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Unequal Power Amplifier Dimensioning for Adaptive Massive MIMO Base Stations

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Abstract—**In this paper, we propose a novel power amplifier (PA) dimensioning method for massive multiple-input multiple-output (MIMO) systems whose number of transmitting antennas is adapted according to the number of user equipments (UEs) in the cell. The dimensioning method sets the maximum output powers of PAs unequally according to the pre-calculated average per-antenna transmission powers for different number of UEs. This allows PAs to operate at higher efficiency when the average per-antenna transmission powers vary due to the adaptive number of transmitting antennas. The performance of the method is evaluated in the symmetric multi-cellular scenario using a comprehensive power consumption model that considers both base station and UEs. When simple class-B PAs are used at the base station, unequal PA dimensioning reduces the PA power consumption up to 42 % when compared to the conventional equal PA dimensioning. This improves the total system energy efficiency. The benefits of the proposed unequal PA dimensioning are that no prior knowledge of the UE distribution is needed and good performance is achieved for all UE densities.**

I. INTRODUCTION

In recent years, improving energy efficiency in cellular networks has been an active research topic [1]. Any improvement on the base station energy efficiency decreases the operational expenses of telecommunications operators. In addition, energy efficiency improvements help to reduce the CO_2 emissions from the electrical energy generation. Unlike for the earlier mobile communication generations, energy efficiency is set as one of the key targets for the 5G systems. It is required that the network energy efficiency in 5G systems should be 100 times than that of IMT-Advanced systems [2]. Other 5G requirements target for improvements in data rates, area capacity, spectrum efficiency, terminal mobility, connection density, and radio network latency.

Massive multiple-input multiple-output (MIMO) [3] has been proposed for 5G systems mainly because it has potential to achieve high area capacity with low transmitted power. Massive MIMO is commonly defined as a time domain duplex (TDD) multi-user MIMO system with a large number of antennas at the base station serving a much smaller number of single-antenna user equipments (UEs) [4]. Having much more base station antennas than UEs provide degrees of freedom that can be used for focusing the received energy into small regions of space. This improves both throughput and reduces the transmitted power levels compared to conventional base stations [5]. The radio frequency (RF) processing of massive MIMO can be built using low-cost, low-power components

[5]. When the number of base station antennas grows towards infinity, the effects of noise, fading, and inter-cell interference are averaged out and the system performance is limited by the pilot contamination [3]. The pilot contamination occurs when the same pilot sequences are re-used in several cells.

Energy efficiency of massive MIMO has recently been studied e.g. in [6]–[8]. A common conclusion in these studies is that it is not optimal to always use all the available base station antennas. In fact, it is possible to find the number of antennas that maximize the energy efficiency for a given number of UEs [8]. Consequently, it is energy-efficient for massive MIMO systems to adapt the number of antennas that are used for transmission and reception. The adaptively selected set of antennas is called as the active antennas for the rest of this paper. It was also shown in [8] that contrary to earlier beliefs, the total transmitted power should increase with the increasing number of antennas. However, the optimal transmitted power increases slower than the number of antennas and thus the per-antenna transmitted power decreases. Unlike earlier works on energy-efficient massive MIMO, the effect of non-constant power amplifier (PA) efficiency is taken into account in [9]. This is especially important when the number of active antennas is adapted because it causes a large dynamic range for the average per-antenna transmitted power. The main idea in [9] is to select the maximum PA output power such that the energy efficiency is maximized over the daily profile on the number of UEs.

In this paper, we consider how to improve the energy efficiency of a massive MIMO system whose number of active antennas and average transmission power adapt to the number of served UEs. As an energy efficiency improvement, we propose to set maximum output powers of PAs unequally according to the pre-calculated average per-antenna transmission powers for different number of UEs. The benefit of the proposed method is that it does not require prior knowledge of the distribution of the number of UEs. Our approach results in lower PA back-off, better PA efficiency, and correspondingly reduced power consumption.

