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Optimal Energy Efficiency Based Power Adaptation for Downlink Multi-Cell Massive MIMO Systems

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ABSTRACT In this paper, the power transmission and energy efficiency (EE) in downlink multi-cell massive multiple-input–multiple-output (MIMO) systems are investigated and optimized. Most of the existing works do not take into account different user's quality of service (QoS) requirements. These models also depend on a fixed transmit power consumption, which cannot reflect the actual EE levels concerning QoS. Therefore, in this paper, a new base station (BS) transmit power adaptation is firstly introduced, termed the BSTPA method. The transmitted power is adapted to channel condition and user-level QoS including data rate requirement and maximum allowable outage probability to minimize the total BS radiated power. An analytical closed-form expression of the average BS transmit power adaptation is derived. Then, a corresponding iterative optimization algorithm is proposed to maximize the average EE per BS and obtain the optimal design parameters. The proposed optimization algorithm aims to globally achieve the optimal EE value with the optimal amount of data rate, the number of BS antennas, and users. Simulation results are demonstrated to verify our analytical findings. For a wide range of different design parameters, the results indicate that the proposed method obtains remarkably higher EE levels compared to the conventional scenario, particularly if per-antenna circuit power is very small. The optimization results show that the case with lower per-antenna circuit power can achieve about 4.5 times better EE gain than the case with higher per-antenna circuit power with 13.3% optimum data rate improvement.

INDEX TERMS Energy efficiency (EE), massive MIMO, quality of service (QoS), base station (BS) transmit power.

I. INTRODUCTION

Global mobile communication data traffic is forecasted to increase seven-fold by 2022 [1] exponentially, which would place a burden on the next generation's mobile networks. This Overgrowth traffic has led to social and economic concerns due to the power expenditure of the information technology industry and the pollution caused by the need for enormous energy consumption relatively [2]. In fact, this concern has urged the academicians and industry to take serious action in the green cellular network, which is a new area of research [3]. As a result, there is a need to design new network architecture and related technologies to let mobile data grow significantly without the need for an increase in power consumption.

Currently, to make the situation smoother, some innovative technologies have been suggested for the fifth-generation (5G) wireless communication networks and beyond. The

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massive multiple-input-multiple-output (MIMO) technology [4]–[6], where the number of antennas at the base station (BS) is considerably more than the number of users that the BS simultaneously served [5]–[7], potentially provides a wide range and a significant spatial multiplexing gain [8], [9]. The massive MIMO transmission is an effective strategy to boost the capacity of wireless communication systems with no demand for extra bandwidth or power transmission. As a matter of fact, the massive MIMO technology is capable of offering higher spectral efficiency (SE) and energy efficiency (EE) levels compared to the current long-term evolution (LTE) technologies, and therefore open the doors to a promising *Green 5G* candidate.

EE improvement has become the primary 5G criterion and determined as the proportion between sum data rate and total energy consumption [8]. It is influenced by many factors such as SE, radiated and circuit power consumption, user equipment (UE) quality of services (QoS) demands, and network architecture [2], [3], [9]. Massive MIMO systems are mainly interested in their capability to concurrently minimize the transmitted power at the part of both BSs and UEs [5], [10]. A large portion of power is drained in power amplifiers (PAs) of BSs, since BSs are the main power-consuming components of cellular networks [11], [12]. Thus, reducing the radiated power of BS radio-frequency (RF) is a practical approach for minimizing BS energy consumption, leading to the overall system EE enhancement.

In the concept of *Green* wireless communication networks, the total BSs power consumption reduction is the initial step of EE improvement, where they account for a large portion of the overall network energy consumption. Since the traffic load changes during the day, the power consumption of BSs grows exponentially with their traffic load in term of the number of active UEs and their QoS [13]. Therefore, BSs must adapt their power consumption to traffic load to save more energy while meeting users restrictions.

The authors in [14] and [10] proposed new scaling lows which the uplink transmission power can meet a specified data rate as long as the power level fulfils the desired QoS. The problem of uplink power allocation for a multi-user MIMO system has been studied in [15]. The author focuses on the impact of total antenna numbers at BS on overall EE of the system. The results show that the entire EE of the system can be enhanced if some specific user antennas are switched off. The authors in [16] have concentrated on optimizing the number of scheduled users and BS antennas in order to maximize the uplink sum-rate capacity for multi-user MIMO networks without QoS consideration. The authors in [17] have demonstrated that the uplink power transmission control is the basic mechanism in any multi-user MIMO networks. As a result, a statistical uplink power control policy was found out where channel state information (CSI) is provided for UEs without the need for rapid feedback. Then, the authors analytically solved a tractable uplink EE maximization problem. The optimization problem was formulated based on the density of BSs, BSs transmitted power level, and the number of antennas and UEs per each BS. The optimal amounts of antennas and users have been investigated in [18] for a given fixed uplink sum-rate in a single-cell setup. However, the study ignores the cost of CSI acquisition that can lead to misleading results. The authors in [19] have derived both uplink and downlink power transmission and a more realistic circuit power consumption model. But, an equal guaranteed data rate is assumed as the only QoS constraint. The joint uplink and downlink EE was maximized concerning user's data rate requirement, the number of antennas and UEs per BS, and transmission power. For a downlink point-to-point MIMO setup, the system EE maximization has been examined in [20]. The authors optimized the number of BS antennas under an equally optimal power allocation algorithm that considers the minimum achievable data rate limitation into account.

Yet, the evolution of BS power transmission to boost the EE becomes more challenging in the case of multi-cell massive MIMO systems where UEs sufferers from inter-cell interference (ICI) and the intertwined factors that impact the power transmission and EE of BS. Reference [21] has investigated joint downlink beamforming and power allocation optimization for a multi-cell multiple-input-single-output (MISO) system. The EE maximization was studied subjected to users' signal-to-interference-plus-noise-ratio (SINR) target and BS transmit power constraint. In [22], the uplink resource allocation optimization has also been investigated for a multi-cell massive MIMO network with zero-forcing (ZF) detector. The authors optimized the number of BS antennas to maximize EE, where a uniform data rate was guaranteed for all UEs. Reference [23] has investigated the EE improvement in the downlink of a multi-cell massive MIMO system under different user location distribution. The authors proposed a new resource allocation scheme to optimize the number of active BS antennas based on the variation of UEs' location without QoS requirements. The study assumes each BS transmits a constant power that uniformly shared among UEs. The authors in [37] have proposed a new pilot design and derive closed-form expressions of SE with Rayleigh fading channels and maximum-ratio transmission (MRT) detection in the uplink of multi-cell massive MIMO systems. Then a max-min fairness problem was formulated by treating the pilot powers and data powers as optimization variables to maximize the uplink EE of the system. Reference [38] has proposed an uplink average transmit power-control-based to optimize the sum-rate in multi-cell massive MIMO systems. Although the proposed model can remarkably enhance total transmit power consumption with a small portion of sum-rate sacrifice, the UE's QoS constraint did not take into consideration.

The authors in [39] have studied joint beamforming and power control in the downlink of a multi-cell massive MIMO system. The asymptotic SINR was derived based on a large number of BS antennas and UEs. Then, a power control problem was formulated to maximize sum SE of the system. However, the study overlooks the cost of system power consumption and UEs' QoS that can lead to inefficient optimal system design. The EE maximization problem has been studied in [24] for the downlink of an interference-limited multi-cell MIMO network. The power allocations were optimized subjected to BS power consumption restriction. In [25], the SE has been analyzed to maximize EE for the downlink of a multi-cell massive MIMO system. The authors investigated the effect of an optimal number of BS antennas and UEs on EE improvement. The study assumes that each BS uses a constant transmission power equitably divides among users without QoS consideration. The total transmit power minimization problem through a centralized solution algorithm has been studied in [40] for the downlink of multi-cell massive MIMO systems. An equivalent achievable SE has also been admitted as the QoS constraint for all UEs. The centralized power allocation algorithm can significantly decrease the amount of exchanged information in terms of both backhaul signalling and complexity. Still, the influence of circuit power consumption on EE and system design parameters has not been examined. In [41], the power allocation problem with perfect CSI has been reviewed to maximize the downlink sum-rate for multi-cell massive MIMO networks. The effect of the user's QoS was not considered. Besides, the study did not investigate the impact of total power consumption on EE. Reference [42] has studied the trade-off between EE and SE for the downlink of multi-cell massive MIMO networks. A power allocation problem was formulated to maximize EE-SE trade-off. The optimal transmit power allocation, and the number of BS antennas were derived where UEs' QoS requirement and circuit power consumption were not taken into consideration. These prior studies do not present a comprehensive overview of the impact of different optimized system design parameters and user-level QoS on BS power transmission and overall system EE. Further, to the authors' best knowledge, no study yet investigated the EE improvement through BS power transmission adaptation to channel condition and QoS requirements (including data rate requirement and maximum allowable outage probability).

