Energy-Efficient Transmit Beamforming and Antenna Selection with Non-Linear PA Efficiency

Yuan Fang∗†, Yi Huang‡, Chuan Ma§, Yinghao Jin§, Gaoyuan Cheng†∗, Guanlin Wu‡, and Jie Xu†∗

∗Future Network of Intelligence Institute, The Chinese University of Hong Kong (Shenzhen),
†School of Science and Engineering, The Chinese University of Hong Kong (Shenzhen),
‡Department of Information and Communication Engineering, Tongji University
§Huawei Technologies Co., Ltd.,

Email: fangyuan@cuhk.edu.cn, huangyi718b@tongji.edu.cn, machuan2@huawei.com, jinyinghao@huawei.com,
gaoyuancheng@link.cuhk.edu.cn, guanlinwu1@link.cuhk.edu.cn, xujie@cuhk.edu.cn.

Abstract—This paper studies the energy-efficient design in a downlink multi-antenna multi-user system consisting of a multi-antenna base station (BS) and multiple single-antenna users, by considering the practical non-linear power amplifier (PA) efficiency and the on-off power consumption of radio frequency (RF) chains at each transmit antenna. Under this setup, we jointly optimize the transmit beamforming and antenna on/off selection at the BS to minimize its total power consumption while ensuring the individual signal-to-interference-plus-noise ratio (SINR) constraints at the users. However, due to the non-linear PA efficiency and the on-off RF chain power consumption, the formulated SINR-constrained power minimization problem is highly non-convex and difficult to solve. To tackle this issue, we propose a high-quality solution based on the technique of sequential convex approximation (SCA). We provide numerical results to validate the performance of our proposed design. It is shown that at the optimized solution, the BS tends to activate fewer antennas and use higher transmit power at each antenna to exploit the non-linear PA efficiency. It is also shown that the proposed design significantly reduces the power consumption at the BS as compared to the conventional designs by considering the fixed PA efficiency and/or ignoring the on-off RF chain power consumption.

Index Terms—Energy-efficient communication, non-linear PA efficiency, transmit beamforming, antenna selection.

I. INTRODUCTION

Fifth-generation (5G) and beyond cellular networks are expected to provide ultra-high data-rate throughput, ultra-high reliability, and ultra-low latency, by exploiting various new technologies such as extremely large-scale multiple-input multiple-output (MIMO) [1]. This, however, may lead to tremendous energy consumption and operational cost, as well as significant carbon emissions [2]. Extensive research efforts have been conducted to achieve green and carbon-neutral communications from different perspectives such as energy-efficient transmit beamforming and antenna selection [3]–[5], user association and base station (BS) activation [6], [7], as well as renewable-powered BSs [8].

Among others, the joint transmit beamforming and antenna on/off selection has attracted a lot of research interests to enhance the energy efficiency (EE) of cellular networks with multi-antenna BSs, in which the BS properly designs the transmit beamforming and switches off some transmit antennas to save the power consumption at the associated radio-frequency (RF) chains. For instance, the work [4] considered a point-to-point MIMO system with one single data stream, in which the transmit power control and antenna selection are jointly optimized to maximize the bits-per-Joule EE. Furthermore, the authors in [9] and [10] studied downlink multiuser multi-antenna systems by considering the linear transmit beamforming and capacity-achieving dirty paper coding, respectively, in which the transmit beamforming/precoding and antenna selection are jointly designed to maximize the EE. In addition, the work [11] considered massive MIMO systems, in which antenna selection algorithms are developed to enhance the EE based on the techniques of binary search. Moreover, such designs have been extended to enhance the EE of extremely large-scale MIMO systems in [12]. Despite the research progresses, these prior works normally assumed fixed power amplifier (PA) efficiency at transmit antennas. This, however, may not be valid in practice, thus making the corresponding designs less energy efficient.

In practice, the PAs at a BS account for about 50%-80% of its total power consumption, and the efficiency of each PA is highly non-linear in general [13], [14]. In particular, the maximum PA efficiency is normally achieved when the PA input signal power reaches a saturation point at which the maximum output signal power is achieved. When the PA input signal power deviates from such saturation point, the PA efficiency may drop significantly, thus leading to rapidly decreased system EE [15], [16]. As a result, how to design energy efficient multi-antenna communication systems by taking into account the non-linear PA efficiency is an important problem that has not been well investigated in the literature yet. This thus motivates our investigation in this work.