PA dimensioning for adaptive massive MIMO systems has been proposed in [9] where the same maximum output power is selected for each PA. Unlike in our proposed method, PA dimensioning in [9] assumes that the daily traffic profile is known already when designing the PAs. This is not a realistic assumption in most cases as it would require tight coopera-
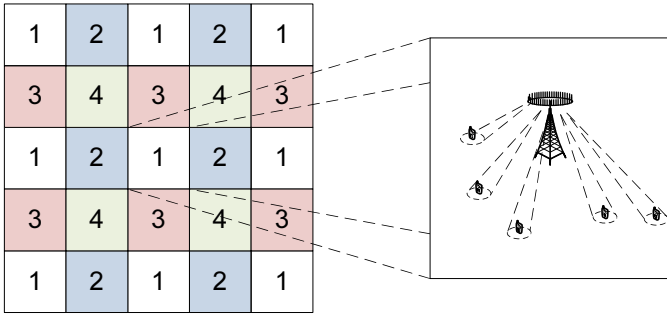
Fig. 1. The pilot reuse pattern of the multi-cell system when $\tau = 4$.

tion between the mobile operator and the PA manufacturer. Unequal PA dimensioning has been proposed in [10] where a PA from a set of PAs with different maximum output power levels is selected to feed an antenna. The selection is done based on the required transmitted power level such that the PA back-off is minimized. Our proposed method can be seen as an extension of idea from [10] into massive MIMO systems where the number of PAs equals the number of antennas.

The remainder of the paper is organized as follows: The system and power consumption models are described in Sections II and III, correspondingly. The research problem and the proposed unequal PA dimensioning method are presented in Section IV. The numerival results are given in Section V. Finally, conclusions are drawn in Section VI.

II. System Model

We consider a multi-cell massive MIMO system where each cell has an M-antenna base station serving K single-antenna UEs that are uniformly distributed across the cell. The number of active antennas $m \leq M$ is adapted according to K. As in [8], we consider a symmetric multi-cell scenario in which the system parameters m, K, and the average sum data rate as well as the UE distribution and channel model are the same for each cell. To alleviate the pilot contamination problem, cells are divided into sets that re-use the same pilot symbols. The multi-cell system under study is depicted in Fig. 1 for pilot reuse factor $\tau = 4$ where different numbers and colors correspond to different sets of orthogonal pilots. It can be seen that each cell has 8 dominant interferers when $\tau = 4$.

The channel is assumed to be doubly block fading [11] such that the channel is static during a time-frequency block of U symbols. The $m \times 1$ vector of channel coefficients for UE k is $\mathbf{h}^{(k)}$ whose each element is complex Gaussian distributed as $h_n^{(k)} \sim \mathcal{CN}(0, \Lambda(d)), \forall n = 1, \ldots, m$ where $\Lambda(d) = \kappa/d^\alpha$ is the path loss at distance d from the base station. The propagation scenario is characterized by the constant κ and the path loss exponent α. As the reciprocal TDD operation is assumed, the first $\zeta^{(\mathrm{ul})}U$ symbols are used for uplink (UL) and the last $\zeta^{(\mathrm{dl})}U$ symbols for downlink (DL) transmission where $\zeta^{(\mathrm{ul})} + \zeta^{(\mathrm{dl})} = 1$. The first τK UL symbols are reserved for pilots. In DL, transmitted power is focused to UE locations and the inter-cell interference is not a problem. Thus the same

symbols are used for DL pilots in all cells and the pilot overhead is only K symbols in DL.

Fairness among the UEs is guaranteed by setting average DL and UL data rates $\overline{R}_k^{(\mathrm{dl})}$ and $\overline{R}_k^{(\mathrm{ul})}$ equal for all $k = 1, \ldots, K$. This requires per-UE power control, which is described in [8]. It is assumed that zero-forcing (ZF) precoding and detection are used for DL and UL, respectively. Taking into account the effects of pilot contamination and imperfect channel estimation, the resulting per-UE gross rate is $\overline{R} = B \log_2(1 + \gamma)$ where B is the system bandwidth and the mean signal-to-interference-plus-noise ratio (SINR) γ can be given as [8]

$$\gamma = \frac{1}{\mathcal{I}_{\mathrm{PC}} - 1 + \left(\mathcal{I}_{\mathrm{PC}} + \frac{1}{\rho K \tau}\right) \frac{1 + K \rho \mathcal{I}}{\rho(m-K)} - \frac{K \mathcal{I}_{\mathrm{PC}^2}}{m-K}}. \quad (1)$$