In this paper, we concentrate on the downlink of a multi-cell massive MIMO system where (i) all UEs are ensured with user-level QoS including a uniform data rate requirement and maximum allowable outage probability; (ii) the effect of multi-cell power control and ICI on both average BS transmit power and EE is complicated; (iii) circuit power consumption can be represented as an affine function of BS antenna and UE numbers which it is imperative to obtain reliable guidelines for EE improvement. Then, the contributions of this paper can be summarized as follows:

- We propose a new method to adjust the average BS transmit power to channel conditions and user-level QoS constraints, termed the BSTPA method. For this purpose, a unique analytical closed-form expression of the average BS transmitted power adaptation is derived. The aim is to minimize the total BS transmitted power to enhance the average EE per BS.
- We investigate and analyze how different system design parameters (the number of UEs served by BS, number of antennas at BS, and data rate requirement) and QoS constraints impact the average BS transmit power and average EE per BS. This analysis provides new insights into the interaction between the propagation environment, system design parameters, and different components of the total BS power consumption model under QoS requirements.
- We propose a corresponding iterative optimization algorithm to maximize the average EE per BS and obtain the optimal design parameters. The proposed algorithm aims to achieve the optimal EE value globally along with the optimal amount of data rate, the number of BS antennas, and number of users. Furthermore, the computational complexity of the proposed algorithm is examined.

In the remainder of this paper, the system model is described in Section II. Section III presents the proposed BS transmit power adaptation (BSTPA) method in a multi-cell massive MIMO system under the assumption of ZF precoding and perfect CSI. The average EE per BS and the total BS power consumption model are shown in Section IV. The EE optimization problem is formulated in Section V to obtain the optimal number of BS antennas, the number of UEs, and data rate requirement. Simulation is used to validate the analytical method in Section VI. Finally, the findings of the study are concluded in VII.

Notation: Matrices and vectors are denoted by boldface upper-case and lower-case letters, respectively. $\mathbf{I}_N$ defines the $N \times N$ identity matrix. Hermitian transpose and matrix inverse are expressed by superscripts $(.)^H$ and $\mathbf{A}^{-1}$, respectively. $\mathbb{R}$ and $\mathbb{Z}$ are the sets of real and integers numbers, respectively. The operator $\|.\|$ and $|.|$ are used for Euclidean norm and absolute number, respectively. $\mathbb{C}^{n\times m}$ describes the set of complex-valued $n \times m$ matrices. The $(i,j)-th$ element of matrix $\mathbf{A}$ is denoted by a_{ij} and similarly the $m-$th element of a vector is described by $[a]_m$. $\mathrm{E}_x\{.\}$ is the expectation with respect to variable x. Finally, $\mathcal{CN}(.,.)$ denotes a multivariate circularly symmetric complex Gaussian distribution. For convenience, the key notations in this paper are summarized in Table 1.

II. SYSTEM MODEL

This paper considers a multi-cell downlink massive MIMO network with a hexagonal layout, as pictured in Figure 1. All cells are operating over bandwidth B (Hz) with full frequency reuse and maximum power transmission of P_{max}. An area $\mathcal{A}$ with BS density λ_{BS} is considered where the total L number of cells ($L = \lambda_{BS}\mathcal{A}$) are indexed by m as the center-cell and $j=\{1, 2, \ldots, L-1\}$ as the interfering cells. Each BS is equipped with a co-located array of total M number of antennas that communicates with N single-antenna UEs simultaneously. The BS antennas can be configured with varying structures, such as; cylindrical, linear, rectangular, and so on [6]. The case of $M \gg N$ is considered which results in the massive MIMO transmission scenario in which ZF is nearly optimal

TABLE 1. Notation summary.

Notation	Description
B, b	system bandwidth, uniform guaranteed data rate of each UE
T, T_{ul}, T_{ul}	coherence block time, portion of uplink and downlink training phase
λ_{BS}	density of BSs
M	number of antennas at each BS
N	number of UEs in each cell
D, D_c	cell radius, in-radius of hexagonal cell
d_{min}	minimum distance of UEs to BSs
$d_{i,m}, d_{i,j}$	distance of the i-th UE to BS m and to interfering BS j, respectively
$\boldsymbol{G}_m$	channel matrix between BS m and its UEs
$\boldsymbol{g}_{i,m}, \boldsymbol{f}_{i,j}$	channel vectors between the i-th UE and serving BS m, and interfering BS j
$h_{i,m}$	small-scale Rayleigh fading channel between UE i and BS m
$\beta_{i,m}$	large-scale fading channel between UE i and BS m
$\bar{K}, \alpha$	Constant propagation loss, Path-loss exponent
$\boldsymbol{W}_m$	downlink ZF precoding matrix between BS m and its UEs
$\boldsymbol{w}_{i,m}, \boldsymbol{w}_{k,j}$	precoder vectors of BS m for its own UE i, and interfering BS j for UE k
$P_{i,m}, x_{i,m}$	transmitted power and signal of BS m to UE i
n_i, σ^2	AWGN noise, variance of noise
$\gamma_{i,m}$	SINR at UE i connected to BS m
$S_{i,m}, I_{i,m}$	desired and ICI signal powers received at the i-th UE connected to BS m
$R_{i,m}, P_{i,m}^{out}$	achievable data rate and outage probability of UE i connected to BS m
η_{out}	maximum allowable outage probability
$\bar{P}, \mathrm{P_{TX}}$	average and total transmitted power of BSs
A_0	QoS constraints parameter
$\overline{S_d}$	expectation of reciprocal of the signal power
$I_{intf}, \bar{\mathrm{I}}$	average ICI, average ICI normalized by power transmission
$\overline{EE}, P_{total}$	average EE and total power consumption per BS
ρ_{PA}, ρ_{PA}	PA efficiency,
$P_{e\&p}$	power consumption of channel estimation and signal processing per BS
P_0, P_{active}	idle power consumption per BS, power consumption per active antenna
P_{max}	maximum transmission power per BS

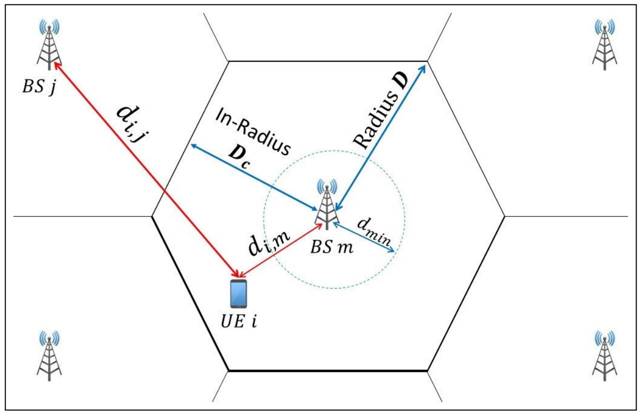


FIGURE 1. Hexagonal network layout.

under low and high SINR conditions [26]. UEs are uniformly distributed in each cell's coverage area between a radius D and minimum distance d_{min} where user i is located from the BS m with distance $d_{i,m}$.

Both UEs and BSs are considered completely coordinated and run according to the time-division duplex (TDD) protocol. Uplink channel estimations without pilot contamination are assumed to be ideal, which employed for downlink precoding computation based on channel reciprocity. We consider a block Rayleigh-fading channel where the channels are static within time-frequency coherence blocks of length T. These T channels are divided into three phases. The uplink training phase takes place first involving NT_{ul} channels where N users send orthogonal uplink signals of length T_{ul} channel. The subsequent downlink training phase consists of T_{dl} channels. In this phase, the BSs broadcast the training signal assisting UEs in estimating the pre-coded equivalent downlink channels. Finally, $T - NT_{ul} - T_{dl}$ channels are used for downlink data transmission phase.

The channel matrix of the BS m is defined as $\boldsymbol{G}_m = [\boldsymbol{g}_{1,m}, \boldsymbol{g}_{2,m}, \ldots, \boldsymbol{g}_{N,m}] \in \mathbb{C}^{N\times M}$ where $\boldsymbol{g}_{i,m} = \boldsymbol{h}_{i,m}\sqrt{\beta_{i,m}}$ is the propagation channel vector between BS m and UE i. $\boldsymbol{h}_{i,m}$ is the vector representing small-scale Rayleigh channel fading with $\mathcal{CN}(0, 1)$ independent and identically distributed (i.i.d) components. $\beta_{i,m} = \bar{K}d_{i,m}^{-\alpha}$ defines the large-scale fading channel where fixed value $\bar{K} > 0$ specifies the constant propagation loss to adjust the channel attenuation at minimal distance d_{min} and $\alpha > 2$ defines path-loss exponent [27]. For analytical tractability, the BSs are assumed to obtain perfect CSI acquisition from the uplink training signals and adopt ZF processing for downlink data pre-coding. ZF beamforming is typically suboptimal, but compared to other beamforming techniques, it is significantly less complex. Also, it achieves the same asymptotic sum data rate as others benefit from the increment in the UE number. Moreover, BSs are able to design their beams to eliminate intra-user interference [28], [36]. The downlink precoding matrix $\boldsymbol{W_m} = [\boldsymbol{w}_{1,m}, \boldsymbol{w}_{2,m}, \ldots, \boldsymbol{w}_{N,m}] \in \mathbb{C}^{N\times M}$ is defined as

$$\boldsymbol{W_m} = \boldsymbol{G_m}(\boldsymbol{G_m^H}\boldsymbol{G_m})^{-1} \tag{1}$$

where $\boldsymbol{w}_{i,m}$ specifies the ZF beam allocated to UE i, and $[.]_{\mathrm{N:1}}$ is the N rows corresponding with N scheduled UEs of BS m.