In this paper, we investigate the energy-efficient joint transmit beamforming and antenna (on/off) selection in a downlink multi-antenna communication system with one multi-antenna BS and multiple single-antenna users, by considering both the non-linear PA efficiency and the on-off power consumption of RF chains at each antenna. We consider a general non-linear PA efficiency model. Under this setup, we formulate the joint transmit beamforming and antenna on/off selection...
design problem, with the objective of minimizing total power consumption at the BS subject to the individual signal-to-interference-plus-noise ratio (SINR) requirements at the users and the per-antenna transmit power constraints at the BS. The formulated problem is highly non-convex due to the non-linear PA efficiency and the binary on-off RF chain power consumption, and thus is difficult to solve. To overcome this issue, we propose an efficient method by utilizing the technique of sequential convex approximation (SCA), together with a beamforming weight-based antenna selection algorithm. Finally, we provide numerical results to validate the performance of our proposed design. It is shown that the BS tends to activate fewer antennas but uses higher transmit power at each antenna. It is also shown that the proposed design significantly reduces the power consumption at the BS, as compared to the conventional designs considering the fixed PA efficiency and/or ignoring the on-off RF chain power consumption.

II. SYSTEM MODEL

A. Signal Model

We consider a downlink multi-antenna multiuser system as shown in Fig. 1, which consists of one BS with $N$ antennas and $K$ users each with one single antenna. Let $\mathcal{N} = \{1, \ldots, N\}$ and $\mathcal{K} = \{1, \ldots, K\}$ denote the set of transmit antennas at the BS and that of users, respectively. Let $s_k$ denote the desired signal for user $k$, which is a random variable with zero mean and unit variance, i.e., $\mathbb{E}[|s_k|^2] = 1$, with $\mathbb{E}[\cdot]$ denoting the statistic expectation. By using the transmit beamforming, the transmit signal at the BS is expressed as

$$x = \sum_{k \in \mathcal{K}} w_k s_k,$$

where $w_k \in \mathbb{C}^{N \times 1}$ denotes the beamforming vector for user $k$. Let $h_k \in \mathbb{C}^{1 \times N}$ denote the channel vector from the BS to user $k$. Then, the received signal at user $k$ is given by

$$y_k = h_k^H w_k s_k + \sum_{i \neq k} h_i^H w_i s_i + z_k,$$

where $z_k$ denotes the additive white Gaussian noise (AWGN) at the receiver of each user $k$ that is a circularly symmetric complex Gaussian (CSCG) random variable with mean zero and variance $\sigma_k^2$. Hence, the SINR at user $k$ is given by

$$\gamma_k = \frac{|h_k^H w_k|^2}{\sum_{i \neq k} |h_i^H w_i|^2 + \sigma_k^2}.$$

B. Power Consumption Model

Next, we consider the power consumption at the BS, which consists of the non-linear power consumption by the PAs, the on-off power consumption by RF chains, and the static power consumption by other components, which are detailed in the following, respectively.

1) Non-Linear Power Consumption by PAs: In practice, the PA efficiency at each antenna $n \in \mathcal{N}$ is non-linear, which is expressed as

$$\eta_n = \eta_{\text{max}} \left( \frac{P_{\text{out}}}{P_{\text{out}}^{\text{max}}} \right)^\beta, 0 < \beta \leq 1 \ [15],$$

where $P_{\text{out}}^{\text{max}}$ is the maximum transmit power or output power of PA at antenna $n$, $P_{\text{out}}$ is the transmit power at antenna $n$, $\eta_{\text{max}}$ is the maximum efficiency of the PA, and $\beta$ is the efficiency factor depending on the specific type of PA. For instance, we have $\beta = 1$ for class-A PA and $\beta = 0.5$ for class-B PA [15]. Notice that based on the signal model in (1), we have

