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Energy-Efficient Power Allocation and Joint User Association in Multiuser-Downlink Massive MIMO System

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ABSTRACT Singular value decomposition is highly essential to achieve a higher performance in signal processing using massive multiple-input multiple-output (MIMO) systems. This paper aims to provide a solution to control power allocation problem identified as an essential metric in a massive MIMO system that maximizes energy efficiency (EE). The network performance was evaluated by measuring circuit power consumption to maximize EE. The computational efficiency to maximize EE power allocation is very important to fifth generation networks (5G). The study aims to maximize the non-convex EE in a downlink (DL) massive MIMO system using a proposed energy-efficient low-complexity algorithm (EELCA) that guarantees optimal power allocation solution based on Newton's methods and joint user's association based on the Lagrange's decomposition method. An optimal power allocation solution in closed form to decrease the complexity of the power subject to both the maximum power and minimum data rate constrained systems was derived. Then, the unconstrained EE power allocation to solve the unconstrained optimal power was used to select the optimal power allocation by computing a root of the first derivative of the EE based on differentiating the instantaneous power allocation to maximize EE was formulated. Simulation results showed that the proposed EELCA with a total transmitted power allocation provided maximum EE for a large number of antennas at the base station (BS), Generally, non-linear schemes outperformed linear schemes. Finally, the large cost of circuit power consumption increased at the BS due to the large loss of radio frequency (RF) chains at every antenna when the signals were transmitted to all users. The maximum EE $= 5.9$ Mbits/joule when the number of distributed users, $K = 33$, with $(p_c, M) = (1000\text{mW}, 200)$. The proposed low complexity algorithm provides the better result EE based on a training channel for a number of distributed users.

INDEX TERMS Massive MIMO, 5G, energy efficiency, EELCA, base station, radio frequency.

I. INTRODUCTION

Massive multiple-input multiple-output systems (MIMO) that provides a high degree of freedom for radio channels have emerged to meet the increasing demand for high data rate transmission in fifth generation (5G) cellular networks. A massive MIMO in a single-cell massive MIMO system provides a flexible platform to enhance network capacity and reliability and maximize energy efficiency (EE) [1]. Ensuring the availability of 5G communication technology is important to multimedia service providers, as the quality of video traffic, digital video broadcasting, and online video stream is important to facilitate large-scale distribution and demand for high rate data transmission, which requires a reduction

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in energy consumption. Massive MIMO wireless communication systems need to overcome challenges like channel variation and inter user interference due to its many large transmission antennas to ensure robustness. The data rate for connected 5G wireless communication system needs to grow 1000 times to an estimated 50 billion by 2020 [2]. Massive MIMO systems support a large antenna array at the transmitter side, which increases the system capacity with a relatively limited number of active users (UEs). The base station (BS) uses a time division duplex (TDD) to estimate the channel. However, massive MIMO systems face user association and power allocation constraints to achieve better loading. Massive MIMO provides many excess degrees of freedom, which can be used to produce asymptotically orthogonal channels and delivers interference-free signals for every UE. Moreover, it can improve the network energy efficiency because more UEs can be worked in parallel with less interference.

Moreover, when the number of antenna arrays increase significantly, the channel estimation for transmitting signals from BS to UEs becomes very large. Channel estimation offers a significant improvement in data rate for it allows several parallel data streams to be sent down an independent parallel channel. To obtain good EE numbers, massive MIMO systems need to focus on power allocation related to channel estimation. BS power allocation allows more users to get channel state information (CSI) based on the level of channel gain. Maximizing EE depends on adaptively transmitting power allocation with perfect channel estimations [3], [4]. Energy consumption has become a critical concern for any communication platform since it is used for hardware, power amplifier, and UE to achieve better EE. Massive MIMO systems require additional hardware circuitries, which consume more energy compared with single-antenna systems [4], [5].

The EE power allocation in a massive MIMO system has been studied based on the analysis of the number of transmission antennas and amount of transmitted power in [6]. Total power consumption consists of circuit power consumption and transmitted power allocation. The EE in [7] analyzed not only transmitted power but also fundamental power. The optimal transmitted power should be measured to minimize power usage by users of cellular networks by decreasing circuit power consumption through optimizing the use of transmission antennas to maximize EE. The energy consumption for a user inside a wireless network represents 0.2% of all carbon emissions [8]. In massive MIMOs, a large number of antenna arrays at BSs result in more power consumption, due to a high number of radio frequency (RFs) chains. RF chains are crucial to optimize power consumption by a large number of transmission antennas. In the case of transmitted signal from BSs to UEs, RF chains consume more power because of processing behaviors in the digital-to-analog converter (DAC), power amplifier, multiplexer, and filter. The research analyzes the problem related to EE maximization by looking into the constraints in transmitted power allocation, which is more practical. To maximize EE involves designing a large antenna for transmitting signals, which requires accounting for transmitted power. Meanwhile, more transmission antennas in the BS will serve the distributed UEs in the same cells with the RF chains working to reduce circuit power consumption [5]. The problem can be alleviated in a single cell due to the small distance between the BS and UEs.

This paper aims to increase energy efficiency in power transmission involving multiple antennas at the UEs taking into account constraints related to power allocation whilst guaranteeing the minimum required rate of each user. The study proposed an energy-efficient low-complexity algorithm to obtain optimal power transmission allocation through iteration for all users at low power. In wireless communication networks, EE optimization is required for correct circuit power consumption. The proposed new 5G network in this paper is designed to optimize power consumption and maximize EE in terms of data rate. When the number of antennas and users are large, hardware cost and power consumption will increase substantially, hence, extensive studies on massive MIMO with inexpensive hardware components are needed.

This study makes the following contributions.

- A novel and simple power allocation using constrained explicit power allocation, minimal data rate constraints, and joint user association with constrained power allocation to maximize EE.
- Formulation of an energy-efficient power allocation that maximizes the DL EE with explicit power allocation and minimum rate constrained with perfect CSI. This is according to the level of the channel, which treats the interfering power from the other UEs as given.
- Maximizing constraint of non-convex EE in a DL massive MIMO system using a proposed EELCA that guarantees optimal power allocation solution. This is based on Newton's methods and joint user's association based on the Lagrange's decomposition methods. This takes into account an optimization problem with constrained transmitted power allocation, and joint user association whilst guaranteeing high minimal rate constraints.
- Unconstrained EE power allocation to solve for unconstrained optimal power by computing the root of the first derivative of the EE based on selecting the optimal power allocation to differentiate for instantaneous power allocation for each channel to improve and maximize the EE.