A. SIGNAL AND SINR MODELS IN MULTI-CELL MASSIVE MIMO SYSTEM

All users are assumed to be served in the same time-frequency resources. We ignore the interference power from outside of the area $\mathcal{A}$. Then, the signal received by the i-th user that is connected to BS m described as the sum of the intended transmitted signal of BS m, the signals from interfering BSs $j \neq m$, and the receiver noise, which is represented as

$$y_{i,m} = \underbrace{\sqrt{P_{i,m}}\boldsymbol{g}_{i,m}^H\boldsymbol{w}_{i,m}x_{i,m}}_{\text{Intended Signal}} + \underbrace{\sum_{j\in\Phi_A/\{m\}}\sum_{k=1}^{N}\sqrt{P_{k,j}}\boldsymbol{f}_{i,j}^H\boldsymbol{w}_{k,j}x_{k,j}}_{\text{Inter-Cell Interference}} + \underbrace{n_i}_{\text{Noise}}, \tag{2}$$

where $P_{i,m}$ presents the transmitted power of BS m to UE i, $x_{i,m}$ is a complex scaler that describes the dispatched information signal of BS m to UE i and $\mathrm{E}\left[|x_{i,m}|^2\right] = 1$. Also, n_i defines the circularly symmetric complex additive white Gaussian noise with variance σ^2. Moreover, $P_{k,j}$ and $\boldsymbol{f}_{i,j} = \boldsymbol{h}_{i,j}\sqrt{\beta_{i,j}}$ show the power that transmitted at neighboring BS j to an own single UE k and the interference channel between BS j and UE i. $\boldsymbol{h}_{i,j}$ and $\beta_{i,j}$ are the small-scale and large-scale fading channels between UE i connected to BS m and the interfering BS j. $\boldsymbol{w}_{k,j}$ is ZF precoding vector of BS j to its associated UE k. Hence, the SINR of the i-th user connected to BS m is defined as

$$\gamma_{i,m} = \frac{P_{i,m}\beta_{i,m}\left|\frac{\boldsymbol{h}_{i,m}^{H}\boldsymbol{w}_{i,m}}{\|\boldsymbol{w}_{i,m}\|}\right|^{2}}{\sum_{j\in\Phi_A/\{m\}}\sum_{k=1}^{N}P_{k,j}\beta_{i,j}\left|\frac{\boldsymbol{h}_{i,j}^{H}\boldsymbol{w}_{k,j}}{\|\boldsymbol{w}_{k,j}\|}\right|^{2}+\sigma^{2}}. \quad (3)$$

The following notations are used for simplicity.

$$S_{i,m} = P_{i,m}\beta_{i,m}\left|\frac{\boldsymbol{h}_{i,m}^{H}\boldsymbol{w}_{i,m}}{\|\ \boldsymbol{w}_{i,m}\ \|}\right|^{2}, \quad (4)$$

$$I_{i,m} = \sum_{j\in\Phi_A/\{m\}}\sum_{k=1}^{N}P_{k,j}\beta_{i,j}\left|\frac{\boldsymbol{h}_{i,j}^{H}\boldsymbol{w}_{k,j}}{\|\ \boldsymbol{w}_{k,j}\ \|}\right|^{2}. \quad (5)$$

where $S_{i,m}$ and $I_{i,m}$ define the desired and ICI signal powers received at user i connected to BS m.

III. THE PROPOSED AVERAGE BS TRANSMIT POWER ADAPTATION (BSTPA) METHOD

The downlink transmitted signal from BS m to the i-th user with allocated power $P_{i,m}$ and a normalized precoding vector $\frac{\boldsymbol{w}_{i,m}}{\|\boldsymbol{w}_{i,m}\|}$ achieves the data rate $R_{i,m}$ (bits/sec) for user i that can be shown as

$$R_{i,m} = B\log_2\left(1+\gamma_{i,m}\right). \quad (6)$$

Let's consider outage performance as the first QoS level to describe the required minimum transmitted power $P_{i,m}$ to the i-th UE. An outage happens when the connection between BS m and UE i cannot carry the desired target rate of b (bits/sec). For simplicity, the same data rate requirement b is assumed for all UEs. Then the outage probability of user i can be determined as

$$\begin{aligned}P_{i,m}^{out} &= \Pr\left\{B\log_2\left(1+\gamma_{i,m}\right) \ < b\right\}\\ &= \Pr\left\{S_{i,m} < \left(I_{i,m}+\sigma^{2}\right)\left(2^{\left(\frac{b}{B}\right)}-1\right)\right\}. \quad (7)\end{aligned}$$

Given distance $d_{i,m}$, $S_{i,m}$ is an exponential random variable. Therefore, the outage probability $P_{i,m}^{out}$ of UE i at distance $d_{i,m}$ from serving BS m can be simplified to

$$P_{i,m}^{out} \approx 1-\exp\left(-\frac{\left(I_{i,m}+\sigma^{2}\right)\left(2^{\left(\frac{b}{B}\right)}-1\right)}{S_{i,m}}\right). \quad (8)$$

Let η_{out} denotes the maximum allowable outage probability of all users. The next inequality must maintain for all UEs as

$$P_{i,m}^{out} \le \eta_{out}. \quad (9)$$

Substituting equation (8) into (9), the minimum transmitted power of BS m to UE i is computed as

$$P_{i,m} = \frac{(I_{i,m}+\sigma^{2})(2^{\left(\frac{b}{B}\right)}-1)}{-ln\left(1-\ \eta_{out}\right)\ \times C_1}, \quad (10)$$

where $C_1 = \beta_{i,m}\left|\frac{\boldsymbol{h}_{i,m}^{H}\boldsymbol{w}_{i,m}}{\|\boldsymbol{w}_{i,m}\|}\right|^{2}$ represents the desired channel gain of UE i. The proof follows the same method used in our relevant work [29].

Note that deriving a closed-form definition for $P_{i,m}$ is challenging because of disparities in user distribution and different channel states. As a result, we attempt to achieve a tractable analytical approximation of minimum transmitted power $P_{i,m}$. Accordingly, a new asymptotic tight lower-bound of the average transmitted power is proposed as

$$\begin{aligned}&\bar{\mathrm{P}}\\ &= \mathrm{E}_{d,h}\left\{P_{i,m}\right\}\\ &= \mathrm{E}\left\{\frac{2^{\left(\frac{b}{B}\right)}-1}{-\ln\left(1-\eta_{out}\right)}\right\}\mathrm{E}\left\{I_{i,m}+\sigma^{2}\right\}\mathrm{E}\left\{\frac{1}{C_1}\right\}\\ &= A_0\left(\mathrm{E}\left\{\sum_{j\in\Phi_A/\{m\}}\sum_{k=1}^{N}P_{k,j}\beta_{i,j}\left|\frac{\boldsymbol{h}_{i,j}^{H}\boldsymbol{w}_{k,j}}{\|\ \boldsymbol{w}_{k,j}\ \|}\right|^{2}\right\}+\sigma^{2}\right)\mathrm{E}\left\{\frac{1}{C_1}\right\}\\ &\triangleq A_0\left(\ \bar{\mathrm{p}}\ \bar{\mathrm{I}}+\sigma^{2}\right)\overline{S_d} \quad (11)\end{aligned}$$

where $A_0 = [2^{\left(\frac{b}{B}\right)}-1]/[-\ln(1-\eta_{out})]$ is the parameter that includes QoS constraints, $\bar{\mathrm{p}}$ denotes the average radiated power of an interfering BS to a single user, $\bar{\mathrm{I}}$ defines the average ICI that is normalized by power transmission, and $\overline{S_d} \triangleq \mathrm{E}\left\{\frac{1}{C_1}\right\}$ is the expectation of reciprocal of the signal power.

The power consumption of all BSs in area $\mathcal{A}$ are statistically identical since the BSs are considered to deploy the same antenna configuration and same circuit power, the same uniform UE distribution in the cells of radius D. Additionally, all channels are distributed identically and independently. For these reasons, the average transmitted power to all UEs are approximately the same as $\mathrm{E}\{p_{i,m}\} = \mathrm{E}\{p_{k,j}\}$. Therefore, the average transmitted power $\bar{\mathrm{P}}$ of BS m is the same with the average radiated power $\bar{\mathrm{p}}$ of any other BS j in equation (11).

The ICI changes with the position of UEs which leads to unsolvable derivation of BS transmitted power. Thus, to approximate the uncertain value, the average ICI of all users' positions is estimated. On the other hand, as shown in [10], channel $\boldsymbol{h}_{i,j}$ is independent from beamforming vector $\boldsymbol{w}_{k,j}$ such that the equivalent interfering channel gain $\left|\frac{\boldsymbol{h}_{i,j}^{H}\boldsymbol{w}_{k,j}}{\|\boldsymbol{w}_{k,j}\|}\right|^{2} \sim exp\,(1)$ for interfering BS $j \neq m$, where $exp\,(1)$ describes the exponential distribution with unit mean.