$$P_{\text{out}} = \sum_{k \in \mathcal{K}} |1_n^T w_k|^2,$$

where $1_n \in \mathbb{C}^{1 \times N}$ is a vector with its $n$-th element being one and others zero, and $(\cdot)^T$ denotes the transpose operator. Hence, the power consumption of the $N$ PAs at the BS is given by

$$P_{\text{PA}}(\{w_k\}) = \sum_{n \in \mathcal{N}} \frac{P_{\text{out}}}{\eta_n} = \sum_{n \in \mathcal{N}} \left( \frac{P_{\text{out}}}{P_{\text{out}}^{\text{max}}} \right)^\beta \left( \frac{P_{\text{out}}^{\text{max}}}{P_{\text{out}}} \right)^{1-\beta}$$

$$= \frac{1}{\eta_{\text{max}}} \sum_{n \in \mathcal{N}} \left( \frac{P_{\text{out}}}{P_{\text{out}}^{\text{max}}} \right)^\beta \sum_{k \in \mathcal{K}} |1_n^T w_k|^2. \quad (4)$$

Further, the maximum sum transmit power at the BS is given by $P_{\text{sum}}$. Based on this together with the maximum transmit power $P_{\text{out}}^{\text{max}}$ at each antenna, we have

$$P_{\text{out}} = \sum_{k \in \mathcal{K}} |1_n^T w_k|^2 \leq P_{\text{out}}^{\text{max}}, \quad (5)$$

$$\sum_{k \in \mathcal{K}} \|w_k\|^2 \leq P_{\text{sum}}. \quad (6)$$

2) On-off Power Consumption by RF Chains: Besides the non-linear power consumption by PAs, the power consumption by RF chains at the BS depends on the on-off status of each RF chain. In particular, if each antenna $n$ is on, i.e., antenna $n$ is transmitting with $P_{\text{out}} > 0$, then the associated RF chain needs to consume a fixed power consumption, given by

$$P_{\text{RF}} = P_{\text{DAC}} + P_{\text{mix}} + P_{\text{filt}} + P_{\text{syn}}, \quad (7)$$

where $P_{\text{DAC}}, P_{\text{mix}}, P_{\text{filt}}$, and $P_{\text{syn}}$ represent power consumption by the digital-to-analog converter (DAC), mixer, filter, and synthesizer at the RF chain, respectively. Otherwise, if antenna $n$ is turned off with $P_{\text{out}} = 0$, then these components can be switched off, such that the power consumption becomes zero. By combining the $N$ RF-chains, the total power consumption by RF chains is given by

$$P_{\text{RF}}(\{w_k\}) = \sum_{n \in \mathcal{N}} \left\{ \sum_{k \in \mathcal{K}} |1_n^T w_k|^2 \right\}. \quad (8)$$

1The BS can activate or inactivate the antenna components by turning off the corresponding power supply through a switch [17].
where \( I \{ \cdot \} \) denotes the indicator function that is defined by
\[
I \{ x \} = \begin{cases} 
0, & \text{if } x = 0 \\
1, & \text{otherwise.} 
\end{cases} 
\] (9)

3) Static Power Consumption: In addition to the PAs and RF chains, other components at the BS such as backhauls, cooling systems, baseband processing, and power supply also consume energy. Their power consumption is generally static and thus is modeled by a constant term \( P_c \).

By combining the power consumption \( P_{PA} \) in (4), \( P_{RF} \) in (8), and constant component \( P_c \), the total power consumption at the BS is given by
\[
P_{BS}^{tot} = P_{PA}(\{\mathbf{w}_k\}) + P_{RF}(\{\mathbf{w}_k\}) + P_c. 
\] (10)

C. Problem Formulation

Our objective is to minimize total power consumption at the BS in (10), while ensuring the minimum SINR requirement \( \Gamma_k \) for each user \( k \in \mathcal{K} \), the per-antenna transmit power constraints in (5), and the sum transmit power constraint in (6). The SINR-constrained power minimization problem is formulated as

\[
(P1) : \min_{\{\mathbf{w}_k\}} P_{PA}(\{\mathbf{w}_k\}) + P_{RF}(\{\mathbf{w}_k\}) + P_c
\]
\[
s.t. \ (11a), \ (11b), \text{ and } (11c). 
\]

Note that in the objective function, the PA power consumption term is a concave function with respect to \( \mathbf{w}_k \). The PA power consumption term is binary and thus non-convex due to the antenna on-off selection. Hence, problem (P1) is a non-convex problem that is difficult to be optimally solved.