II. RELATED WORKS

The energy efficiency is critical when taking into the account circuit power consumption. The optimal transmission power and joint user association are important aspects of improving EE in massive MIMO systems. Power allocations in the MIMO systems have been widely investigated in the literature. The authors in [9] addressed the problem of energy-efficient power allocation using a specific low-complexity algorithm to maximize EE. They maximized EE by evaluating both power constraint and data rate constraint. The authors in [10] proposed a power allocation algorithm to optimize EE in a massive MIMO system by using linear precoding maximum ratio transmission according to convex optimization theory. The author in [11] achieved nearly optimal EE in a massive MIMO system using a joint antenna selection, power optimization algorithm, and user selection that eases calculations. The power consumption model has been studied in [6]. It analyzed a circuit's power consumption in downlink (DL) massive MIMO systems, the number of transmission antenna arrays and how to maximize EE. The authors in [12] proposed a single low-noise amplifier in the uplink to reduce cost and power consumption to maximize EE. They proposed an efficient algorithm and the bisection–gradient-assisted interior point as a practical solution to solve an EE maximization problem. The authors in [13] proposed the use of circuit power and channel conditions in a closed form to maximize EE. The authors in [14] analyzed quality of service issues to maximize EE in a single-cell massive MIMO system. They analyzed total power transmission from users and data rate constraints based on a constrained nonconvex optimization problem to maximize EE. Reference [15] proposed a low-complexity EE optimization solution based on maximum transmitted power and minimum data rate constraint by using fractional programming, learning, and game theory.

Transmitted power allocation, consumption circuit power, and EE were used to evaluate network performance in [16]. The authors in [16] proposed power allocation in a DL single-cell massive MIMO system by increasing the number of transmitting antenna arrays and number of users to increase network capacity and reduce power consumption. Reduced low-complexity energy and good network performance in single-cell massive MIMO systems were achieved by using a joint several-antenna selection and power optimization algorithm in [11]. The author in [17] proposed to improve EE while achieving high spectral efficiency in massive MIMO systems by using a power amplifier and a power allocation algorithm based on zero-forcing. From the existing works, the study focuses on an EE optimization problem for a DL single-cell massive MIMO system with perfect CSI. The perfect CSI applies to the k th user and it can be exploited according to the properties of high- dimensional channel vector.

EE maximization has been studied in many works, for example, [4] proposed low complexity power allocation for maximizing EE based on exact closed-form expressions of the system sum-rate with channel aging. Reference [4] seek to maximize EE in massive MIMO using enabled AF multi-way relay networks (MWRN). This was coupled with non-pairwise zero-forcing transmission to transmit power and with minimum quality-of-service constraints. EE can be improved using an optimal number of transmission antennas. The cost of power consumption can be reduced by optimizing the number of radio-frequency chains that make up the circui's power consumption per antenna. Turning off the radio frequency chains transmitted by sedentary antennas can save energy [18], [19]. Reference [20] proposed using a single antenna per user for point-to-point radio cognition. This improves EE in term of power allocation with average constraints. EE optimization has been studied in terms of the number of antennas and power allocation in a single cell MU-MIMO system under limited feedback at the transmitter [19]. The author in [6] proposed using a new realistic power consumption model in single-cell massive MIMO systems. The circuit power consumption can be similar to or constant dominating the transmit power by proposing that every user is equipped with only one antenna. The EE has a concave function when the number of transmitted antennas increases to infinity and when the transmitted power is large enough. Reference [21] studied the EE of a downlink multi-user single-cell MIMO under perfect CSI with zero-forcing precoding by utilizing the Lagrangian dual method to obtain the optimal number of antennas selection and power allocation. Reference [22] stated that under perfect CSI EE can be optimized for optimum transmission antenna selection and transmitted power for advanced binary search (ABS). These proposed algorithms guarantee a global optimum.

Other works focused on the user association and/or power allocation [23]–[27]. To achieve the desired power consumption depended on joint user association and power allocation with better loads and transmitted power constraints [23].

An explicit expression of the controlling power allocation in single-cell massive MIMO systems has not been explored. The author in [28] investigated power allocation optimization in downlink by calculating the total rate for all users based on an actual power consumption model. Reference [28] also investigated the different levels between base stations and users using a pseudo-convex form controlled by a Lagrange multiplier besides communication between the base station and active users. Reference [29] proposed a solution to a non-convex optimization problem by using constraints that include the outage probability limit. This involved a non-orthogonal multiple access (NOMA) single-cell bit per joule downlink to improve EE. A proposed iterative algorithm with energy-efficient user scheduling and power allocation can improve EE. This involves a large number of multiplexed users sharing the same sub-channel using the maximum power whilst minimizing data rates. Reference [13] used an iterative numerical algorithm to maximize EE in a point-to-point MIMO system. Reference [13] also applied singular value decomposition as optimal solution in a closed-form to optimize EE in terms of occupied active transmission antennas, circuit power, and noise power.

The remainder part of this paper is organized as follows: Section II presents a review of related research. System model and mathematical formulation are presented in Section III. In Section IV, simulation results and performance of the proposed scheme are discussed. Finally, Section V presents the concluding remarks of the proposed approach with directions for future work.

III. SYSTEM MODEL

A. RECEIVED SIGNAL MODEL

This paper discussed a DL massive multiple-user MIMO system in a single cell. The BS is equipped with a large number of antennas M serving $M \gg K$ active users that are scheduled at the same time-frequency resource. We focus on the transmit power allocation and user association in the DL. The complex channel gain transmitted signal between BSs and the UEs is defined by $z_k = [z_1, z_2, \ldots.., z_K]$; $Z \in \mathbb{C}^{M\times K}$ is the channel gain matrix with z_k. The channel model involved a fast fading (small-scale fading) and dissimilar antenna correlation such as path loss (large-scale fading). The fading coefficient z_k can be expressed as:

$$z_k = \sqrt{\delta}\, \boldsymbol{h_k} \tag{1}$$

where $\boldsymbol{h_k}$ is the fast fading coefficient transmitted from BSs $m\ th$ antenna to $k\ th$ UEs, the vector channel matrix from BSs to all UEs $\hbar_k = [\boldsymbol{h}_1, \boldsymbol{h}_2, \ldots, \boldsymbol{h}_M]^T$, and δ is the large-scale fading. The channel gain matrix is

$$Z = \sqrt{D}\, H \tag{2}$$

where $D = \text{diag}(\delta_1, \delta_2, \ldots., \delta_M)$, and $H \in \mathbb{C}^{M\times K}$ is the vector channel matrix to represent small-scale fading between the transmit antenna and users $H = h_k$. The complex CSI is assumed perfect at the transmitter and receivers. It was impractical to use each M to provide high data rates, which can be acquired as independent and identically distributed (i.i.d.) complex Gaussian random variables with zero mean and unit variance. The growth of transmitted signal from active BS antennas due to sufficiently large transmission M to K UEs, and the DL received signal $\chi \in \mathbb{C}^{M\times 1}$ for all UEs can be represented as

$$\chi = \sqrt{\mathcal{P}_k D}\, H \mathcal{Y} + n \tag{3}$$

where $\mathcal{Y} \in \mathbb{C}^{M\times 1}$ is the vector Gaussian transmitted signal in the DL, $\mathcal{P}_k = [\mathcal{P}_{1,}, \mathcal{P}_2, \ldots., \mathcal{P}_K]$ is the transmitted power allocation to every UEs, and $n \sim \mathcal{CN}(0, \sigma^2)$ is the independent Gaussian noise. The transmitted information symbol from BS to all K UEs is $\nu_k = [\nu_1, \nu_2, \ldots.., \nu_K]^T$, and the information symbol convinces $\mathbb{E}[\nu_k\, \nu_k^H] = I$. The channel model can be denoted as