$\mathcal{I}$, $\mathcal{I}_{\mathrm{PC}}$, and $\mathcal{I}_{\mathrm{PC}^2}$ are the relative received power terms that are defined using the mean ratio of path losses between the interfering cell l and serving cell j, $\mathcal{I}_{jl} = E[\Lambda(d_l)/\Lambda(d_j)]$ where d_l and d_j are the distances to interfering and serving base stations, respectively. The sum of relative received powers from all cells $\mathcal{I}$ is defined as $\mathcal{I} = \sum_{l=1}^{J} \mathcal{I}_{jl}$ where J is the number of cells in the system. The sum of relative received powers $\mathcal{I}_{\mathrm{PC}}$ and squared powers $\mathcal{I}_{\mathrm{PC}^2}$ for the set of cells sharing the same UL pilot symbols $\mathcal{Q}_j$ as cell j are given as $\mathcal{I}_{\mathrm{PC}} = \sum_{l \in \mathcal{Q}_j} \mathcal{I}_{jl}$ and $\mathcal{I}_{\mathrm{PC}^2} = \sum_{l \in \mathcal{Q}_j} \mathcal{I}_{jl}^2$ where $\mathcal{Q}_j \subset \{1, \ldots, J\}$. The design parameter ρ is related to the average per-antenna DL transmission power P_{Tx} and the average UL per-UE transmission power $P_{\mathrm{Tx, UE}}$ such that

$$\rho = \frac{m P_{\mathrm{Tx}}}{B \sigma^2 E\left[(\Lambda(d))^{-1}\right] K} = \frac{P_{\mathrm{Tx, UE}}}{B \sigma^2 E\left[(\Lambda(d))^{-1}\right]} \quad (2)$$

where σ^2 is the spectral density of the additive white Gaussian noise (AWGN) noise and $E\left[(\Lambda(d))^{-1}\right]$ is the average inverse channel attenuation.

The number of UEs in a cell follows a daily traffic profile according to $K \sim \mathrm{Pois}(\lambda_h)$ where the average number of UEs is $\lambda_h = c(h)\hat{K}$. The average number of UEs during the busy hour $\hat{K}$ is multiplied by the hourly traffic level multiplier $c(h) \leq 1$ that is defined according to [12]. Traffic level multiplier $c(h)$ as a function of hour of day is shown in Fig. 2a. An example probability density function (pdf) of K over a day is shown in Fig. 2b when $\hat{K} = 30$.

III. Power Consumption Model

A realistic power consumption model is extremely important when studying the energy efficiency of massive MIMO systems. We have modelled the power consumption of the majority of base station functional blocks according to [13]. UE power consumption is modelled as in [14], MIMO processing as well as channel estimation power consumption according to [8], and PA power consumption according to [15]. The total system power consumption is defined as

$$P = \frac{P_{\mathrm{PA}} + P_{\mathrm{RF}} + P_{\mathrm{BB}} + P_{\mathrm{OH}}}{\eta_{\mathrm{PS}}} + K P_{\mathrm{UE}} \quad (3)$$
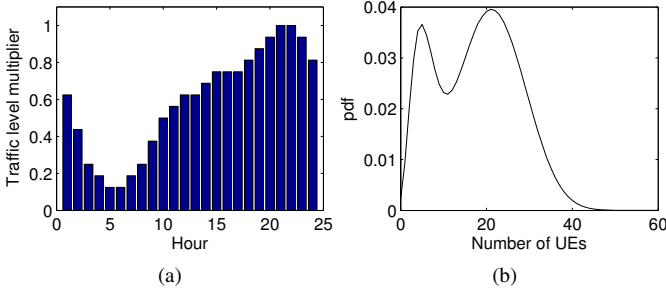
Fig. 2. Hourly traffic level multiplier (a) and an example pdf of K over a day when $\hat{K} = 30$ (b).

where P_{PA} is the average PA power consumption, P_{RF} is the analog RF circuit power consumption, P_{BB} is the digital baseband power consumption, P_{OH} is the overhead power consumption of platform control and network processing, η_{PS} is the power conversion efficiency of the power system, and P_{UE} is the average consumed power of each UE.

In massive MIMO systems, PAs should be simple to keep the cost of the RF module low. It is reasonable to assume that class-B PAs that reach good linearity with reasonable efficiency are used in the base station. The most promising candidates for 5G waveforms are based on multicarrier modulation [16], which results in PA input signals that can be approximated by complex Gaussian processes. The average efficiency of class-B PAs for Gaussian input signal has been presented in [15]. Assuming a soft limiter model, the average efficiency $\overline{\eta}_{\text{PA}}$ can be given as [15]

$$\overline{\eta}_{\text{PA}} = \frac{\sqrt{\pi}}{2} \frac{1 - e^{-\xi}}{\sqrt{\xi}\,\text{erf}\left(\sqrt{\xi}\right)} \tag{4}$$

where $\xi = P_{\text{Tx}}^{\max}/P_{\text{Tx}}$ is the output power back-off defined as the ratio of the maximum PA output power and the average per-antenna transmission power. The average consumed PA power is then simply

$$P_{\text{PA}} = \frac{m\zeta^{(\text{dl})} P_{\text{Tx}}}{\overline{\eta}_{\text{PA}}}. \tag{5}$$