Before solving problem (P1), we need to check its feasibility by solving the following feasibility problem:

\[
(P2) : \ \text{Find } \{\mathbf{w}_1, \ldots, \mathbf{w}_K\}
\]
\[
s.t. \ (11a), (11b), \text{ and } (11c). 
\]

Notice that constraint (11a) is equivalent to the following convex second-order cone (SOC) constraint [7].
\[
\sqrt{\sum_{i \neq k} |h_{k i}^{H} \mathbf{w}_i|^2 + \sigma_k^2} \leq \frac{1}{\sqrt{\mathcal{R}(h_{k k}^{H} \mathbf{w}_k)}}, 
\] (12)

where \( \mathcal{R}(\cdot) \) denotes the real component of a complex number. By replacing (11a) with (12), problem (P2) becomes a convex problem that can be optimally solved by standard convex solvers such as CVX [18]. In the sequel, we focus on the case when problem (P1) is feasible.

III. SCA-BASED SOLUTION TO PROBLEM (P1)

In this section, we propose an efficient algorithm to solve problem (P1) by SCA together with a heuristic antenna selection design.

First, we deal with the indicator function involved in the on-off RF chain power consumption. Notice that the indicator function can be equivalently rewritten as [19]
\[
I \{ x \} = \lim_{\epsilon \to 0} \frac{\log (1 + \epsilon x)}{\log (1 + \epsilon)}, \quad x \geq 0. 
\] (13)

Accordingly, the indicator function can be approximated as
\[
\frac{\log (1 + \epsilon x)}{\log (1 + \epsilon)}, \quad \epsilon \text{ under a properly chosen } \epsilon, \text{ where the approximation becomes more accurate when } \epsilon \text{ becomes smaller.}
\]

As a result, the total RF chain power consumption \( P_{RF}(\{\mathbf{w}_k\}) \) is approximated as
\[
\hat{P}_{RF}(\{\mathbf{w}_k\}) = P_{RF} \sum_{n \in \mathcal{N}} \frac{\log (1 + \sum_{k \in \mathcal{K}} |1^n_k \bar{\mathbf{w}}_k|^2 \epsilon^{-1})}{\log (1 + \epsilon^{-1})}, 
\] (14)

which is concave with respect to \( \sum_{k \in \mathcal{K}} |1^n_k \bar{\mathbf{w}}_k|^2 \). As a result, problem (P1) is approximated as follows by omitting the constant term \( P_c \) in the objective function.

\[
(P3) : \ \min_{\{\mathbf{w}_k\}} P_{PA}(\{\mathbf{w}_k\}) + \hat{P}_{RF}(\{\mathbf{w}_k\})
\]
\[
s.t. \ (11a), (11b), \text{ and } (11c). 
\]

Then, we use the SCA technique to solve (P3), in which (P3) is approximated into a series of convex problems in an iterative manner. Specially, we consider a particular iteration \( j \geq 1 \). Let \( \{\bar{\mathbf{w}}_k^{(j)}\} \) be the local point of \( \{\mathbf{w}_k\} \) at the \( j \)-th iteration of SCA. Note that any concave function is globally upper-bounded by its first-order Taylor expansion. Thus, with given local point \( \{\bar{\mathbf{w}}_k^{(j)}\} \) and taking the Taylor expansion with respect to the point, the PA power consumption term \( P_{PA}(\{\mathbf{w}_k\}) \) in (4) is approximated by its upper bound \( \hat{P}_{PA}^{(j)}(\{\mathbf{w}_k\}) \), i.e.,
\[
\hat{P}_{PA}^{(j)}(\{\mathbf{w}_k\}) = \sum_{n \in \mathcal{N}} \frac{P_{max}}{n^\beta} \sum_{k \in \mathcal{K}} |1^n_k \bar{\mathbf{w}}_k^{(j)}|^2 - (1 - \beta) \sum_{n \in \mathcal{N}} \frac{P_{max}}{n^\beta} \sum_{k \in \mathcal{K}} \left( |1^n_k \bar{\mathbf{w}}_k^{(j)}|^2 \right)^{\frac{1}{1 - \beta}} \sum_{k \in \mathcal{K}} \left( |1^n_k \mathbf{w}_k|^2 - |1^n_k \bar{\mathbf{w}}_k^{(j)}|^2 \right). 
\] (16)