$$\chi = \sqrt{\mathcal{P}_k D}\, H \nu_k + n \tag{4}$$

The transmitted power allocation from BS to every UE $\mathcal{P}_k$ allowed more users to perform CSI according to the level of channel fading gain $\hbar_k$ [30]–[32]. From the effective channel, the maximum signal-to-noise ratio (SNR) by transmitting beam forming with CSI applied in the transmitter can be expressed as

$$\Gamma_k = \frac{\mathcal{P}_k\, |\hbar_k|^2}{\sigma^2} \delta_k \tag{5}$$

where σ^2 is the additive noise power. The small-scale fading varied rapidly, which requires the computation for the reality of channel estimation, while in large-scale fading, δ_k variations were slow, and channel estimation was easy to obtain. The correlation channel for different users in dimensions, was better than i.i.d., denotes $\mathcal{P}_k$ as the transmission SNR of user k with perfect CSI, where the CSI was performed by transmitting signal from BS to users with precoding $[1, 2, \ldots..K]$. Perfect CSI at the transmitter was assumed. It was impractical to use all the antennas to achieve minimum rate constraint due to costly RF chains for every active antenna [21]. The complexity overhead scheme provides the nearly optimal rate performance when using perfect CSI. Besides, the perfect CSI is assumed to be available at BS to generate the correlation channel and high channel gain for different users as high - dimensional channel vector. To offer data rate transmission to users with a transmission target, the target data rate of the transmitting antenna [5] can be written as

$$R_{j,k} = \log_2\left(1 + \Gamma_{j,k}\right) = \log_2\left(1 + \frac{\mathcal{P}_{j,k}\, \left|\hbar_{j,k}\right|^2}{\sigma^2} \delta_{j,k}\right) \tag{6}$$

B. ENERGY-EFFICIENT FORMULATION IN MASSIVE MIMO SYSTEM

Energy efficiency is defined as the ratio of data rate to consumed transmitted power allocation at the increase of a large number of antenna arrays at the BS. This increasing in the number of BS antennas requires more RF chains and lead to a higher circuit power consumption cost, thus degrades system performance in terms of maximum EE. Where, a higher number of RF chains, in both BS and UE consume more power due to the processing activities in the DAC, power amplifier, multiplexer, and filter that created nonlinear distortion at a transmitter. Thus, reducing the power consumption of a BS is necessity to achieve lower RF power consumption and reduce the operational costs. The proposed EELCA maximizes EE depends on optimizing the objective function over all transmitted power allocation. Existing power allocation was developed using a perfect CSI. To control the transmission rate, the overall transmitted power consumption should be decreased. Power control is essential to improve system performance by optimizing high achievable data rate and EE. To minimize the UE's, transmitted power, the total power consumption model for DL is adopted.

$$p_t = \sum\nolimits_k \frac{\beta \mathcal{P}_k}{\Omega} + p_c \tag{7}$$

where p_t is the total power consumption, which is the calculation of the transmitted power $\mathcal{P}_k$; Ω is the power amplifier efficiency; β is the bandwidth; and p_c is the supposed real circuit power consumption incurred by signal processing and circuit power through the digital-to-analog converter. From [5], [33]–[36], the circuit power consumption can be written as

$$p_c = \sum\nolimits_1^M p_a + \sum\nolimits_{k=1}^K p_u \tag{8}$$

where p_a represents the circuit power consumption of every RF chain connected to several transmission antenna selections, and p_u represents the RF chain at $k\ th$ active UE.

The energy-efficient power allocation problem can be written as

$$EE_{j,k}=\frac{\beta\log_2\left(1+\frac{\mathcal{P}_{j,k}\left|\hbar_{j,k}\right|^2}{\sigma^2}\delta_{j,k}\right)}{\sum_k\frac{\beta\mathcal{P}_{j,k}}{\Omega}+p_c}\quad(9)$$

From (9), the numerator $\beta\log_2\left(1+\frac{\mathcal{P}_{j,k}\left|\hbar_{j,k}\right|^2}{\sigma^2}\delta_{j,k}\right)$ is a concave function and the denominator in terms of power $\mathcal{P}_{j,k}$ in (9) is not a concave function, which requires a conversion into a convex optimization problem. In this work, energy-efficient power allocations maximize the DL EE under an explicit power allocation and minimum rate constrained with perfect channel estimation is provided. The concept of data rate for user association, represented by $R=\sum_j\sum_k\mathcal{X}_{j,k}R_{j,k}$, the user association $\mathcal{X}_{j,k}\in\{0,1\}$denotes whether the UE is associated with BS to UE. If the UE k is connected with BS the $\mathcal{X}_{j,k}=1$, otherwise $\mathcal{X}_{j,k}=0$.

Consequently, the objective function in (9), which is a quasi-concave function, confirmed that there exists a unique global optimal transmit power allocation.

C. CONSTRAINED EE FOR POWER ALLOCATION AND JOINT USER ASSOCIATION

Based on optimization theory [37], energy-efficiency (9) is formulated in the key optimization problem under the overall transmitted power and minimal data rate constraints. This paper assumed that users consumed a different rate; the hardware consists of a large number of RF chains for every user for signal processing. Here, the optimization problem can be described as.

$$\begin{aligned}
&s.t.\ \log_2\left(1+\frac{\mathcal{P}_{j,k}\left|\hbar_{j,k}\right|^2}{\sigma^2}\delta_{j,k}\right)\geq \text{Ɍ}_{\min}\\
&C_1:\quad R^{EE}_{j,k}=\sum_{k\in K}\sum_{j=1}^{M}\log_2\left(1+\frac{\mathcal{P}_{j,k}\left|\hbar_{j,k}\right|^2}{\sigma^2}\right)\\
&\qquad\geq \text{Ɍ}_{\min}\\
&C_2:\quad \frac{\beta\mathcal{P}_{j,k}}{\Omega}+p_c\leq p_t\quad \forall k=1,2,\ldots\ldots,K\\
&C_3:\quad \min_{\mathcal{P}_k\geq 0}\sum_{j\in M}\mathcal{P}_{j,k}\geq 0\\
&C_4:\quad \mathcal{P}_{j,k}\left|\hbar_{j,k}\right|^2\leq I_{th}\\
&C_5:\quad \sum_{j\in M}\mathcal{X}_{j,k}\leq k_j,\quad \forall j\\
&C_6:\quad \sum_{j\in M}k_j=K\\
&C_7:\quad \sum_{j\in M}\mathcal{X}_{j,k}=1,\quad \mathcal{X}_{j,k}\in\{0,1\},\ \forall j,k
\end{aligned}\quad(10)$$

where, I_{th} is the maximum allowable interference at k, k_j is the load of the antennas $j=[1,\ldots\ldots,M]$ and Ɍ$_{\min}$ represents the minimum certain data rate requirement per user. Energy-efficient low-complexity algorithm (EELCA) is used based on different Ɍ$_{\min}$ and constraint p_t to reduce the number of activated antennas for strict Ɍ$_{\min}$. To achieve the optimization problem in (9), C_1 guarantees the minimal rate constraint for each user k th channel, which requires guaranteeing the delivery of the minimal rate constraint as obtained by the globally optimal transmit power $\mathcal{P}_k^*$ allocation, which achieves optimal EE based on different Ɍ$_{\min}$ and constraint p_t according to (C_1) and (C_3).