For analog RF circuit power consumption modelling, we apply the model from [13]. To simplify the notation, we have omitted the parameters that are constant in our work. These parameters include bandwidth, digital processing quantization resolution, and scaling with technology evolution. The analog RF circuit power consumption is modelled as

$$P_{\text{RF}} = m\left(P_{\text{FRQ}} + \zeta^{(\text{dl})} P_{\text{RF,DL}} + \zeta^{(\text{ul})} P_{\text{RF,UL}}\right) + \sqrt{m} P_{\text{CLK}} \tag{6}$$

where P_{FRQ} is the power required for frequency synthesis, $P_{\text{RF,DL}}$ and $P_{\text{RF,UL}}$ are the power consumption of RF transmission and reception circuits, and P_{CLK} is the power required for clock generation.

The digital baseband power consumption can be given as

$$P_{\text{BB}} = m\left(P_{\text{OFDM}} + \hat{\zeta}^{(\text{ul})} P_{\text{SYNC}}\right) + \frac{R^{(\text{dl})}}{\epsilon_{\text{COD}}} + \frac{R^{(\text{ul})}}{\epsilon_{\text{DEC}}} + P_{\text{MIMO}}$$
$$+ P_{\text{CE}} + K P_{\text{MAP}}\left(\frac{\overline{R}_k^{(\text{dl})}}{\hat{R}}\right)^{1.5} + K P_{\text{DEM}}\left(\frac{\overline{R}_k^{(\text{ul})}}{\hat{R}}\right)^{1.5} \tag{7}$$

where P_{OFDM} is the power consumption of orthogonal frequency division multiplexing (OFDM) processing, filtering, and sampling, $\hat{\zeta}^{(\text{ul})} = \left(\zeta^{(\text{ul})} U - \zeta^{(\text{ul})} K\right)/U$ is the fraction of UL data transmission, P_{SYNC} is the power consumption of synchronization, $R^{(\text{dl})}$ and $R^{(\text{ul})}$ are DL and UL sum rates, ϵ_{COD} and ϵ_{DEC} are the channel coding and decoding energy efficiencies (in bit/J), $\overline{R}_k^{(\text{dl})}$ and $\overline{R}_k^{(\text{ul})}$ are the average per-UE DL and UL data rates, $\hat{R}$ is the reference data rate, and P_{MAP} and P_{DEM} are the power consumptions of modulated symbol mapping and demapping. The power consumption of channel estimation is modelled as [8]

$$P_{\text{CE}} = \frac{2\tau m K^2 B}{\epsilon_{\text{DSP}} U} \tag{8}$$

where ϵ_{DSP} is the energy efficiency of digital signal processing (DSP) (in floating point operations per joule). The ZF processing power consumption can be given as [8]

$$P_{\text{MIMO}} = \frac{B\left(K^3/3 + mK^2(1 - 2\tau) + mK(1 + 2U)\right)}{\epsilon_{\text{DSP}} U}. \tag{9}$$

Power consumption of overhead processing is given as [13]

$$P_{\text{OH}} = \sqrt{m} K^{0.2}\left(\zeta^{(\text{dl})} P_{\text{CDL}} + \zeta^{(\text{ul})} P_{\text{CUL}}\right) + \frac{\overline{R}_k^{(\text{dl})}}{\epsilon_{\text{NDL}}} + \frac{\overline{R}_k^{(\text{ul})}}{\epsilon_{\text{NUL}}} \tag{10}$$

where P_{CDL} and P_{CUL} are the platform control processing powers for DL and UL, respectively. The energy efficiencies for DL and UL network processing are ϵ_{NDL} and ϵ_{NUL}.