Similarly, the approximate RF chain power consumption term \( \hat{P}_{RF}^{(j)}(\{\mathbf{w}_k\}) \) in (14) is further approximated by its upper bound \( \hat{P}_{RF}^{(j)}(\{\mathbf{w}_k\}) \), i.e.,
\[
\hat{P}_{RF}^{(j)}(\{\mathbf{w}_k\}) = \sum_{n \in \mathcal{N}} \frac{P_{RF}}{n^\beta} \sum_{k \in \mathcal{K}} |1^n_k \bar{\mathbf{w}}_k^{(j)}|^2 + \frac{1}{\sum_{k \in \mathcal{K}} |1^n_k \bar{\mathbf{w}}_k^{(j)}|^2 + 1} \sum_{k \in \mathcal{K}} \left( |1^n_k \mathbf{w}_k|^2 - |1^n_k \bar{\mathbf{w}}_k^{(j)}|^2 \right). 
\] (17)

By replacing \( P_{PA}(\{\mathbf{w}_k\}) \) and \( P_{RF}(\{\mathbf{w}_k\}) \) with \( \hat{P}_{PA}^{(j)}(\{\mathbf{w}_k\}) \) and \( \hat{P}_{RF}^{(j)}(\{\mathbf{w}_k\}) \), respectively, problem (P3) is transformed into the following problem at iteration \( j \) of SCA:

\[
(P4,j) : \ \min_{\{\mathbf{w}_k\}} \hat{P}_{PA}^{(j)}(\{\mathbf{w}_k\}) + \hat{P}_{RF}^{(j)}(\{\mathbf{w}_k\})
\]
\[
s.t. \ (11b), (11c), \text{ and } (12). 
\]
Problem (P4.\(j\)) is a convex problem that can be solved by convex optimization tools such as CVX [18]. Let \(\{w^*_{k(j)}\}\) denote the obtained solution to (P4.\(j\)) at the \(j\)-th iteration, which is then updated as \(\{w^*_{k(j+1)}\}\). Note that as \(\hat{P}_{RF}^k(\{w_k\})\) in (16) and \(\hat{P}_{RF}^j(\{w_j\})\) in (17) serve as upper bounds of \(P_{PA}^k(\{w_k\})\) in (4) and \(P_{RF}^j(\{w_j\})\) in (14), respectively. Therefore, it is clear that the total power consumption value of (P3) achieved by \(\{w^*_{k(j)}\}\) is always no greater than that by \(\{w_{k(j)}\}\). In other words, the achieved power consumption value of problem (P3) is non-increasing after each iteration of SCA. Besides, the optimal value of problem (P3) is lower bounded due to its non-negativity. By combining the two facts, the convergence of the proposed SCA-based algorithm is guaranteed. Let \(\{w^*_k\}\) denote the converged solution to problem (P3).

Finally, we propose a beamforming weight based method to determine the antenna on-off selection based on the obtained approximate solution \(\{w_k\}\). First, we define the beamforming weight for each antenna \(n\) as \(v_n = \sum_{k=1}^{K} \left| w_{k,n} \right|^2\), where \(w_{k,n}\) is the \(n\)-th element in \(w_k\). The weight factor \(v_n\), thus captures the transmit power at antenna \(n\). It is clear that if \(v_n\) is smaller, then antenna \(n\) would have a higher priority to be switched off. Next, we sort the beamforming weights of different antennas in ascending order and then determine the on-off status of antennas iteratively. In particular, for each iteration, we switch off one more antenna based on ordering of \(\{v_n\}\), and accordingly check the correspondingly achieved power consumption value. If the power consumption value is further reduced, the iteration will proceed; otherwise, the iteration will terminate and the antenna on-off selection solution is obtained.