The instantaneous CSI becomes much higher because both the large-scale channel δ_k and the small-scale channel coefficient need to obtain the optimal power allocation. In (10), the constraint C_4 indicates that the total interference power should be smaller than the allowed interference I_{th}. C_2 represents the total transmitted constraint at BS, in a case where $\mathcal{P}_k>p_t$ the channel $\left|\hbar_{j,k}\right|^2<\frac{\sigma^2}{\delta_{j,k}p_t}\left(2^{\frac{\text{Ɍ}_{\min}}{\beta}}-1\right)$; this means that the channel gain is less than the required allowable interference. According to the user association constraint in C_5, it is assumed that every user can only access to one base station. The user rate $R_{j,k}$ can be written as the products between the binary association and data rate $\sum_{j=1}^{M}\mathcal{X}_{j,k}R_{j,k}$. From (10) in C_5 and C_6 the association constraints reflect that each user is associated with multiple antennas in BS. This means that, every user can only associate with only one base station. Meanwhile, the minimal data rate constraints are maximized by optimizing power allocation among UEs, the Ɍ$_{\min}$ and EE are impacted with greater number of UEs. When $\mathcal{P}_k\leq p_t$, more transmit data rates are provided to users with high channel gain, which improves the EE [4], [21], [38]. It is difficult to reduce the cost of hardware and maximize the EE. To solve this original optimization problem, a two-step solution, which consists of both power allocation sub-problem and user association sub-problem is proposed.

D. CONSTRAINED EE FOR POWER ALLOCATION SCHEME

In this subsection, the optimization problem proved that the EE is still quasi-concave when the total transmit power is used for the circuit power consumption, $\frac{\beta\mathcal{P}_k}{\Omega}+p_c$. The EE is a positive function through the differentiable function for every $\mathcal{P}_k\geq 0$, corresponding to the nonconvexity of the problem in (9), which can be converted into a convex optimization problem by computing Newton's method of the EE maximization problem based on the instantaneous power allocation $\mathcal{P}_k$ and minimal rate constraint. To solve problem (9), based on the constraint in (10), the study used the Newton method to solve the optimization problem as

$$max_{\mathcal{P}_k\epsilon\mathbb{Y}}\,\mathfrak{h}\left(\mathcal{P}_k\right)=\frac{f_1\left(\mathcal{P}_k\right)}{f_2\left(\mathcal{P}_k\right)}\quad(11)$$

where $\mathbb{Y}\dot{\subseteq}\Phi$, $f_1,f_2:\mathbb{T}\rightarrow\Phi$, $f_1\left(\mathcal{P}_k\right)\geq 0$, and $f_2\left(\mathcal{P}_k\right)\geq 0$. The fractional program in (11) resemble concave-convex conditions, where $f_1\left(\mathcal{P}_k\right)$ is concave and $f_2\left(\mathcal{P}_k\right)$ is convex on $\mathbb{T}$ [10]; the maximum EE constraint can be formulated as

$$s.t\quad \frac{f_1\left(\mathcal{P}_k\right)}{f_2\left(\mathcal{P}_k\right)}-\mathfrak{h}\geq 0\quad(12)$$

(12) can be rewritten to obtain the optimal solution to the optimization problem in terms of the fractional program, as

$$\xi\left(\mathfrak{h}\right)=max_{\mathcal{P}_k} f_1\left(\mathcal{P}_k\right)-\mathfrak{h}f_2\left(\mathcal{P}_k\right)=0 \tag{13}$$

where f_1 and f_2 represent the concave, $\mathfrak{h}f_2\left(\mathcal{P}_k\right)$represents the fixed value with the concave, and $\mathfrak{h}$ is the optimum value of the objective function in (11). The optimal solution in (13) equivalent to the practical value of $\mathfrak{h}$, which is given by $h^*=f_1\left(p_k\right)/f_2\left(\mathcal{P}_k\right)$.

Following (9), the problem for the joint optimal transmitted power allocation can be written as

$$\mathcal{P}_k^*=arg\ \max_{\mathcal{P}_k}\frac{\beta\log_2\left(1+\frac{\mathcal{P}_k\left|\hbar_{j,k}\right|^2}{\sigma^2}\delta_k\right)}{\sum_k\frac{\beta\mathcal{P}_k}{\Omega}+p_c} \tag{14}$$

From (14), the numerator of $EE(\mathcal{P}_k^*)$ is concave, and the denominator is convex. The study used EELCA to obtain the optimal transmitted power allocation by updating the iteration transmitted power for all users to find the root of $\xi\left(\mathfrak{h}_n\right)$, which can be evaluated using Newton's method to solve the root of $\xi\left(\mathfrak{h}_n\right)$. There exists a unique globally optimal $\mathcal{P}_k^*$ allocation, achieving the optimal EE given by

$$\mathfrak{h}_{n+1}=\mathfrak{h}_n-\frac{\xi\left(\mathfrak{h}_n\right)}{\xi'\left(\mathfrak{h}_n\right)}=\frac{f_1\left(\mathcal{P}_k^*\right)}{f_2\left(\mathcal{P}_k^*\right)} \tag{15}$$

where $\mathcal{P}_k^*$ represents the optimal value for $\xi\left(\mathfrak{h}_n\right)$; the function can also be represented as $f_1\left(\mathcal{P}_k^*\right)=\beta\log_2\left(1+\frac{\mathcal{P}_k\left|\hbar_{j,k}\right|^2}{\sigma^2}\delta_k\right)$ and as $f_2\left(\mathcal{P}_k^*\right)=\sum_k\frac{\beta\mathcal{P}_k}{\Omega}+p_c$. The goal was to obtain EELCA for an optimal transmitted power allocation using the constrained transmitted power in (10). Moreover, the optimal transmitted power allocation $\mathcal{P}_k^*$ is optimal for $\xi\left(\mathfrak{h}_n\right)$and can be obtained using (16) when the value of p_c is small; the optimal power allocation for users increases, which does not affect the value of p_c.

$$\mathcal{P}_k^*=\left[\frac{\Omega}{\beta\mathfrak{h}_n ln2}-\frac{\sigma^2}{\delta_k\left|\hbar_{j,k}\right|^2}\right] \tag{16}$$

Here, $\mathfrak{h}_n$converges to ideal values of optimal transmitted power when the constrained conditions can be achieved according to (C_1–C_4). In (16), the optimal power allocation for EE is shown; when $0\leq\mathcal{P}_k\leq\mathcal{P}_k^*$, the energy efficiency strictly increases with respect to $\mathcal{P}_k>0$, and when $\mathcal{P}_k>\mathcal{P}_k^*$, the energy efficiency strictly decreases.

