}$ (traffic-independent power) is the fixed power consumption of every backhaul that is based on the distances between the CPU and the APs as well as the system structure, B is the bandwidth of the system, and $P_{bt,m}$ is referred to as the traffic-dependent power in watts per bit/second. By dividing the network's entire throughput (bit/s) (information rate) by its overall power consumption (watt), one can get the network's overall energy efficiency (bit/Joule) that can be expressed as **(Ngo et al., 2018)**

$$Ee = \frac{B\ SE}{P_{total}} \tag{24}$$

4. ACCESS POINTS SELECTION

For CF-MIMO systems, more backhaul connections are needed to send data between both the APs and the CPU **(Ngo et al., 2018)**

$$Ee = \frac{B\ SE}{\sum_{m=1}^{M} P_m + \sum_{m=1}^{M} P_{bh,m}} \tag{25}$$

and that is reflected in the second part of the denominator in Eq. (25), so if the m-th AP only provides services to a selected group of users instead of all users, then it only needs to deliver the data related to these users. Consequently, the backhaul power consumption will be reduced, where only these users' spectral efficiencies can determine the backhaul power consumption and as a result, the total energy efficiency will be improved. Let U_m be the group of users that is being served by m-th AP, then only the expression of $P_{\mathrm{bh},m}$ provided in Eq. (23) will be changed to the following **(Ngo et al., 2018)**

$$P_{bh,m} = P_{0,m} + B \cdot \sum_{U_m} SE_k\ P_{bt,m} \tag{26}$$

The technique for APs selection that is used in this research is the largest large-scale fading-based selection APs, motivated by **(Ngo et al., 2018; Palhares et al., 2020)**, opposite to the method **(Ngo et al., 2018)**, where the contribution of each chosen AP to overall large-scale coefficients determine the number of APs chosen and performed with conjugate beamforming precoding technique, and unlike the method in **(Palhares et al., 2020)**, where the number of selected APs is fixed and performed with minimum mean-square error (MMSE) precoding technique. The proposed large-scale APs selection with a dynamic (non-fixed) number of APs, where each user chooses the number of APs that have the largest large-scale coefficient, based on spectral efficiency constraint that must be fulfilled to choose the proper number of APs to each user and the proposed algorithm performed using ZF precoding technique. The proposed algorithm improves energy efficiency by reducing the total power consumption by APs selection while maintaining the sum rate for the system. The proposed algorithm is listed below:

1. Find the estimation of large-scale coefficient $\beta\ \ \forall\, k, m$.
2. Sort β_k to all users in descending order.

3. Put a range for choosing the largest β APs, where the minimum number of selected APs for each user is denoted by L_min and the maximum number is denoted by L_max.
4. Put a spectral efficiency constraint (SE-constraint) that must be satisfied by each user.
5. Go through each user and choose the largest L_min APs and assign zero to the rest of the APs. This step must be done for all users.
6. Calculate the SE_k for each user, where $k = 1, \dots, K$ then we must check if SE_k satisfies the SE-constraint, if SE_k to each user that does not satisfy the SE-constraint, two more APs will be added, $L\_min = L\_min + 2$, to that user and recalculate the SE_K and so on till the user satisfies the SE-constraint. It should be noted that the addition of APs is limited by L_max.
7. Let SA_k , $k = 1, \dots, K$ be a vector that counts the number of selected APs for each user, which depends on L_min at each loop of calculating SE for each user.

5. RESULTS AND DISCUSSION

The edges of the considered square area (of 1×1 km^2) are wrapped around to prevent boundary effects. APs and users inside this area are located randomly. The pilot assignment approach used is random. The path loss is represented by the three-slope path loss model as in Eq. (3) and the noise power N_0 can be calculated as (**Ngo et al., 2017)**

$$N_0 = B \times k_B \times T_0 \times noise\ figure\ (W) \tag{27}$$

where B represents the system's bandwidth, $k_B = 1.381 \times 10^{-23}$ represents Boltzmann constant (J/K), and T_o of 290 represents the temperature of the noise measured (K).
The valued variables used in this work are listed in **Table 1.**

Table 1. Parameters used for the simulation **(Ngo et al., 2017; Ngo et al., 2018)**

Parameters	Value	Parameters	Value
Area distance, D	1 km	Noise figure	9 dB
Carrier frequency, f	1900 MHZ	Pilot power, ρ_p	1 W
Bandwidth, B	20 MHZ	Downlink power, ρ_d	0.2 W
Coherence interval length, τ_c	200 sample	Number of APs, M	30
Pilot length, τ_p	10	Number of users, K	10
Breakpoints of three slope models, d_0 and d_1	10 m, 50 m	Power amplifier efficiency, α_m , $\forall m$	0.4
Height of AP, h_{AP}	15 m	Power consumption per antenna, $P_{tc,m}$, $\forall\ m$	0.2 W
Height of UE, h_U	1.65 m	Fixed power consumption for backhaul, $P_{0,m}$, $\forall m$	0.825 W
The standard deviation of shadow fading, σ_{sh}	8 dB	Traffic-dependent backhaul power, $P_{bt,m}$, $\forall m$	0.25 W/(Gbits/s)