### IV. Numerical Results

This section provides numerical results to validate the effectiveness of our proposed algorithms. In the simulation, the users are randomly generated in a \(1 \times 1\) km\(^2\) area and the BS is located at the center of the area. We set the maximum transmit power as \(P_{\text{sum}} = 46\) dBm, the noise power as \(-94\) dBm. We also set \(P_{\gamma} = 1.5W\), \(P_{RF}^s = 0.35W\), \(P_s = 20W\), and \(\eta_{\text{max}} = 0.38\) [5], [7]. Furthermore, the Rayleigh fading channel model is considered for each user, and the SINR constraints at different users are set to be identical, i.e., \(\Gamma_k = \Gamma\), \(\forall k \in K\).

![Fig. 2. The transmit power allocation at different transmit antennas, where \(M = 32\), \(K = 8\), and \(\Gamma = 12\) dB. Upper subfigure: conventional joint design with fixed PA efficiency, Lower subfigure: our proposed joint design with non-linear PA efficiency.](image)

We compare the performance of our proposed joint design with non-linear PA efficiency scheme, versus the following benchmark schemes by considering the fixed PA and/or ignoring the on-off RF chain power consumption.

- **Joint design with fixed PA efficiency**: This corresponds to the design that ignores the non-linear RF efficiency by setting \(\beta = 0\). The design has been widely considered in the literature [3]–[5].

- **Beamforming only with non-linear PA efficiency**: This corresponds to the design that ignores the on-off antenna selection by considering that all RF chains are switched on. In this case, we have \(P_{RF} = NP_{RF}^s\) being a constant and the transmit beamformers \(\{w_k\}\) are optimized only based on the algorithm in Section III.

- **Beamforming only with fixed PA efficiency**: This design considers fixed PA efficiency and ignores the on-off antenna selection. This corresponds to the design with \(\beta = 0\) and \(P_{RF} = NP_{RF}^s\).

![Fig. 3. The total power consumption versus SINR constraint \(\Gamma\) with \(M = 32\) and \(K = 8\).](image)

Fig. 3 shows the total power consumption at the BS versus the SINR constraint \(\Gamma\) at each user, where \(M = 32\) and \(K = 8\). It is observed that in the whole SINR regime, our proposed joint design with non-linear PA efficiency achieves the lowest power consumption among all schemes. In the low SINR regime, the joint design with fixed PA efficiency is observed to perform close to that with non-linear PA efficiency and outperforms the beamforming only design with non-linear or fixed PA efficiency. This is because in this case, activating a small number of antennas is sufficient to meet the SINR constraints, and thus antenna on-off selection is critical for power saving. Furthermore, in the high SINR regime, it is observed that the power consumption values of the four schemes become similar. This is because in this case, the BS has to activate all antennas with full transmit power to meet the stringent SINR requirements for users.
This paper studied the energy-efficient beamforming and antenna selection in a multi-antenna multiuser communication system by considering both the non-linear PA efficiency and the on-off RF-chain power consumption. In order to minimize the total power consumption at the BS while ensuring the SINR constraints at users, we proposed an efficient transmit beamforming design algorithm by using the SCA and an antenna selection algorithm based on beamforming weights. Numerical results showed that the proposed algorithm significantly reduces the total power consumption at the BS as compared to the conventional designs by considering the fixed PA efficiency and/or ignoring the on-off RF-chain power consumption. How to extend such designs in other setups with, e.g., hybrid beamforming and/or non-linear PA distortion will be interesting problems to be investigated in future work.

V. CONCLUSION

This paper studied the energy-efficient beamforming and antenna selection in a multi-antenna multiuser communication system by considering both the non-linear PA efficiency and the on-off RF-chain power consumption. In order to minimize the total power consumption at the BS while ensuring the SINR constraints at users, we proposed an efficient transmit beamforming design algorithm by using the SCA and an antenna selection algorithm based on beamforming weights. Numerical results showed that the proposed algorithm significantly reduces the total power consumption at the BS as compared to the conventional designs by considering the fixed PA efficiency and/or ignoring the on-off RF-chain power consumption. How to extend such designs in other setups with, e.g., hybrid beamforming and/or non-linear PA distortion will be interesting problems to be investigated in future work.