E. CONSTRAINED JOINT USER ASSOCIATION

In this subsection, the efficiency of EE depends on studying the power allocation and joint user association based on EELCA. Because of the difficulties with the non-convex optimization problem related to user association, the UE minimum rate requirement with maximum transmitted power constraint for each BS is applied. To allocate the user association with higher minimum-rate requirements, it is assumed that $\mathcal{X}_{j,k}=1$ is the maximum user rates that can be adopted by solving the UE association with BSs. From optimization theory in [37], the effect of the data rate $R_{j,k}$ of UEs is associated with a number of antennas, $j=1,\ldots.M$, which can be formulated as the user rate association with maximizing the log utility of user rate as $\max_{x,z}\sum_{k=1}^K\sum_{j=1}^M\mathcal{X}_{j,k}\log R_{j,k}$ [23]–[27]. Where $R_{j,k}=\ln s_{jk}$ is defined as the data rate.

With transmitted power problem $\mathcal{P}_k$, and based on the constraints in (10), the study introduces auxiliary variables $k_j=\sum_{k=1}^K\mathcal{X}_{j,k}$and weight coefficient $\mathcal{C}$ represents the performance of energy consumption is $0\leq\mathcal{C}\leq\sum_k\max_j\ln s_{j,k}/p_t$. The problem of joint user association as an optimization problem which maximizes the EE of the BSs under the transmitted power constraint of the BSs and the minimum rate constraint of the user equipment is formulated. Corresponding to the nonconvexity of the problem in (9), this can be converted into a convex optimization problem with the help of the Lagrangian dual problem

$$\begin{aligned}\mathcal{P}_{\boldsymbol{k}}:\quad &\max_{x,\mathcal{P},k}\sum\nolimits_{k\in K}\sum\nolimits_{j\in M}\mathcal{X}_{j,k}\ln s_{j,k}-\mathcal{C}p_t\\ &\text{s.t:}\ C_1-C_7\end{aligned} \tag{17}$$

The non-negative Lagrangian multiplayer associated with users can be written as

$$\begin{aligned}&\max_{x,\mathcal{P},k}\sum\nolimits_k\sum\nolimits_j\mathcal{X}_{j,k}\ln\left(\mathrm{Q}_{j,k}\right)-\sum\nolimits_j k_j\ln\left(k_j\right)\\ &\text{s.t:}\ C_5-C_7\end{aligned} \tag{18}$$

$$\begin{aligned}\mathcal{L}\left(\mathcal{X},k,\gamma,\mu\right)&=\sum\nolimits_k\sum\nolimits_j\mathcal{X}_{j,k}\left(\ln\mathrm{Q}_{j,k}\right)\\ &-\sum\nolimits_j\left(k_j lnk_j\right)+\sum\nolimits_j\gamma_j\left(k_j-\sum\nolimits_k\mathcal{X}_{j,k}\right)\\ &+\mu\sum\nolimits_j\left(k_j-\sum\nolimits_k\mathcal{X}_{j,k}\right)\end{aligned} \tag{19}$$

where $\mathrm{Q}_{j,k}=k_j s_{j,k}$, for a given set of Lagrangian multipliers γ,μ, we set $\boldsymbol{\gamma}=\gamma_j$ and represent the nonnegative Lagrangian multipliers. Corresponding Lagrangian dual function can be written as:

$$\mathfrak{g}\left(\boldsymbol{\gamma}\right)=\sum\nolimits_k\mathfrak{g}_k\left(\boldsymbol{\gamma}\right)+\mathfrak{g}_k\left(\boldsymbol{\gamma},\mu\right) \tag{20}$$

The first term in (20) can be written as

$$\begin{aligned}\mathfrak{g}_k\left(\boldsymbol{\gamma}\right)&=\max_x\sum\nolimits_k\left(\sum\nolimits_j\mathcal{X}_{j,k}\left(\ln\mathrm{Q}_{j,k}-\gamma_j\right)\right)\\ &\text{s.t}\ C_6,C_7\end{aligned} \tag{21}$$

While the second term in (20) can be written as

$$\begin{aligned}\mathfrak{g}_k\left(\boldsymbol{\gamma},\mu\right)&=\max_k\sum\nolimits_j k_j\left(\gamma_j+\mu-\ln k_j\right)\\ &k_j\leq\mathcal{X}_{j,k}\end{aligned} \tag{22}$$

The optimal solution for dual optimization problem can be written as

$$\min_{\boldsymbol{\gamma}}\sum\nolimits_k\mathfrak{g}_k\left(\boldsymbol{\gamma}\right)+\mathfrak{g}_k\left(\boldsymbol{\gamma},\mu\right) \tag{23}$$

The non-convex optimization problem $\mathcal{P}_k$ in (17), can be transformed into a convex optimization. The optimal solution of user association can be obtained by applying the KKT conditions to set the partial derivative $\partial \mathbb{g}_k(\boldsymbol{\gamma}) \big/ \partial k_j = 1$ when a user association $\mathcal{X}_{j,k} = 1$, as

$$j_k^{\blacksquare} = \arg\max_j \left(\ln \text{Q}_{j,k} - \gamma_j\right) \tag{24}$$

The proposed EELCA can guarantee the optimal data rate of UEs $R_{j,k}$ association with optimal a number of antennas of BSs $j = 1, \ldots, M$, if $j = j_k^{\blacksquare}$, $\mathcal{X}_{j,k} = 1$.

While if a user association $\mathcal{X}_{j,k} = 0$. To solve the problem, the optimal association rate for users can be calculated by using the KKT conditions to set the partial derivative $\partial \mathbb{g}_k(\boldsymbol{\gamma}) \big/ \partial k_j = 0$ and then have

$$k_j^{\blacksquare} = \min\left(\left(e^{\gamma_j + \mu - 1}\right), \mathcal{X}_{j,k}\right) \tag{25}$$

F. UNCONSTRAINED EE POWER ALLOCATION

Because of the nonconvexity of the problem in (9), the unconstrained problem can be solved by proposing the exact solution to obtain the unconstrained nonconvex optimization problem used to select the optimal power allocation for each jth channel to maximize the EE. This entails using $\gamma_k = \frac{\left\|\boldsymbol{h}_{j,k}\right\|^2}{\sigma^2}\delta_k$. The objective is to find an explicit expression of the optimal power that maximizes the EE based on EELCA. Also, the optimal solution to problem is obtained in (9) by computing for the root of the first derivative of the EE based on the differentiable instantaneous power allocation $\mathcal{P}_j \geq 0$ as

$$\frac{\partial EE}{\mathcal{P}_k} = \frac{\beta \gamma_k}{\log(2)\left(1 + \gamma_k \mathcal{P}_k\right) p_t} - \frac{\beta \sum_j^M \log_2\left(1 + \gamma_j \mathcal{P}_j\right)}{\log(2)\left(p_t\right)^2} \tag{26}$$