Let's assume any user i is located at distance $d_{i,m}$ from its serving BS m. Each elementary surface $xdxd\theta$ located at a distance x from i includes $\lambda_{BS}xdxd\theta$ base stations that contribute to ICI. Then, the average ICI, denoted as I_{inf}, is approximated using the integration surface by a ring with center i and bounds $(2\,D_c-d_{i,m},\ D_{nw}-d_{i,m})$ as follow [30],

[31]

$$\begin{aligned} I_{inf} &= \mathrm{E}\left\{ \sum_{j\in\Phi_A/\{m\}} \sum_{k=1}^{N} P_{k,j}\beta_{i,j} \left| \frac{\mathbf{h}_{i,j}^H \mathbf{w}_{k,j}}{\| \mathbf{w}_{k,j} \|} \right|^2 \right\} \\ &= \mathrm{E}\left\{ \bar{\mathrm{p}}\bar{K} \sum_{j\in\Phi_A/\{m\}} \sum_{k=1}^{N} d_{i,j}^{-\alpha} \left| \frac{\mathbf{h}_{i,j}^H \mathbf{w}_{k,j}}{\| \mathbf{w}_{k,j} \|} \right|^2 \right\} \\ &= \bar{\mathrm{p}}\bar{K} \int_0^{2\pi} \int_{2\,D_c-d_{i,m}}^{D_{nw}-d_{i,m}} \lambda_{BS}\, x^{-\alpha}\, dx\, d\theta \\ &= \bar{\mathrm{p}} \frac{2\pi\lambda_{BS}\bar{K}}{\alpha-2} \left[\left(2D_c - d_{i,m}\right)^{2-\alpha} - \left(D_{nw} - d_{i,m}\right)^{2-\alpha} \right], \quad (12) \end{aligned}$$

where $D_c = (3D)/(2\sqrt{3})$ is the in-radius of the hexagonal cell and R_{nw} is the radius of area $\mathcal{A}$.

Since UEs are distributed uniformly within the coverage area of each cell with in-radius D_c, the average I_{inf} conditioned on the location of all users can be approximated as [31]

$$\begin{aligned} I_{inf} = \bar{\mathrm{p}} \frac{2\pi\lambda_{BS}\bar{K}}{\alpha-2} \int_{d_{min}}^{D_c} \left[(2D_c - z)^{2-\alpha} - (D_{nw} - z)^{2-\alpha} \right] \\ \times \left(\frac{2z}{D_c^2 - d_{min}^2} \right) dz = \bar{\mathrm{p}}\,\bar{\mathrm{I}}, \quad (13) \end{aligned}$$

where $(2z)/(D_c^2 - d_{min}^2)$ is probability distribution function (PDF) of distance z that spread uniformly in the area of a cell containing in-radius D_c and minimum distance d_{min} from the center.

Since BS m serves a total number of N users, the channel gain $\left| \frac{\mathbf{h}_{i,m}^H \mathbf{w}_{i,m}}{\|\mathbf{w}_{i,m}\|} \right|^2$ follows a gamma distribution with expected value $(M - N)$ that defines the degree of freedom (DoF) of users served by BS m [10], [19]. Afterward, $\overline{S_d}$ defines jointly the desired channel gain and average attenuation that characterized as

$$\overline{S_d} \triangleq \mathrm{E}\left\{ \frac{1}{C_1} \right\} = \frac{D^{\alpha+2} - d_{min}^{\alpha+2}}{\bar{K}\left(1+\frac{\alpha}{2}\right)\left(D^2 - d_{min}^2\right)(M-N)}. \quad (14)$$

Eventually, based on equation (11) and total power consumption defined in equation (17), the average BS transmit power $\mathrm{P_{TX}}$ for BS m equipped with a total number of M antennas and serving N active users can be derived as

$$\begin{aligned} \mathrm{P_{TX}} &= \frac{(T - NT_{ul} - T_{dl})}{T} N\bar{\mathrm{P}} \\ &= \frac{(T - NT_{ul} - T_{dl})}{T} \frac{N\sigma^2}{\left(A_0\overline{S_d}\right)^{-1} - \bar{\mathrm{I}}}, \quad (15) \end{aligned}$$

where $\mathrm{P_{TX}}$ is respectively parameterized and formulated with respect to uniform data rate b (bits/sec), maximum allowable outage probability η_{out}, total M number of BS antennas, N number of UEs, cell-radius D, and minimal distance d_{min}.

IV. ENERGY EFFICIENCY AND TOTAL POWER CONSUMPTION MODEL

In the field of communication systems, the average EE per BS is generally determined in (bits/Joule) and is the proportion of the average downlink throughput to the total power consumption of a BS (Watt), where the throughput is the sum data rate of all UEs of the BS (bits/sec) [3]. Accordingly, the average EE per BS ($\overline{\mathrm{EE}}$) assuming a uniform data rate requirement b (bits/sec) is represented as

$$\overline{\mathrm{EE}} = \frac{\left(\frac{T - NT_{ul} - T_{dl}}{T}\right) N\, b}{P_{total}}. \quad (16)$$

Besides the average BS transmit power to meet all user-level QoS constraints, the circuit power consumption of different BS components must also be taken into account. Consequently, the BS circuit power consumption model adopted from [14], [19] is expressed as

$$P_{total} = \rho_{\mathrm{PA}}\mathrm{P_{TX}} + P_{e\&p} + P_0, \quad (17)$$

where, ρ_{PA} denotes the PA efficiency of BSs. P_0 is a fixed component that describes the idle power consumption of the BS for cooling, analog/digital conversion, and backhaul. $P_{e\&p}$ defines circuit power consumption per BS for channel estimation, ZF detection, and signal processing at each BS transceiver chain, respectively. Hence, $P_{e\&p}$ can be computed as

$$\begin{aligned} P_{e\&p} = MP_{active} + \frac{BN^3}{3T\rho_{\mathrm{C}}} \\ + \frac{3BMN^2 + 2MNT_{ul}B + BMN}{T\rho_{\mathrm{C}}}, \quad (18) \end{aligned}$$

where, ρ_{C} is the computational efficiency at BSs measured in (flops/W) and P_{active} is the circuit power that BSs use to keep active one antenna.

V. ENERGY EFFICIENCY ANALYSIS AND OPTIMIZATION

In this section. the average EE per BS is first analyzed and then optimized based on different combination of system design parameters. From equations (16) and (17), the average EE and total power consumption are simultaneously affected by the number of BS antennas (M), the number of active UEs (N), and the guaranteed user data rate (b). In the following, the average EE per BS is maximized through optimizing M, N, and b. Therefore, the optimization problem of this study is formulated as

$$\begin{aligned} \mathcal{P}1: \max_{M,N,b}\ \overline{\mathrm{EE}} &= \frac{\left(\frac{T - NT_{ul} - T_{dl}}{T}\right) N\, b}{P_{total}} \\ \text{s.t. } \mathcal{C}1: &\ \mathrm{P_{TX}} \le P_{max} \\ \mathcal{C}2: &\ M \ge N+1 \\ \mathcal{C}3: &\ M \le M_{max} \quad (19) \end{aligned}$$

where $\mathcal{C}1$ denotes the constraint that guarantees the average BS transmit power will not exceed the maximum BS transmission capability P_{max}. $\mathcal{C}2$ and $\mathcal{C}3$ represent the constraints

TABLE 2. System model parameters.

Parameter	Value	Parameter	Value
Maximum BS transmit power (P_{max}) [2]	40 Watt	Constant propagation loss ($\bar{K}$) [28]	$10^{-3.53}$
Density of BSs (λ_{BS}) [32]	$1/(\pi D^2)$	System bandwidth (B) [19]	20 MHz
Cell radius (D) [19]	250 m	Maximum outage probability (η_{out}) [33]	5%
Minimum distance to BS (d_{min}) [19]	35 m	Total noise power (σ^2) [19]	-96 dBm
Path-loss exponent (α) [28]	3.76	PA efficiency at BSs (ρ_{PA}) [2]	1/0.388
Computational efficiency at BS (ρ_C) [19]	12.8 Gflops/Watt	Per-antenna circuit power (P_{active}) [14]	32 mWatt or 1 Watt
T, T_{ul}, T_{dl} [34]	1800, 9.69, 24.2	Idle power consumption of BSs (P_0) [19]	18 Watt

resulting in the massive MIMO transmission scenario and the requirement of ZF precoding scheme, where M_{max} is the maximum available number of antennas at BS.

In the following, this study aims at finding the EE-optimal value of either M, N, and b separately that solves $\mathcal{P}1$, when the other two parameters are fixed. This method provides the means to solve problem (19) by an alternating optimization approach. Although an exhaustive search can be used to find the optimal solution, it requires exponential computational complexity, which is unpractical with large parameter values. An exhaustive search may potentially check every single element in three nested loops to find what it is looking for, which means that the expected worst-case complexity scales directly with the size of the parameters. To solve $\mathcal{P}1$ with low computation complexity, an iterative optimization algorithm is proposed in the following.

A. OPTIMAL NUMBER OF BS ANTENNAS M

The optimal value of M to maximizes $\overline{\text{EE}}$ can be calculated in a closed-form expression stated in the following lemma.