Finally, the UE power consumption is modelled as [14]

$$P_{\text{UE}} = \zeta^{(\text{dl})}\left(P_{\text{DL}} + P_{\text{Rx,RF}}(P_{\text{Rx}})\right) + P_{\text{Rx,BB}}\left(\overline{R}_k^{(\text{dl})}\right)$$
$$+ \zeta^{(\text{ul})}\left(P_{\text{UL}} + P_{\text{Tx,RF}}(P_{\text{Tx,UE}})\right) + P_{\text{ON}} \tag{11}$$

where P_{DL} is the constant power consumed when receiving data, P_{Rx} is the average received power, P_{UL} is the constant power consumed when transmitting data, and P_{ON} is the constant power consumed when the cellular subsystem is turned on. The variable terms in (11), i.e. power consumptions of DL RF processing $P_{\text{Rx,RF}}(P_{\text{Rx}})$, DL baseband processing $P_{\text{Rx,BB}}\left(\overline{R}_k^{(\text{dl})}\right)$, and UL RF processing $P_{\text{Tx,RF}}(P_{\text{Tx,UE}})$, are defined in Table 4 of [14].

IV. Unequal power amplifier dimensioning

The studied problem is to maximize the system energy efficiency ϵ with respect to the number of active antennas m and the transmission power related design parameter ρ

$$\max_{m \geq 0, \rho \geq 0} \epsilon = \sum_{k=0}^{\infty} \frac{k \left(\overline{R}_i^{(\text{dl})} + \overline{R}_i^{(\text{ul})} \right)}{P} \Pr(K = k)$$

$$\text{s. t.} \quad \overline{R}_i^{(\text{dl})} = \zeta^{(\text{dl})} \left(1 - \frac{K}{U\zeta^{(\text{dl})}} \right) \overline{R}, \forall i = 1, \ldots, K \quad (12)$$

$$\overline{R}_i^{(\text{ul})} = \zeta^{(\text{ul})} \left(1 - \frac{\tau K}{U\zeta^{(\text{ul})}} \right) \overline{R}, \forall i = 1, \ldots, K$$

where $\Pr(K = k)$ is the probability mass function of K.

A procedure for solving (12) numerically is provided in [8] for each $K = k$ independently, i.e. assuming that $\Pr(K = k) = 1$ and $\Pr(K \neq k) = 0$. The idea of our proposed method is to solve the optimum m and ρ for each possible value of K, apply (2) to get the DL average per-antenna transmission power, and use these power levels to set the maximum output powers of PAs accordingly.

Let's assume that the number of PAs equals M and their smallest allowed back-off is given by $\hat{\xi}$. The maximum number of UEs in the cell is assumed to be $K_{\max}$. The algorithm for unequal PA dimensioning is given as follows

1) Initialize the $K_{\max} \times 1$ average per-antenna transmission power and number of active antennas vectors $\mathbf{P}^{(\text{Tx})}$ and $\mathbf{m}$: $P_k^{(\text{Tx})} = 0, \forall k = 1, \ldots, K_{\max}$ and $m_k = 0, \forall k = 1, \ldots, K_{\max}$. Set $k = 1$.
2) Set $\Pr(K = k) = 1$ and $\Pr(K \neq k) = 0$.
3) Solve the optimum $\hat{m}$ and ρ from (12). Set $m_k = \hat{m}$.
4) Solve P_{Tx} from (2) using $\hat{m}$ and ρ and store it to $\mathbf{P}^{(\text{Tx})}$.
5) If $k < K_{\max}$, set $k = k + 1$ and go back to Step 2.
6) Set the total number of antennas $M = m_{K_{\max}}$.
7) Initialize the $M \times 1$ PA maximum output power vector $\mathbf{P}^{\max}$ to $P_m^{\max} = 0, \forall m = 1, \ldots, M$.
8) Set $P_{\tilde{m}}^{\max} = \hat{\xi} P_1^{(\text{Tx})}$, for $\tilde{m} = 1, \ldots, m_1$. Set $k = 2$.
9) Set $P_{\tilde{m}}^{\max} = \hat{\xi} P_k^{(\text{Tx})}$, for $\tilde{m} = m_{k-1} + 1, \ldots, m_k$.
10) If $k < K_{\max}$, set $k = k + 1$ and go back to Step 9.

As illustrated in [8], P_{Tx} decreases with increasing m. If the maximum output power of each PA is fixed to the worst case value of $P_1^{\max}$, the average PA efficiency decreases as $k \to K$. The above algorithm sets the maximum output power of PAs stepwise and guarantees that always $m_k - m_{k-1}$ PAs operate at the smallest allowed back-off. When the average per-antenna transmission powers vary due to the antenna adaptation, this allows PAs to operate at higher efficiency. Obviously, the knowledge about the expected propagation environment is required for calculating the mean SINR given in (1) prior to PA dimensioning. For this standardized channel models or channel measurements can be used. However, no prior knowledge of the distribution of K is needed. If the number of UEs in the cell exceeds $K_{\max}$, the same energy efficiency can be achieved by round-robin scheduling of UEs.