The analytical power for every user in (26) can be obtained by using the powers of the other users $\mathcal{P}_j$, $j \neq n$; for $j = 1, \ldots.M$, the EE is positive for $\mathcal{P}_j$ and mitigates the interdependence between users. The optimal power solution $\mathcal{P}_k^*$ for users can be achieved by equating this derivative in (28) to zero:

$$\frac{\gamma_k}{\left(1 + \gamma_k \mathcal{P}_k^*\right)} = \frac{\sum_j^M \log_2\left(1 + \gamma_j \mathcal{P}_j^*\right)}{\sum_j^M \frac{\beta \mathcal{P}_j^*}{\Omega} + p_c} \tag{27}$$

From the right end in (27), the numerator $\sum_j^M \log_2 \left(1 + \gamma_j p_j\right) \Big/ \sum_j^M \frac{\beta p_j^*}{\Omega} + p_c$, selecting a number of RF chains can be adjusted by turning off the radio frequency chains of inactive antennas to decrease the total power consumption. The selection of a number of RF chain transmits different data stream supplied by the baseband from the connected antenna. Moreover, the number of active RF chains is optimized for each user to maximize EE whilst guaranteeing the minimum data rate. From (27), the transmitted power increases with more distributed UEs and decreased with the number of RF chains.

However, this is still a nonconvex problem that is hard to solve. To solve (27) and obtain a preliminary expression of the optimal transmit power allocation $\mathcal{P}_k^*$ for UEs, the Lambert function is used for the non-negative real numbers d, t, and w as defined in [9], [13], [31], [39]–[42]:

$$\frac{d}{(1 + dw)} = \frac{\log(1 + dw) + a}{t + w} \tag{28}$$

By using some algebraic manipulations as

$$\begin{aligned}
&w + dt \\
&\quad = (1 + dw)\left(\log(1 + d(w) + b\right) \\
&\Longrightarrow dt - 1 = (1 + dw)\left(\log(1 + dw) + b - 1\right) \\
&\Longrightarrow (dt - 1)\, e^{b-1} = (1 + dw)\, e^{b-1}\left(\log(1 + dw)\, e^{b-1}\right) \\
&\Longrightarrow (dt - 1)\, e^{b-1} = e^{\log(\mathbb{W})} \log(\mathbb{W})
\end{aligned} \tag{29}$$

where $\mathbb{W} = (1 + dw)\, e^{b-1}$

$$\Longrightarrow \mathbb{W} = exp\left(\omega\left(\frac{dt - 1}{e^{b-1}}\right)\right) \tag{30}$$

In the closed-form solution of w, which contains the zero gradient condition, the Lambert function $\omega(.)$ is increasing for $\left(\frac{dt-1}{e^{1-b}}\right) > -\frac{1}{e}$, that is, $dt + e^{-b} > 1$ and described over $[-\frac{1}{e}, \infty]$ is given by

$$\Longrightarrow w = \frac{1}{d}\left(exp\left(1 - b + \omega\left(\frac{dt - 1}{e^{1-b}}\right)\right) - 1\right) \tag{31}$$

For a positive $\mathcal{P}_k^*$ the w is always non-negative. From (31), when $dt + e^b > 1$, the optimal power solution that is not satisfied undertakes a low power consumption p_c. The optimal transmitted power levels maximizing EE based on (26) can be written as

$$\mathcal{P}_k^* = \left[\frac{1}{\gamma_k}\left(\exp\left(1 - \Psi + \omega\left(\frac{\gamma_k \varsigma - 1}{e^{1-\Psi}}\right)\right) - 1\right)\right]^+ \tag{32}$$

The optimal transmitted power obtained by solving (27), gets a preliminary expression in (32). Transmitted signal from antenna arrays at BS to users, in this case, the switching on or off RF chains will have a different impact on the performance of multiple users. Employing more antennas dynamically select the optimal subset of antennas than RF chains to maximize EE whilst satisfying the minimum data rate requirement. The power maximization EE in (9) is given for $j = 1, \ldots\ldots, M$, where $[.]^+ = \max\{., 0\}$. To satisfy the analysis for optimal unconstrained energy efficiency, when a proper value of $\frac{\varsigma - 1}{e^{1-\Psi}}$, is chosen, the value of Lambert $\omega\left(\frac{\gamma_k \varsigma - 1}{e^{1-\Psi}}\right)$ will be a small positive condition of power to mitigate the interdependence for users $j \neq n$. From (27) EELCA for a number of RF chains and the optimal transmitted power at the BS are adapted to decrease the circuit power consumption with minimal data rate from multiple users. The optimal power levels for energy efficiency obtained based on data rate $\Psi = \frac{1}{K}\sum_k \log\left(\frac{\gamma_j}{\gamma_k}\right)$ and total power $\varsigma = p_c + \frac{1}{K}\sum_k\left(\frac{1}{\gamma_k} - \frac{1}{\gamma_j}\right)$, has values for Ψ and ς written as

$$\Psi = \frac{1}{K}\sum_k \log\left(\frac{\gamma_j}{\gamma_k}\right) \tag{33}$$

$$\varsigma = p_c + \frac{1}{K}\sum\nolimits_k \left(\frac{1}{\gamma_k} - \frac{1}{\gamma_j}\right) \quad (34)$$

Based on the analysis in (33) and (34), which are independent represent power solutions according to (31) for a given $j \in [1, ...M]$, the condition $dt + e^{-b} > 1$, where d and t are positive. Based on $\sum_k \left(\frac{1}{\gamma_k} - \frac{1}{\gamma_j}\right)$ in (34), the large number of users K in downlink massive MIMO is limited to a maximum number of antennas $j = 1, ...M$. From (32), when Ψ and ς are independent, the optimal transmit power can be directly obtained to maximize EE.

$$\mathcal{P}_k^* = \left[\frac{1}{\gamma_k}\left(\exp\left(1 - \frac{1}{K}\sum\nolimits_k \log\left(\frac{\gamma_j}{\gamma_k}\right)\right.\right.\right. \\ \left.\left.\left. + \omega\left(\frac{\gamma_k\left(p_c + \frac{1}{K}\sum_k\left(\frac{1}{\gamma_k} - \frac{1}{\gamma_j}\right)\right) - 1}{e^{1-\frac{1}{K}\sum_k \log\left(\frac{\gamma_j}{\gamma_k}\right)}}\right)\right) - 1\right)\right]^+ \quad (35)$$