Lemma 1: For fixed and given values of N and b, the optimal number of BS antennas to maximize $\overline{\text{EE}}$ can be expressed as

$$M^* = \left\lfloor \sqrt{\frac{a_2}{a_4}} + a_3 \right\rceil \tag{20}$$

with

$$\begin{aligned}
a_2 &= \rho_{PA}\left(\frac{T - NT_{ul} - T_{dl}}{T}\right) N\sigma^2 A_0\, \overline{\text{S}},\\
a_3 &= N + \bar{\text{I}}\, A_0\, \overline{\text{S}},\\
a_4 &= P_{active} + \frac{2NT_{ul}B + 3BN^2 + BN}{T\,\rho_C},\\
A_0 &= \frac{2^{(\frac{b}{B})} - 1}{-\ln(1 - \eta_{out})},\\
\overline{\text{S}} &= \frac{D^{\alpha+2} - d_{min}^{\alpha+2}}{\bar{K}\left(1 + \frac{\alpha}{2}\right)\left(D^2 - d_{min}^2\right)},
\end{aligned}$$

where $\lfloor . \rceil$ defines either the closest larger or closest smaller integer to M^*, and can be easily determined through the corresponding $\overline{\text{EE}}$ comparison.

Proof: The proof is given in Appendix. ■

B. JOINT OPTIMAL NUMBER OF USERS AND OPTIMAL DATA RATE

The objective function in problem $\mathcal{P}1$ is non-linear and non-convex concerning N and b. Thus, it is hard to acquire optimal closed-form solutions directly. Additionally, the $\overline{\text{EE}}$ defined in equation (19) is a classic two-dimensional real optimization problem for N and b with high optimization complexity. Consequently, a simple optimization algorithm is needed to solve $\mathcal{P}1$ for the optimal amount of N and b that maximize $\overline{\text{EE}}$.

The average EE per BS is a concave function for N and b as will be shown in section VI. Accordingly, the three-dimensional optimization problem $\mathcal{P}1$ can be transformed into three sub-problems to reduce the complexity. The basic idea is finding the optimum values alternatively in an iterative algorithm until the convergence is reached. The aim is to find the joint global optimum amounts of all parameters M, N, and b that maximize average EE per BS. At each iteration, two parameters are considered fixed to optimize the other one that maximizes $\overline{\text{EE}}$. To do so, the search only needs several iterations to reach the global optimum. The detailed procedures of the proposed algorithm are presented in Algorithm 1 that is partly adopted and improved from [35].

In the proposed Algorithm 1, δN and δb represent the length of the searching step for the number of active UEs and the required data rate, respectively. M_0, N_0 and b_0 are the initial values and N_{min} is the minimum number of available UEs. We also denote b_{max} and b_{min} as the maximum and minimum achievable data rate. M_{ch} is the value to check the optimal number of BS antennas and convergence point. Lastly, M^{opt}, N^{opt}, b^{opt}, and $\overline{\text{EE}}^{opt}$ denote the final optimization result. The second and third steps of the algorithm obtain the optimum value of N and b through a semi-exhaustive search. Semi-exhaustive search is applied because it employs both lower and upper boundary constraints as well as limiting the search domain for each parameter to find the best optimum value more quickly. Therefore, the search domain limitation produces a smoother convergence to the optimal solution and requires a significantly reduced computational complexity compared to the conventional exhaustive search. Since N and b are positive numbers, the global optimum can be achieved by a semi-exhaustive search over all possible set of pair (N, b) and then computing the optimal

Algorithm 1 Iterative Energy Efficiency Optimization Algorithm

Step 1: Initialize $M = M_0$, $N = N_0$, $b = b_0$, $\delta N = \delta N_0$, $\delta b = \delta b_0$.
Step 2: Iteration over N with given M and b
  if $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N + \delta N, b)\right)$
    while $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N + \delta N, b)\right)$ && $(N < M)$
      $N = N + \delta N$
    end while
  else if $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N - \delta N, b)\right)$
    while $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N - \delta N, b)\right)$ && $(N > N_{min})$
      $N = N - \delta N$
    end while
  end if
Step 3: Iteration over b with given M and N
  if $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N, b + \delta b)\right)$
    while $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N, b + \delta b)\right)$ && $(b \leq b_{max})$
      $b = b + \delta b$
    end while
  else if $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N, b - \delta b)\right)$
    while $\left(\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N, b - \delta b)\right)$ && $(b > b_{min})$
      $b = b - \delta b$
    end while
  end if
Step 4: Calculate M_{ch} using Lemma 1
  if $(M_{ch} \leq M_{max})$ && $\left(\overline{\text{EE}}(M_{ch}, N, b) > \overline{\text{EE}}(M, N, b)\right)$
    $M = M_{ch}$
    Go to **Step 2**
  else
    Return $M^{opt} = M$, $N^{opt} = N$, $b^{opt} = b$, $\overline{\text{EE}}^{opt} = \overline{\text{EE}}(M, N, b)$
    Break.
  end if

number of BS antennas M using Lemma 1. Then, N and b can be increased or decreased step-by-step until the EE start to drop and consequently no need to search for all integers.

C. COMPUTATIONAL COMPLEXITY ANALYSIS

Now we address the computational complexity of the proposed optimization algorithm. It consists of two nested loops. It is easy to see that the major computational complexity involves the iteration complexity of steps 2 and 3 in each iteration of Algorithm 1. In each iteration of the algorithm, step 2 will be terminated whenever $\overline{\text{EE}}(M, N, b) \geq \overline{\text{EE}}(M, N + \delta N, b)$ or $M - N = 1$ is satisfied. Otherwise, step 2 will be terminated whenever $\overline{\text{EE}}(M, N, b) < \overline{\text{EE}}(M, N - \delta N, b)$ or $N - N_{min} = 0$ is met. In the worst case, the maximum number of iterations will be $K_2 = max \left\{\frac{M-N}{\delta N}, \frac{N-N_{min}}{\delta N}\right\}$. Similar to step 2, in the worst case of step 3, the maximum number of iterations is defined as $K_3 = max \left\{\frac{b_{max}-b}{\delta b}, \frac{b-b_{min}}{\delta b}\right\}$. On the one hand, in step 4 of the proposed algorithm, the optimal M has a closed-form expression of the complexity order one, making the proposed algorithm easy to implement. Additionally, this also remarkably accelerates the convergence speed. As a result, the estimated complexity of the proposed algorithm is $K_{iter} O(K_2 + K_3)$ where K_{iter} is the required number of iteration for convergence.

VI. RESULTS AND DISCUSSION

This section presents the simulation and analytical results to validate the performance of the proposed BSTPA method obtained in section III along with average EE per BS under ZF processing and perfect CSI in a multi-cell massive MIMO setup. Then, we discuss how the average BS transmit power and the average EE per BS are affected by different design parameters, followed by comparison and optimization findings for two different per-antennas circuit power cases.

We simulated the area $\mathcal{A}$ at a radius of 1000 meters, where the performance of the central-cell is only examined. The corresponding system model parameters are defined in Table 2 adopted from a variety of prior studies as well as the 3GPP propagation environment presented in [27] and [19]. For both simulation and analytical, the maximum BS transmission power constraint P_{max} is considered. Moreover, the circuit power consumption model independent of data rate is selected from [19], [33].

Observe that some data rates b (bits/sec) cannot be supported for any transmit powers. In such a case, P_{TX} would lead to either negative value or the values larger than the maximum BS power transmission capacity P_{max}. Additionally, ZF processing yields a coherent beamforming gain of $M - N$. Therefore, we only evaluate the case of $M \geq N + 1$ where the BS antennas are much larger than the number of UEs to result in a massive MIMO transmission scenario.

Throughout the results, three different BS antennas and user numbers are presented for a better understanding of this effect on system performance. We consider 100 BS antennas for the minimum number to ensure that the massive MIMO system complies with $M \gg N$ condition. The maximum number is set to 220 adopted from [19] and 160 as the average number. Also, 60 UEs are regarded to be the maximum number to fulfill the massive MIMO condition $M \gg N$.

A. SYSTEM MODEL EVALUATION OF THE PROPOSED METHOD AND EE

Figures 2-4 present the impact of different design parameters including M, N, and b on the average BS transmit power (P_{TX}). Figures 5-7 analyze the average EE per BS ($\overline{\text{EE}}$) with respect to the above stated design parameters.

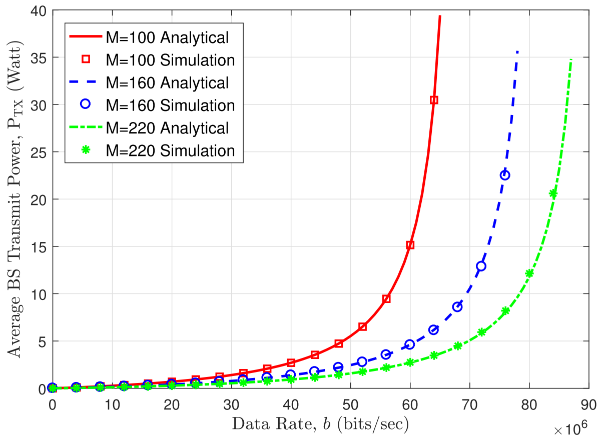


FIGURE 2. **Average BS transmit power P_{TX} for different data rate b (bits/sec) with three cases of BS antenna numbers M and the total number of users $N = 10$.**