V. NUMERICAL RESULTS

The performance of the proposed method is evaluated by simulations. The simulator was built upon the freely available Matlab source code for generating the result figures in [8].

TABLE I
PARAMETER VALUES FOR SIMULATIONS.

Parameter	Value
Distance between base stations	500 m
Minimum distance between a UE and a base station	35 m
Pilot reuse factor, τ	4
Number of symbols in coherent block, U	1800
Path loss constant, κ	$10^{-3.53}$
Path loss exponent, α	3.76
Fraction of DL/UL transmission, $\{\zeta^{(\text{dl})}, \zeta^{(\text{ul})}\}$	$\{0.6, 0.4\}$
Number of cells in the system,[1] J	25
Number of cells reusing the UL pilots, $\|\mathcal{Q}_j\|$	9
Transmission bandwidth, B	$B = 20$ MHz
Noise spectral density, σ^2	-169 dBm/Hz
Power conversion efficiency, η_{PS}	0.846
Frequency synthesis power, P_{FRQ}	102 mW
RF transmission power, $P_{\text{RF,DL}}$	287 mW
RF reception power, $P_{\text{RF,UL}}$	413 mW
Clock generation power, P_{CLK}	61 mW
OFDM, filtering, and sampling power, P_{OFDM}	237 mW
Synchronization power, P_{SYNC}	52 mW
Channel coding energy efficiency, ϵ_{COD}	2.25 Gbit/J
Channel decoding energy efficiency, ϵ_{DEC}	366 Mbit/J
Reference data rate, $\hat{R}$	75.4 Mbit/s
Symbol mapping power, P_{MAP}	33.5 mW
Symbol demapping power, P_{DEM}	69.5 mW
DSP energy efficiency, ϵ_{DSP}	15.5 Gflop/J
DL platform control power, P_{CDL}	104 mW
UL platform control power, P_{CUL}	38.6 mW
DL network processing energy efficiency, ϵ_{NDL}	225 Mbit/J
UL network processing energy efficiency, ϵ_{NUL}	340 Mbit/J
Maximum number of UEs in the cell,[2] $K_{\max}$	139
Minimum PA output power back-off, $\hat{\xi}$	15.85

The numerical parameter values shown in Table I are used in simulations. The parameter values related to the system model are reused from [8]. The values for power consumption parameters are derived from [13] and [14] for base station and UEs, respectively. When using parameters from [13], we have assumed DSP quantization resolution of 16 bits and that the components are from year 2016. Instead of optimistic technology scaling assumptions in [13], we have assumed that the DSP power consumption is reduced by 20 % annually [17]. To keep the relative technology scaling between DSP and RF processing the same as in [13], we have assumed an annual reduction of 4.9 % for analog RF processing. The UE power consumption parameters are given in Table 4 of [14], which are multiplied with the same technology scaling factors as for the base station. The power consumption $P_{\text{Tx,RF}}$ is dominated by the PA and thus no technology scaling is applied for it.

[1]The center cell in Fig. 1, which represents any cell in the symmetric multi-cell scenario, is considered.

[2]When $\lambda_h = 100$, $K_{\max} = 139$ is the smallest value fulfilling $\Pr(K > K_{\max}) < 10^{-4}$.
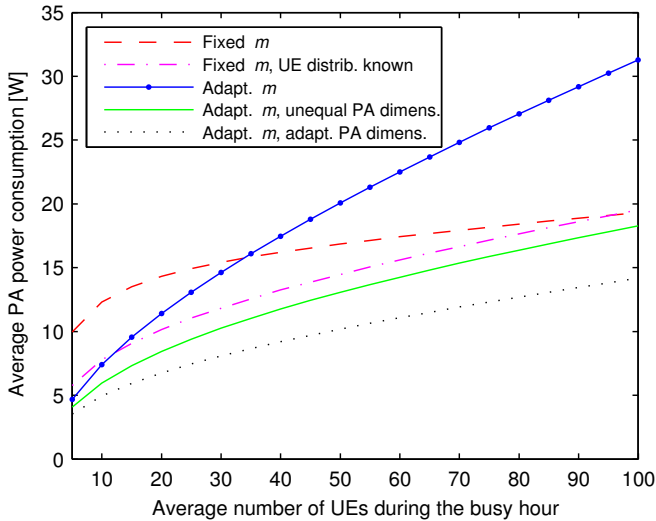
Fig. 3. Average PA power consumption as a function of $\hat{K}$.