From (35), the proper allocation of the transmitted power allocation among each user K is critical for achieving maximum EE. The optimal power allocation can be satisfied from the initial values to the powers by computing the updated Ψ^τ and ς^τ in (33) and (34) based on EELCA, where Ψ^τ and ς^τ are the actual data rate and power of UE at iteration $\tau \leftarrow \tau + 1$ and $j = [1, ...M]$, respectively. The compromise between the optimal transmitted power and the number of RF chains depends on the circuit power for every RF chain [35], [41]. From (27), using more than one inactive antenna can be assigned to every RF chain to select the optimal subset of antennas. From the numerator and the denominator in (27), the explicit of the optimal power allocation $\mathcal{P}^*{}_k$ of UE that maximizes the EE can be determined. The optimal transmitted power allocation $\mathcal{P}^*{}_k$ to every UE allows more UEs to perform CSI according to the level of the channel $\gamma_k = \frac{\left\|\hbar_{j,k}\right\|^2}{\sigma^2}\delta_k$, which treats with the interfering power from the other UEs. Where, the total interference power should be smaller than the allowed interference, the optimal EE is given by

$$EE^* = \frac{\gamma_k}{\log_2\left(1 + \left[\mathcal{P}^*{}_k\right]^\tau\right)} \quad (36)$$

The initial value of EE^0 can be determined by using (27) and computing the updated optimal power solution $\left[\mathcal{P}^*{}_k\right]^\tau$ according to (35) until the convergence is proven with the number of iteration$\left|[EE]^\tau - [EE]^{\tau-1}\right|^2 \le \varepsilon$ where $\varepsilon > 0$.

IV. RESULTS AND DISCUSSIONS

This section discussed the EE performance with power allocation. The number of Monte Carlo simulations was set to 10000 using MATLAB. The simulation parameters are listed in Table 1. The proposed algorithms are evaluated based on different benchmark metrics. These metrics are commonly used to evaluate the performance of the conventional approaches in massive MIMO systems [4], [9], [11], [13], [14], [21], [22], [24], [38].

TABLE 1. Simulation parameters.

Parameter	Value
p_t	43dBm
$\mathcal{P}^*{}_k$	0.01W
β	10MHz
M	200
K	20
Ω	0.38W
p_c	0.2W
p_a	10W
σ	-174dBm/Hz
Cell coverage	500m

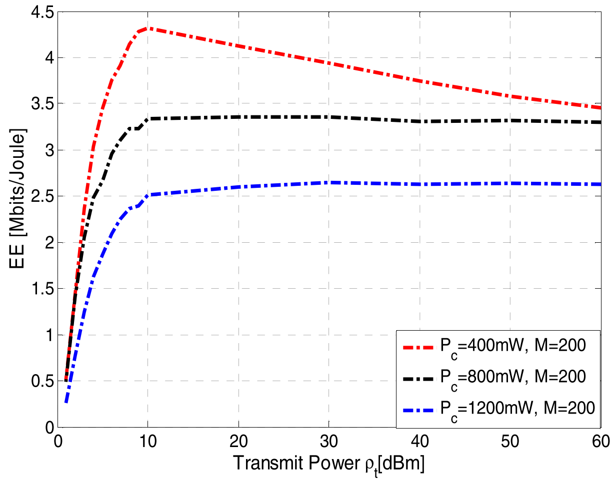

FIGURE 1. EE versus maximum transmit power constraint p_t for different p_c.

A. CONSTRAINED ENERGY EFFICIENCY RESULTS

Figure 1 shows the EE versus the maximum transmitted power for different values of p_c. The proposed low-complexity algorithm increased EE with total transmitted power allocation p_t. From Fig. 1, the maximum EE increased when the transmitted power was small. After reaching the maximum EE value, the EE increased initially and then decreased depending on the increased in transmitted power and large number of distributed users.

The optimal EE can be achieved based on the optimal transmit power $\mathcal{P}_k^*$. The EE was concave according to the numerator in (14) and when the transmitted power was more than the circuit power consumption according to (C_2) in (10). The study analyzed a massive MIMO system with $M = 200$ transmit antennas and $p_c = 400$mW in Fig. 1; from the proposed low-complexity algorithm, with maximum EE because of the large number of antennas at the BS, and generally, nonlinear schemes outperformed linear schemes. From Fig. 1, when the maximum EE $=$ 4.4 Mbits/joule, the transmitted power $\mathcal{P}$ $=$ 10 dBm with (p_c, M) $=$ (400mW, 200). Compared with [4], Fig. 5 shows that based on used equal power allocation (EPA), the EE increased with maximum value of EE $=$ 7 Mbits/joule, based on the transmitted power $=$10dBm, when the number of antennas $=$128, and the consumption circuit power $p_c = 10$W, which consumed more power and showed a deterioration. While in [42], Fig.1(a) shows that the EE starts increasing and giving the maximum value of EE $=$ 3Mbits/joule, when the saturation transmits power $=$ 25dBm, and the consumption circuit power $p_c = 100$mW. From [42] the value of EE was smaller than the value of EE in this study while the total transmitted power $=$ 25dBm, which consumed more power compared with this study's results for EE vs. total transmitted power.

However, when the circuit power consumption is large, $(p_c, M) = (800\text{mW}, 200)$, the transmitted power $\mathcal{P} =$ 20 dBm, and the maximum EE $=$ 3.4 Mbits/joule. Moreover, when the circuit power consumption increased to $(p_c, M) = (1200\text{mW}, 200)$, the transmitted power $\mathcal{P} = 30$ dBm, and the maximum EE $=$ 2.7 Mbits/joule. This shows that when the total circuit power consumption increases, the transmitted power slowly increases, and the maximum EE decreases.

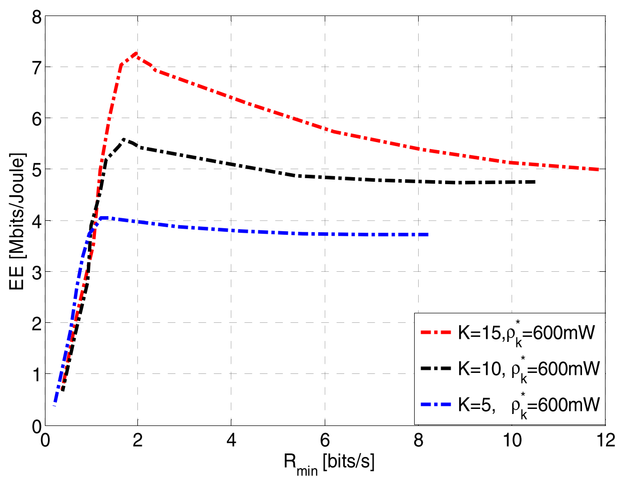

FIGURE 2. EE versus minimum rate constraint R_{min} for different users.