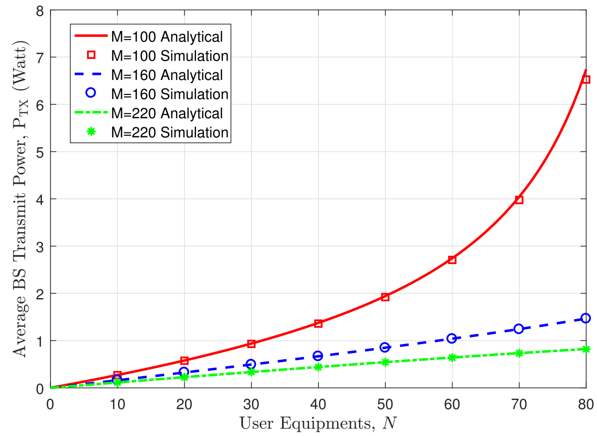


FIGURE 4. **Average BS transmit power P_{TX} for different number of user N with three cases of BS antenna numbers M and data rate $b = 10$ (Mbits/sec).**

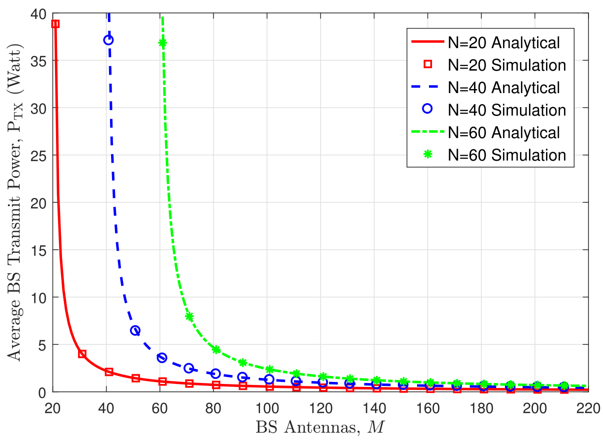


FIGURE 3. **Average BS transmit power P_{TX} for different BS antennas number M with three cases of user numbers N and data rate $b = 10$ (Mbits/sec).**

Figure 2 represents the average BS transmit power P_{TX} for different data rate b (bits/sec) in the case of three different numbers of BS antennas M and total number of UEs $N = 10$. While the same pattern can be seen from the figures for different cases of BS antennas M, the increase in P_{TX} grows more severe as data rate requirement b grows gradually. The figure also shows less P_{TX} increment with more significant numbers of M compared to the fewer BS antennas M. That is explained by the fact that a fewer number of BS antennas contribute to DoF deductions, which potentially may increase the inter-user interference. It is worth noting that a different number of BS antennas can only support a certain data rate requirements because for both analytical and simulation, the maximum BS power transmission constraint is taken into account. When the data rate continually grows, the average BS transmit power needs to be increased, leading to more inter-user interference appears. Consequently, extra BS transmit power is required to overcome the additional interference. The findings correspond to previous studies in [7], [32], [34].

Figure 3 illustrates the average BS transmit power P_{TX} changes as a function of different BS antennas M, for three cases of users N and data rate requirement $b = 10$ (Mbits/sec). As anticipated, the average BS transmit power P_{TX} decreases while BS antennas M steadily increases, leading to the validation of the preliminary analysis. It should be noted that the gain (saving BS transmit power P_{TX}) for gradual M increment is very significant at fewer numbers of M and a larger number of users N. But the saving diminishes as M grows to infinity. Besides, P_{TX} increases at N faster than linear while decreasing linearly to M. It should be taken into account that increasing M will improve the DoF degree. The higher DoF will suppress more inter-user interference and, therefore, the more P_{TX} reduction. Obviously, both simulation and analytical results are close-fitting, particularly at significant large numbers of M, since inter-user interference will be reduces respectively at lower numbers of N. These findings are consistent with prior studies investigating the effect of BS antennas number on BS power transmission [10]. Nevertheless, increasing M becomes more challenging when the cost of per-antenna circuit power is involved in the total BS power consumption, which is investigated in the next three parts of average EE per BS.

Figure 4 presents the average BS transmit power P_{TX} for different UEs N with three cases of BS antennas M and data rate requirement $b = 10$ (Mbits/sec). The same patterns for different BS antennas M can be observed from the figure, but increasing N will mainly increase P_{TX} significantly at a fewer number of M because the system has to suppress extra caused inter-user interference. The analysis results correspond closely to the simulation, effectively at the more significant numbers of M. As expected, the BS antennas number has a significant impact on P_{TX}, where the average

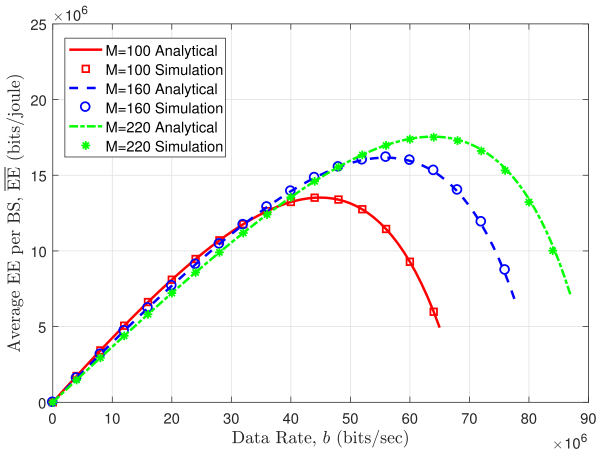


FIGURE 5. **Average EE per BS for different data rate *b* (bits/sec) with three cases of BS antenna numbers *M* and the total number of users *N* = 10.**

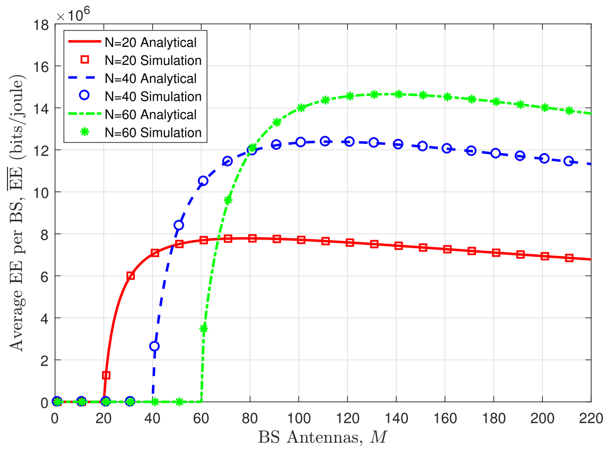


FIGURE 6. **Average EE per BS for different BS antennas number *M* with three cases of users number *N* and data rate *b* = 10 (Mbits/sec).**

BS transmit power improved with M, and BS radiated power will be saved due to significant antenna array gain.

Figure 5 shows the relation between the average EE per BS ($\overline{\mathrm{EE}}$) and different data rate requirements for three cases of BS antennas M and $N = 10$. As shown in the figure, EE is a uni-modal data rate function for every M number. It means that the average EE per BS will raise as data rate requirement continuously grows to an average EE maximum level. The average EE, however, starts to decline from this point on with the further increase in data rate. That is because there is a need for more BS power transmission and more significant antenna numbers to support a higher data rate, which increases the BS circuit power and consequently, total BS power consumption. It is apparent from the figure that the EE versus data rate curves will be flattened since M is growing due to BS circuit power consumption increment shown in equation (17). As a result, there needs to be a cost-performance trade-off, especially in massive MIMO setups where the BS is provided with M antennas requiring M RF chains. Every RF chain has several components such as PAs, analog and digital converters, etc., [32].

Figure 6 illustrates the average EE per BS for different BS antennas M with three cases of users N and data rate $b = 10$ (Mbits/sec). The figure indicates that a large number of M to reduce the P_{TX} cannot always maximize $\overline{\mathrm{EE}}$. From figure 3 and 6, we can conclude the great impact of BS antennas M on optimal P_{TX} reduction. This means that in massive MIMO setups, the BS antenna number M and average transmit power P_{TX} are major design parameters for the average EE maximization.

Figure 7 presents the average EE per BS for different users N with three cases of BS antennas M and data rate requirement $b = 10$ (Mbits/sec). With the continuous increment of N for every M value, the average EE will be improved. As a consequence of the interference limitation, maximum EE-rate exists at any M value. Therefore, the EE starts to drop with further increment on N since the inter-user interference grows

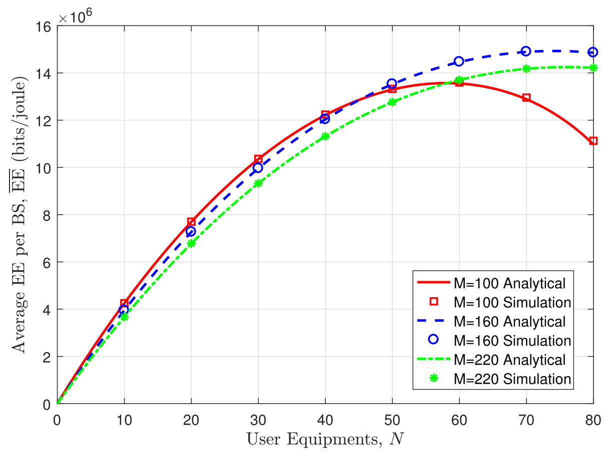
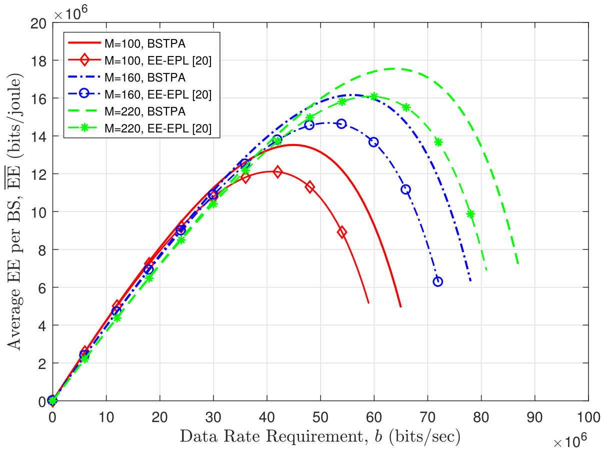