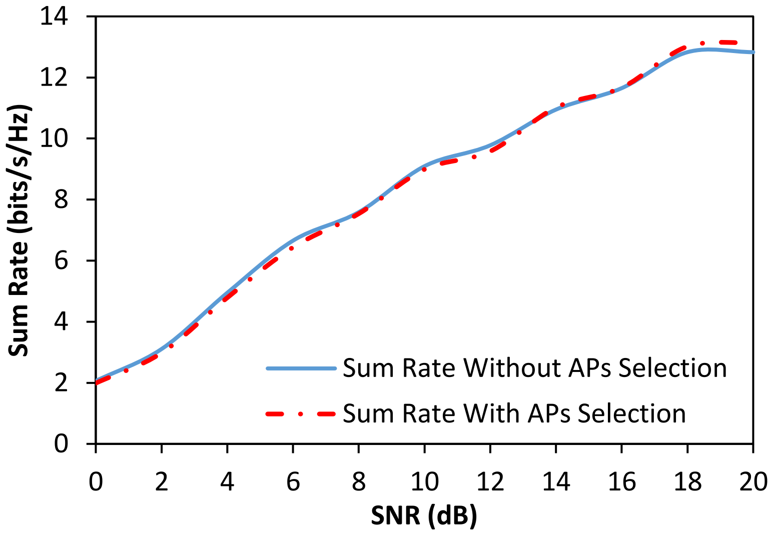

Figure 2. Sum Rate versus SNR with $M = 30$, and $K = 10$.

Fig. 2 shows a comparison between the proposed algorithm for APs selection and the case where users are served by all APs. The comparison in sum rate Eq. (16) versus the signal-to-noise ratio (SNR). The result shows that the sum rate with the proposed algorithms is close to the case where there is no APs selection, meaning the proposed scheme maintains the sum rate in a zone around the case where there is no APs selection because it chooses the best APs for each user and by selecting APs with the largest large scale fading coefficients, the interference between APs can be reduced because the selected APs are more likely to be farther away from each other and therefore provide weaker interfering signals to each other. The results lead to the practical implementation of cell-free massive MIMO with APs selection can be made possible.

A comparison of the energy efficiency (EE) of CF-MIMO versus SNR in three cases is shown in **Fig. 3**. Case 1, without APs selection, case 2, with fixed APs selection **(Palhares et al., 2020)** but with ZF precoding and $L_{fixed} = 10$, where L_{fixed} is the number of selected APs. Case 3, with the proposed algorithms by choosing the minimum number of selected APs $L\_min = 6$ and the maximum number of APs $L\_max = 10$ with spectral efficiency constraint for each user is 1 bits/s/Hz. The result shows that the EE is significantly better with APs selection because the backhaul power consumption is reduced, where each AP needs to send the data to the CPU just for the users that served. The simulation result of case 3 reveals a 45 percent improvement in EE at SNR equal to 6 dB over case 2 due to the optimal selection of APs based on channel condition, where most of the users satisfy the spectral efficiency constraint with the minimum number of selected APs and that means the backhaul power consumption will be much less than the case 2. EE will continue to improve with SNR above 8 dB but at a slower rate. This implies that the slope of the EE versus SNR will become flatter as the system gets closer to its maximum EE limit. However, there will come a time when boosting SNR further won't produce a noticeable improvement in EE.