Fig. 4. Energy efficiency as a function of $\hat{K}$ for fixed and adaptive m.

We compare the following cases: In the 'Fixed m' case, the number of active antennas is fixed to $m = K_{\max} + 1 = 140$. In the 'Fixed m, UE distrib. known' case, we allow that the optimum m is selected for each $\hat{K}$ separately. Obviously, this would require that the distribution of K is known during the base station design. In the 'Adapt. m' case, the optimum m is selected for each K and the maximum PA output power is set to $P_{\text{Tx}}^{\max} = \hat{\xi} P_{\text{Tx}}(1)$ for all PAs. This can be seen as the conventional way of designing a multi-antenna system with adaptive number of active antennas. Our proposed method is called as the 'Adapt. m, unequal PA dimens.' case. Finally for a reference, we have considered the 'Adapt. m, adapt. PA dimens.' case in which $P_{\text{Tx}}^{\max}$ can be adapted according to m, which is not possible with conventional PAs.

The conventional equal PA dimensioning results in poor average PA efficiency when the number of active antennas is high in adaptive massive-MIMO systems. The average PA power consumption as a function of mean number of UEs during a busy hour is shown in Fig. 3. Unequal PA dimensioning achieves 12–42 % reduction of average PA power consumption when compared to the conventional equal PA dimensioning. In addition, it has lower PA power consumption than the cases with fixed m. Also in the fixed m cases, the average per-antenna transmission power is adaptive because of the power control. The power control increases the average per-antenna transmission power as K increases.

The benefit from adapting the number of active antennas is illustrated in Fig. 4 in which the energy efficiency is shown as a function of average number of UEs during a busy hour. For low UE density, the capacity gain from the fixed $m = 140$ is not enough to compensate the high power consumption. On the other hand for high UE density, $m = 140$ is too small for reliable ZF precoding and detection. For these reasons, the energy efficiency performance in the 'Fixed m' case is poor for low and high UE densities. In the 'Fixed m, UE
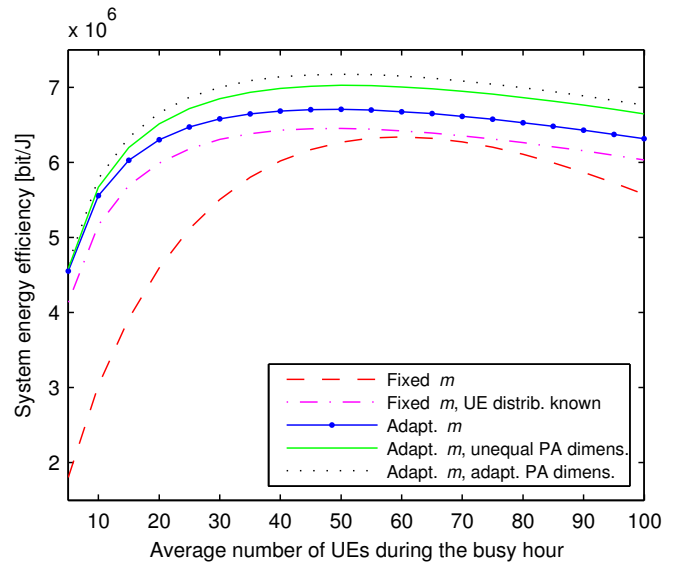
distrib. known' case, the energy efficiency stays at a good level independent of the UE density. Slightly better energy efficiency is achieved, when m is adapted. However, the increased PA power consumption, as seen in Fig. 3, reduces the achievable gain from antenna adaptation. Our proposed method, 'Adapt. m, unequal PA dimens.', further improves the energy efficiency by reducing PA power consumption. The achieved energy efficiency is very close to the reference upper limit on the energy efficiency that can be reached by PA dimensioning, i.e. the 'Adapt. m, adapt. PA dimens.' case.