FIGURE 7. **Average EE per BS for different number of users *N* with three cases of BS antenna numbers *M* and data rate *b* = 10 (Mbits/sec).**

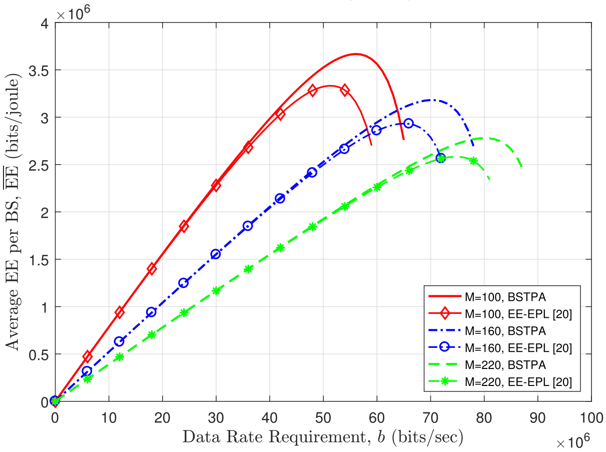
faster from this point. Looking at figure 4, it is observed that a higher amount of M results in smaller P_{TX}. On the other hand, Figure 7 indicates BS circuit power consumption is predominant to P_{TX} particularly at large M and N values. These observations point out that transmit-circuit power consumption trade-off is necessary for optimal EE achievement.

B. EE COMPARISON OF THE BSTPA METHOD AND CONVENTIONAL SCHEMES

Figures 8–10 show EE improvement by BS transmit power reduction. In contrast, the achieved average EE per BS through BSTPA method is compared with the energy-efficient equal power loading (EE-EPL) algorithm proposed in [20] in which the BS always employs equal power that shared between all active users. The figures plot $\overline{\mathrm{EE}}$ obtained by the two scenarios, which also tested for two different per-antenna circuit powers to express the importance of BS circuit power consumption. However, the figures confirm that

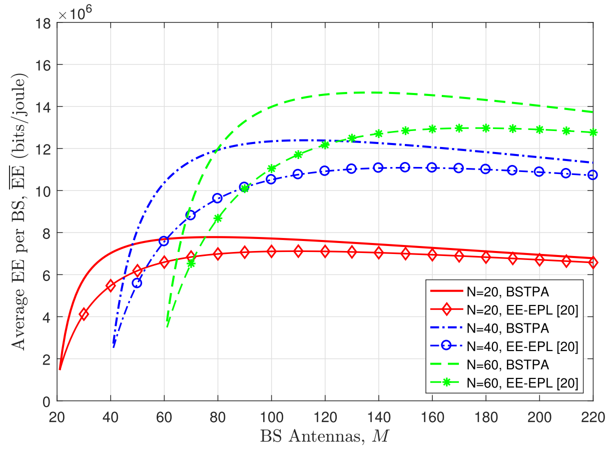


(a) $P_{active} = 32$ (mWatt)

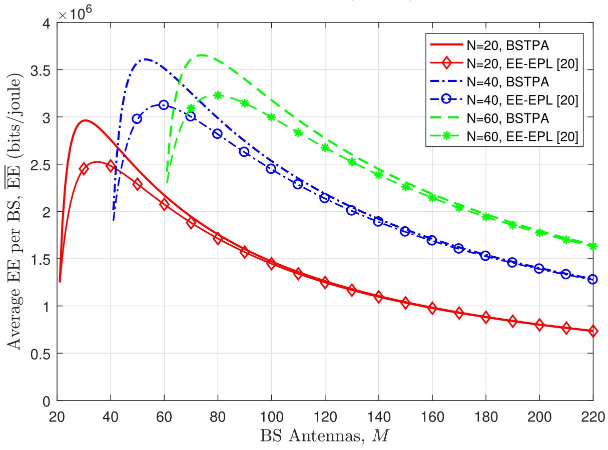


(b) $P_{active} = 1$ (Watt)

FIGURE 8. Average EE comparison of proposed method and conventional scheme versus different data rate b (bits/sec) for per-antenna circuit power $P_{act} = 32$ (mWatt) and $P_{act} = 1$ (Watt), three different numbers of M, and $N = 10$.



(a) $P_{active} = 32$ (mWatt)



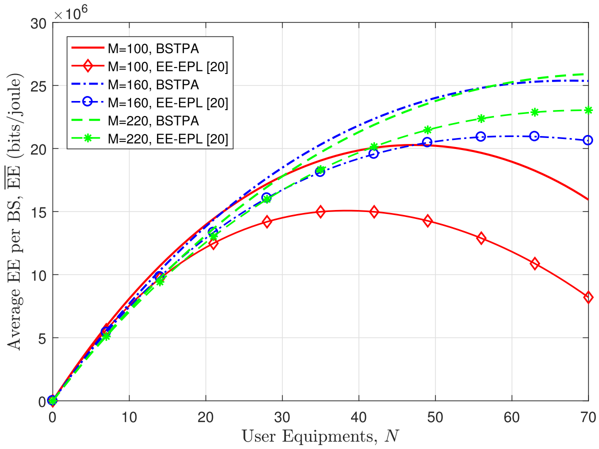
(b) $P_{active} = 1$ (Watt)

FIGURE 9. Average EE comparison of proposed method and conventional scheme versus different BS antennas M for per-antenna circuit power $P_{act} = 32$ (mWatt) and $P_{act} = 1$ (Watt), three different numbers N, and data rate $b = 10$ (Mbits/sec).

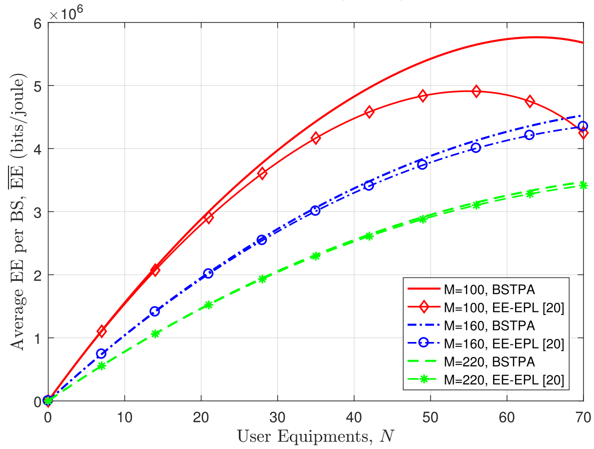
the EE gain of the BSTPA method outperforms the EE-EPL algorithm proposed in [20].

Figure 8 compares the average EE per BS versus different data rate requirements with three different numbers of BS antennas M and 10 active UEs N. The numerical results of EE-EPL algorithm are obtained based on the iterative power control proposed in Algorithm 1 in [20], which computes the total transmit power to satisfy the minimum achievable data rate requirements of all active UEs. One can see that only a specific minimum data rate can be supported for any number of antenna configurations since maximum BS transmit power constraint is considered in the simulations. We can see that the minimum achievable rate for BSTPA is higher than EE-EPL scheme. Moreover, lower per-antenna circuit power provides favourably better EE gain since it leads to lower circuit power and total power consumption. For example, in the case of 100 BS antennas (figure 8-(b)), the proposed BSTPA method achieves more than 11% better EE gain compared to EE-EPL algorithm and 6 (Mbits/sec) higher minimum achievable rate. However, for both per-antenna circuit powers, the $\overline{\text{EE}}$ increases to a certain maximum point. But beyond this point, the EE curves show a substantial decrease with further increment in data rate, since the increase in sum data rate is dominated by the average BS transmitted and circuit power consumption. In figure 8-(b), even though more significant antenna numbers provide better BS transmit power reduction, the increment in BS circuit power consumption is dominant to BS transmit power reduction and achieve less EE level for both BSTPA and EE-EPL schemes.

Figures 9 and 10 illustrate $\overline{\text{EE}}$ under different number of antennas and users. For both figures, the average EE grows by the increment in the number of UEs since (i) more parallel stream for data rate can be multiplexed; (ii) the increase in sum-rate predominates the additional overall power consumption. For instance, in figure 9-(b), the proposed BSTPA method can reach more than 17% better EE gain compared to EE-EPL algorithm and five fewer antennas in the case of 20 UEs with the same achievable data rate requirement.