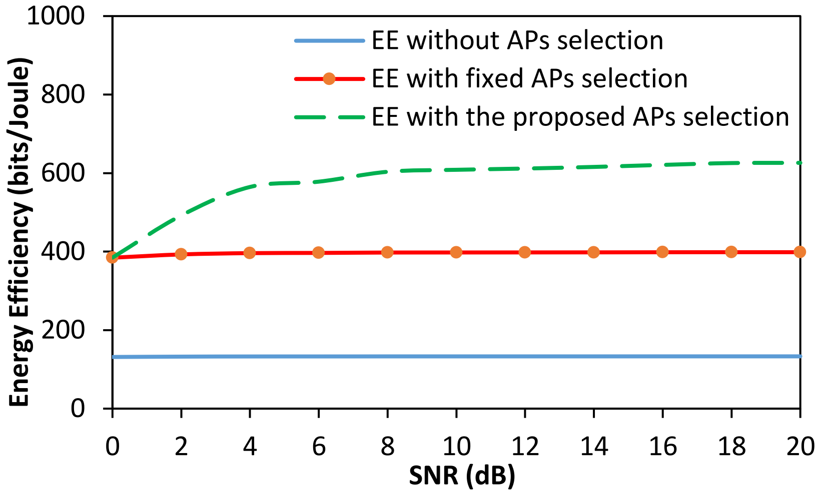

Figure 3. Total Energy Efficiency versus SNR

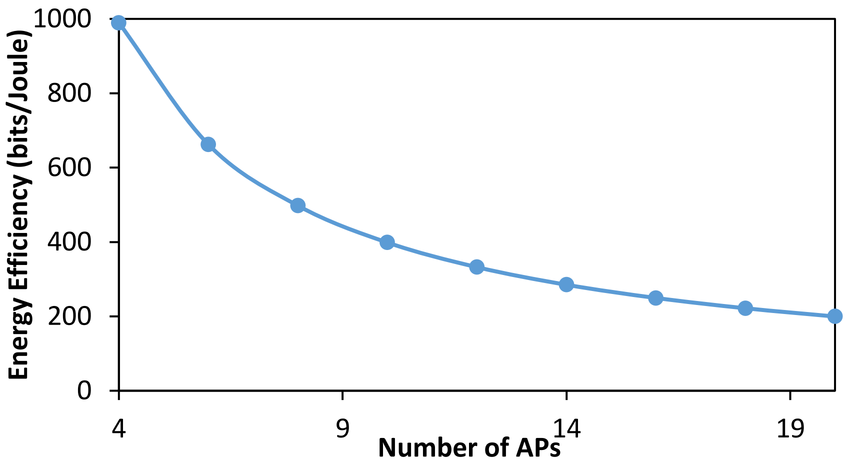

Figure 4. EE vs. The Number of APs

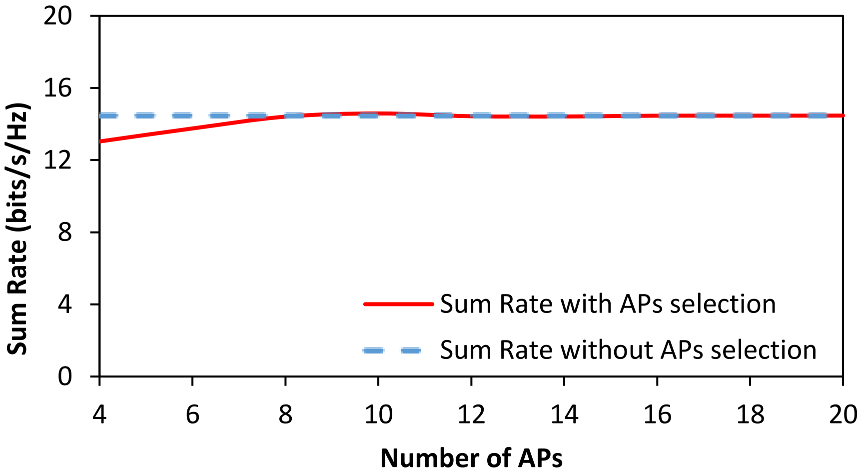

Figure 5. Sum Rate vs. The Number of APs

Fig. 4 shows energy efficiency (EE) versus the number of APs and **Fig. 5** shows the sum rate versus the number of APs for the same experiment. The pattern of APs selection in this experiment is fixed and changed from 4 to 20 out of 30 total APs with the minimum SE required by each user being 1 bits/s/Hz. The result in **Fig. 4** shows that the EE increases when the number of selected APs decreases and that because of the backhaul power term in total power consumption decreases, which is inversely propositional with EE. The result in **Fig. 5** shows that when the number of selected APs is 4 the sum rate is slightly less than the case with no APs selection. In general, when we want to improve energy efficiency by APs selection it is important to maintain the sum rate for the system so we must choose the right number of APs which can improve energy efficiency while maintaining the sum rate as we see in **Fig. 5** when we increase the number of APs the sum rate becomes close to the case that without APs selection. The optimal case achieved in this experiment is when the number of APs is 8 so we must balance between the number of APs used and the sum rate when improving energy efficiency for the cell-free system.

6. CONCLUSIONS

This research proposes dynamic APs selection with uniform power allocation to maximize the total energy efficiency for downlink transmission of a cell-free massive MIMO network. The proposed algorithm improves energy efficiency by decreasing the total power consumption while guaranteeing the minimum spectral efficiency satisfies each user. The selection of APs was performed by relying on large-scale fading coefficients. The research compared energy efficiency with three cases: without APs selection, fixed APs selection, and dynamic (non-fixed) APs selection. The simulation results showed an improvement in energy efficiency with the proposed APs selection algorithm.

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