It is also useful to compare the performance of the unequal PA dimensioning method to the method presented in [9] that also adapts m but sets $P_{\text{Tx}}^{\max}$ to the same value for each PA. Note that unlike in [9], the sum transmission power is also adapted in our work resulting in better energy efficiency performance for all considered methods. The results of the comparison are presented in Fig. 5. It can be seen that if the distribution of K is known and the optimum $P_{\text{Tx}}^{\max}$ is selected for each $\hat{K}$, the method from [9] performs very close to the upper limit. However, the UE distribution is not usually known at the PA design phase. More realistic cases are marked as '[13], low UE density' and '[13], high UE density' for assuming that $\hat{K} = 5$ and $\hat{K} = 100$, respectively. These cases illustrate that when a certain UE distribution is assumed at the PA design phase, the energy efficiency performance is degraded when the real UE distribution does not follow the assumption. This is visible in Fig. 5 for cases '[13], low UE density' at $\hat{K} > 25$ and '[13], high UE density' at $\hat{K} < 30$. The benefit of our proposed unequal PA dimensioning is that no prior knowledge of the UE distribution is needed and good performance is achieved for all UE densities.

The proposed method can reach energy efficiency gain of 9–11 % compared to the 'Fixed m, UE distrib. known' case. The energy efficiency gain compared to the 'Adaptive m' case is
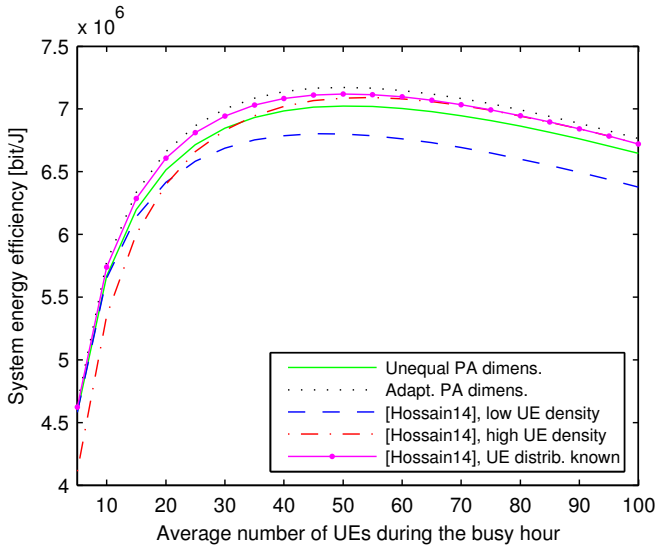
Fig. 5. Energy efficiency comparison to the method from [9].

1–5 %. The gains are relatively low because the PA power consumption is a fraction of the total power consumption. For example in the 'Adaptive m' scenario when $\hat{K} = 50$, $P_{\text{PA}} = 20.3$ W, and the fraction P_{PA}/P is only 12.6 %. With the proposed unequal PA dimensioning method, PA power consumption is decreased to $P_{\text{PA}} = 13.2$ W that is 8.4 % of the total power consumption. However if the power consumption of digital and analog processing scales down as predicted in [13], the significance of PA power consumption in the total power budget increases. Additionally if larger coverage for a cell is required, the fraction of PA consumption and the energy efficiency gain from the proposed method are increased.

VI. Conclusions

In this paper, we have studied how to improve energy efficiency of a massive MIMO system whose number of active antennas and average transmission power are adapted to the number of UEs in the cell. Our proposed method first solves the optimum number of antennas m_k and optimum per-antenna transmission power for each number of UEs. Then different maximum output power levels for PAs are set stepwise such that always $m_k - m_{k-1}$ PAs operate at the smallest allowed back-off. This allows PAs to operate at higher efficiency than with conventional equal dimensioning when the average per-antenna transmission powers vary due to the antenna adaptation. For the performance evaluation, a power consumption model for the whole massive MIMO system has been derived by combining the existing power consumption models of sub-systems. The proposed method reduces the PA power consumption by 12–42 % when compared to the conventional way of setting the same maximum output power for all PAs. This results in improved system energy efficiency. The proposed method can be applied in the design phase of

adaptive massive MIMO base stations when there is prior knowledge of the expected propagation environment.

The benefit of the proposed unequal PA dimensioning is that no prior knowledge of the UE distribution is needed and good performance is achieved for all UE densities. The energy efficiency gain compared to the conventional adaptive scenario is 1-5 %. The gain is at a relatively low level because the PA power consumption is only a small fraction of the total power consumption. If PAs contribute to a larger fraction in the total power budget, the gain from the proposed method increases. This can happen e.g. when a larger coverage is required for a cell. The effect of different cell sizes to the average energy efficiencies is left for further study.

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