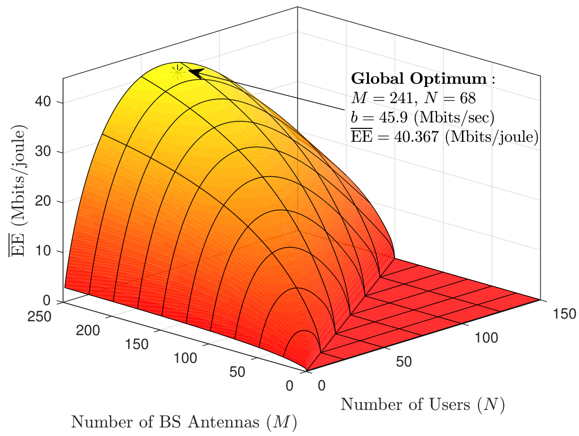


(a) $P_{active} = 32$ (mWatt)

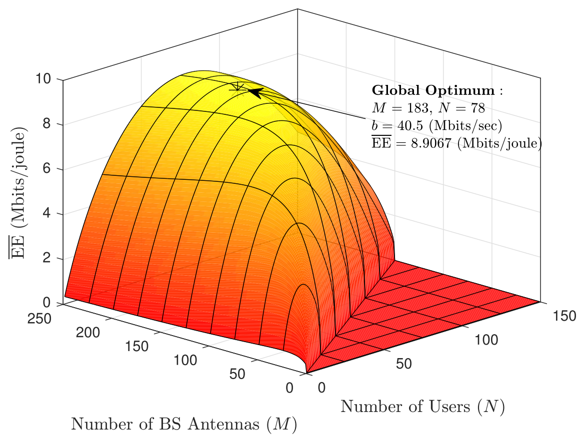


(b) $P_{active} = 1$ (Watt)

FIGURE 10. Average EE comparison of proposed method and conventional scheme versus different numbers *N* for per-antenna circuit power $P_{act} = 32$ (mWatt) and $P_{act} = 1$ (Watt), three different numbers *M*, and data rate $b = 10$ (Mbits/sec).



(a) $P_{active} = 32$ (mWatt)



(b) $P_{active} = 1$ (Watt)

FIGURE 11. Average EE per BS with different combination of *M* and *N* for per-antenna circuit power $P_{act} = 32$ (mWatt) and $P_{act} = 1$ (Watt). The global optimum is marked with star.

Also, BSTPA obtains around 32% better EE gain and additional nine UEs to serve compared with EE-EPL scheme in the case of 100 BS antennas in figure 10-(a). However, $\overline{\text{EE}}$ reduces at some points in the figures because BS circuit power consumption grows faster than sum data rate for a further users increment. From this point, circuit power addition is predominant to P_{TX} reduction for a further increment of M. These figures are similar to figure 8 for large P_{active} value where smaller BS transmit power is achieved due to larger M value. Still, lower $\overline{\text{EE}}$ is realized as circuit power consumption dominates to BS transmit power in both BSTPA and EE-EPL schemes. Finally, the proposed BSTPA method always exceeds the EE-EPL algorithm, and the EE gap for a wide range of M and N values is significant, notably with smaller P_{active}.

In general, there are optimal values of system design parameters that can be optimized for maximizing the average EE per BS globally. Also, figures 8-(b), 9-(b), and 10-(b) show that transmit and circuit power need to be traded off, and the EE should be optimized for the stated data rate requirement, BS antenna numbers, and the total number of UEs.

C. EE OPTIMIZATION RESULT

Figure 11 presents the three-dimension EE surfaces for different values of M and N (note that $M \geq N+1$ for ZF processing scheme). The figure indicates that there is an optimum EE point globally at both P_{active} cases marked in the sub-figures with a star. An exhaustive search is applied (defined as the third step of Algorithm 1) to compute optimal data rate b^* that maximizes EE at each pair of (M, N). It can be observed that the surface is concave, and the results seem to change in the circuit power consumption considerably. The achieved peak EE in the case $P_{active} = 32$ (mWatt) is approximately 4.5 times higher compared to the peak EE gain with a $P_{active} = 1$ (Watt) and 13.3% optimal data rate improvement but more BS antenna numbers. This is due to the lower circuit power consumption, which indicates the significance of the transmit-circuit power trade-off in the EE maximization concept.

Overall, the findings indicate while a more significant number of BS antennas provide better BS transmit power reduction, the EE improvement is somehow small and determined with the value of design parameters that the proposed BSTPA method considered. The EE gap between various antennas deployments is substantially reduced, as shown in Section VI-A, because the BS power consumption is based more on the total user and antenna numbers when the other parameters such as data rate are constant. Therefore, to better model EE improvement, a more comprehensive set of design parameters are also needed. This paper has proposed the BS antennas number, the total number of UEs, and data rate requirement in modeling system-level power consumption minimization and EE maximization.

VII. CONCLUSION

Massive MIMO systems present the possibility to improve EE by energy consumption reduction. Therefore, this paper investigated and optimized the BS power transmission and EE for the downlink of multi-cell massive MIMO systems. Contrast to most previous power transmission models, a simple analytical closed-form approximation of the average BS transmit power was derived (termed as BSTPA method) with ZF beamforming and perfect CSI. The proposed method adaptively adjusts the BS transmit power according to channel condition and user QoS, including data rate requirement and maximum allowable outage probability. Then, the impact of different system design parameters and QoS constraints on the BS power consumption and EE were analyzed, potentially yielding different information. Lastly, a corresponding iterative optimization algorithm was proposed to maximize the average EE per BS and obtain the optimal design parameters. The proposed algorithm aims to obtain the global optimal EE value along with the optimum amount of data rate, the number of BS antennas, and the number of UEs.

The findings show that despite the BS transmit power can be saved due to large antenna array gain, but the problem of increasing the number of BS antennas becomes more challenging especially with different per-antennas circuit power consumption. For a wide range of design parameters, simulation results indicate that the proposed BSTPA method resulted in a significantly higher EE gain than the energy-efficient equal power loading (EE-EPL) algorithm, especially if per-antenna circuit power consumption is significantly small. Finally, the optimization results show that the case with smaller per-antenna circuit power can achieve about 4.5 times better EE gain than the case with larger per-antenna circuit power. Also, the results indicate a 13.3% optimum data rate improvement but with a larger antennas number and slightly fewer UEs. This points out that massive MIMO systems can be developed using low-power consumption BS equipment as an alternative to conventional high-power to attain relatively higher EE levels. Therefore, the results indicate that achieving higher EE levels needs a transmit-circuit power consumption trade-off.

The proposed BSTPA method can be extended to take into account changes in system design parameters (e.g., non-uniformly BS and UE distribution, different large scale path-loss models, and imperfect CSI) for future work. Also, the impact of various parameters on the overall system performance can be investigated. It is also of interest to adopt the proposed method to varying traffic loads by idling active BS antennas that are not required to deliver the requested UEs' data rate with minimal power consumption.

APPENDIX
PROOF OF LEMMA 1

For given values of N and b, the $\overline{\mathrm{EE}}$ can be reformulated as a function of M which is expressed as

$$\overline{\mathrm{EE}}(M) = \frac{a_1}{\frac{a_2}{M-a_3} + a_4 M + a_5} \tag{21}$$

where

$$\begin{aligned}
a_1 &= \left(\frac{T - NT_{ul} - T_{dl}}{T}\right) N\, b,\\
a_2 &= \rho_{\mathrm{PA}} \left(\frac{T - NT_{ul} - T_{dl}}{T}\right) N\sigma^2 A_0\, \overline{\mathrm{S}},\\
a_3 &= N + \bar{\mathrm{I}}\, A_0\, \overline{\mathrm{S}},\\
a_4 &= P_{active} + \frac{2NT_{ul}B + 3BN^2 + BN}{T\rho_{\mathrm{C}}},\\
a_5 &= \frac{BN^3}{3T\rho_{\mathrm{C}}},\\
A_0 &= \frac{2^{\left(\frac{b}{B}\right)} - 1}{-\ln(1-\eta_{out})},\\
\overline{\mathrm{S}} &= \frac{D^{\alpha+2} - d_{min}^{\alpha+2}}{\bar{K}\left(1+\frac{\alpha}{2}\right)\left(D^2 - d_{min}^2\right)}.
\end{aligned}$$

All coefficients a_1-a_5, A_0, and $\overline{\mathrm{S}}$ are positive and constant. Without loss of generality, the derivative of $\overline{\mathrm{EE}}(M)$ is first calculated as $\frac{\partial \overline{\mathrm{EE}}(M)}{\partial M}$ to maximize the average EE per BS. The details of this derivative is omitted for simplicity since it is too complex. Thus, the focus is on solving $\frac{\partial \overline{\mathrm{EE}}(M)}{\partial M} = 0$ where, the optimal M is a root to quadratic polynomial function

$$(a_1 a_2)M^2 - (2a_1 a_3 a_4)M + (a_1 a_4 a_3^2 - a_1 a_2) = 0. \tag{22}$$

Since $a_1 a_2 \neq 0$, equation (22) has two solution as

$$M^*_{[1]} = -\frac{\sqrt{a_2 a_4} - a_3 a_4}{a_4}, \tag{23}$$

$$M^*_{[2]} = \frac{\sqrt{a_2 a_4} + a_3 a_4}{a_4}. \tag{24}$$

Nevertheless, note that the value of M must be always positive integer. Since σ^2 and $\bar{\mathrm{I}}$ are relatively small, and $a_4 \gg 1$, it is obvious that $M^*_{[1]}$ is always negative. Therefore, $\lfloor M^*_{[2]} \rceil$ is the optimal solution to $\frac{\partial \overline{\mathrm{EE}}(M)}{\partial M} = 0$.

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