REFERENCES

[1] M. Cui and L. Dai, “Channel estimation for extremely large-scale MIMO: Far-field or near-field?” IEEE Trans. Commun., vol. 70, no. 4, pp. 2663–2677, Jan. 2022.
[2] B. Mao, F. Tang, Y. Kawamoto, and N. Kato, “AI models for green communications towards 6G,” IEEE Commun. Surv. Tuts., vol. 24, no. 1, pp. 210–247, Firstquarter 2022.
[3] O. Mehanna, N. D. Sidiropoulos, and G. B. Giannakis, “Joint multicast beamforming and antenna selection,” IEEE Trans. Signal Process., vol. 61, no. 10, pp. 2660–2674, Mar. 2013.
[4] C. Jiang and L. J. Cimini, “Antenna selection for energy-efficient MIMO transmission,” IEEE Wireless Commun. Lett., vol. 1, no. 6, pp. 577–580, Aug. 2012.
[5] S. Lao, R. Zhang, and T. J. Lim, “Downlink and uplink energy minimization through user association and beamforming in C-RAN,” IEEE Trans. Wireless Commun., vol. 14, no. 1, pp. 494–508, Aug. 2014.
[6] W.-C. Liao, M. Hong, Y.-F. Liu, and Z.-Q. Luo, “Base station activation and linear transceiver design for optimal resource management in heterogeneous networks,” IEEE Trans. Signal Process., vol. 62, no. 15, pp. 3939–3952, Jul. 2014.
[7] Y. Shi, J. Zhang, and K. B. Letaief, “Group sparse beamforming for green cloud-RAN,” IEEE Trans. Wireless Commun., vol. 13, no. 5, pp. 2809–2823, Apr. 2014.
[8] J. Xu, L. Duan, and R. Zhang, “Cost-aware green cellular networks with energy and communication cooperation,” IEEE Commun. Mag., vol. 53, no. 5, pp. 257–263, May 2015.
[9] S. He, Y. Huang, J. Wang, L. Yang, and W. Hong, “Joint antenna selection and energy-efficient beamforming design,” IEEE Signal Process. Lett., vol. 23, no. 9, pp. 1165–1169, Jul. 2016.
[10] J. Xu and L. Qiu, “Energy efficiency optimization for MIMO broadcast channels,” IEEE Trans. Wireless Commun., vol. 12, no. 2, pp. 690–701, Jan. 2013.
[11] H. Li, L. Song, and M. Debbah, “Energy efficiency of large-scale multiple antenna systems with transmit antenna selection,” IEEE Trans. Commun., vol. 62, no. 2, pp. 638–647, Jan. 2014.
[12] J. C. Marinello, T. Abrão, A. Amiri, E. De Carvalho, and P. Popovski, “Antenna selection for improving energy efficiency in XL-MIMO systems,” IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 13 305–13 318, Sep. 2020.
[13] H. Bogucka and A. Conti, “Degrees of freedom for energy savings in practical adaptive wireless systems,” IEEE Commun. Mag., vol. 49, no. 6, pp. 38–45, Jun. 2011.
[14] M. B. Salman and G. M. Guvenc, “On the effects of PA nonlinearities and their impact on flow-level performance of 5G networks,” in Proc. IEEE ICC, 2020, pp. 1–7.
[15] S. C. Cripps, RF Power Amplifiers for Wireless Communications. Artech house Norwood, MA, 2006.
[16] J. Joung, C. K. Ho, and S. Sun, “Spectral efficiency and energy efficiency of OFDM systems: Impact of power amplifiers and countermeasures,” IEEE J. Sel. Areas Commun., vol. 32, no. 2, pp. 208–220, May 2013.
[17] F. E. Salem, A. Gati, Z. Altman, and T. Chahed, “Advanced sleep modes and their impact on flow-level performance of 5G networks,” in Proc. IEEE VTC-Fall, 2017, pp. 1–7.
[18] M. Grant and S. Boyd, “CVX: Matlab software for disciplined convex programming, version 2.1,” 2014.
[19] B. K. Sriperumbudur, D. A. Torres, and G. R. Lanckriet, “A majorization-minimization approach to the sparse generalized eigenvalue problem,” Machine Learning, vol. 85, no. 1, pp. 3–39, Oct. 2011.