Figure 2 shows the EE versus the minimum data rate. The proposed logarithm guarantees the optimal EE, which can be achieved with minimum rate requirement R_{min} according to (C_1) in (10). Fig. 2 shows that the EE starts increasing based on the total power and is sufficient, which requires the minimum rate R_{min}; after that, the EE starts decreasing depending on serving several distributed users and sufficient transmitted power for every user $\mathcal{P}_k^*$. Providing the minimum data rate R_{min}, this means less power transmitted to a user gradually decreases the EE. The EE decreases quickly with increasing data rate because more power is allocated to users with bad channels according to (C_1) in (10). Transmitting more data to every user depends on high channel gain; the EE decreases with an increase in data rate requirement. When the rate requirement is high, more power is allocated to every user. The EELCA is more achievable of EE when the data rate is more than R_{min} with rate constraint according C_1 in (10). When the minimum data rate R_{min} is high, there is no power limitation, which requires transmitting more power to meet the data rate requirement. From Fig. 2, when the number of users $K = 15$ and $\mathcal{P}_k^* = 600$mW, the maximum EE $=$ 7.2 Mbits/joule, and the achievable data rate $R_{min} =$ 2 (bits/s). However, when the number of users is decreased, $K = 10$, and the optimal transmitted power allocation for users $\mathcal{P}_k^* = 600$mW, the maximum EE $=$ 5.6 Mbits/joule, and the achievable data rate starts decreasing to $R_{min} =$ 1.8 (bits/s). Moreover, when the number of users decreases, $K = 5$, and $\mathcal{P}_k^* = 600$mW, the maximum EE $=$ 4.05 Mbits/joule, and the minimum achievable data rate $R_{min} = 1.2$ (bits/s). Compared to [4], Fig. 6, based on used equal power allocation (EPA), the related EE with minimum data rate R_{min}, the EE becomes saturated with a maximum value of EE $=$ 8.8 Mbits/joule, when the number of UEs $=$ 20, and the minimum rate $R_{min} =$ 2bits/s/Hz, after this value, the EE starts to decrease gradually to zero according to the equal power allocation (EPA). Fig. 2 results show that the EE starts increasing based on the total power and minimum R_{min} after reaching maximum, the EE begins to decrease due to an increase in the number of RF chains and the large a number of distributed users. Then, the EE starts decreasing and becomes saturated depending on the numbers of distributed users and sufficient transmitted power to every user $\mathcal{P}_k^*$.

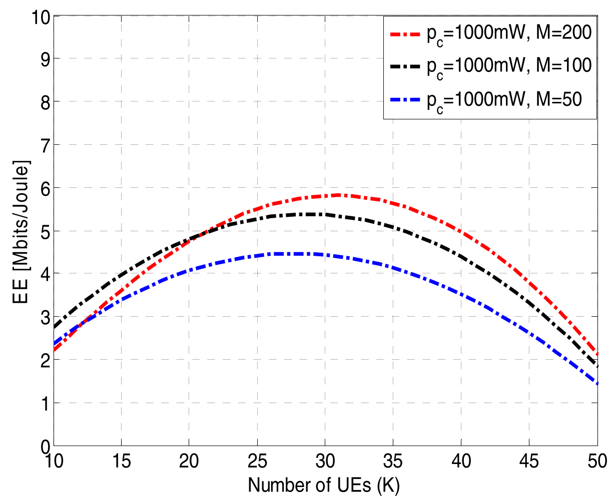

FIGURE 3. EE versus number of users for different antennas.

Figure 3 shows the EE versus the number of users, presented for the proposed EELCA. In DL transmission in massive MIMO systems, the large consumed circuit power increases at the BS because of transmitted signals to every UE. Figure 3 shows, the EE in the proposed EELCA increases when the number of users is small. When the number of users is large, the EE becomes slower. When the number of users continues to increase, the EE starts to decrease because of the tradeoff between data transmission and power consumption according to (14).

The proposed EELCA produces the maximum EE, and generally, nonlinear schemes will outperform linear schemes with a distributed number of users for a large number of transmission antennas. Due to the high loss caused by the distance between BS and UEs, the transmitted power will increase, which decreases the EE. Figure 3 shows that there is an optimal number of users resulting in maximum EE for different numbers of antennas. From Fig. 3, the maximum EE = 5.9 Mbits/joule when the number of distributed users, $K = 33$, with $(p_c, M) = (1000\text{mW}, 200)$. However, when the number of antennas is small, $(p_c, M) = (1000\text{mW}, 100)$, the number of distributed users, $K = 30$, and the maximum EE = 5.4 Mbits/joule. Moreover, when the number of antennas decreases to $(p_c, M) = (1000\text{mW}, 50)$, the distributed users, $K = 28$, and the maximum EE = 4.5 Mbits/joule. The proposed low-complexity algorithm aims to provide maximum EE depending on the movements of several users related to a specific number of antennas. Compared to [29], Fig.1, based on Iterative Power Allocation Algorithm (IPAA) for user scheduling scheme, the maximum EE = 4.7 Mbits/joule, is reached when the number of users = 75, and the circuit power consumption = 1000mW.

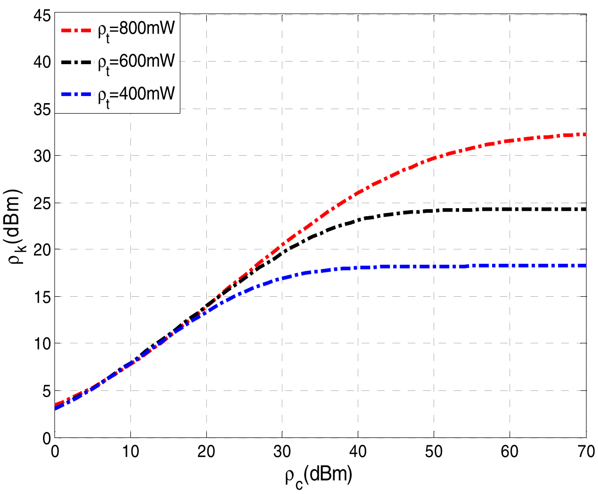

FIGURE 4. Transmit power allocation for users $\mathcal{P}_k$ versus circuit power.

Figure 4 shows the transmitted power allocation for users versus circuit power consumption, where the circuit power value started from 0 dBm to 70 dBm. The figure shows that the transmitted power for users increased slowly when the consumption circuit power was low because more antennas were used to satisfy the minimum data rate requirement. The proposed EELCA was used to decrease the number of activated antennas and satisfy the transmitted power requirement to save energy when the maximum transmitted power for users increased.

From (14), when more power was used for data transmission rather than channel estimation, at increased circuit power, the transmitted power was constrained because more antennas had to be activated to maximize power. From Fig. 4, when the circuit power was high, the transmitted power for users became constant because of the amplifier efficiency for every antenna that accounted for the power dissipation in the amplifier, which depended on the hardware quality employed at the BS. In addition, the circuit power consumption increased linearly because of the power cost for RF chains with increasing antenna numbers. The figure also shows that the optimal transmitted power allocation for users obtained at $\mathcal{P}_k^* = (33, 24, 18)$ dBm with total transmitted power $p_t = (800, 600, 400)$ mW and became constant when the transmitted circuit power $p_c = (70, 50, 40)$dBm.

B. UNCONSTRAINED ENERGY EFFICIENCY RESULTS

In order to characterize the proposed EE power allocation, the EELCA is computed when more antennas are equipped, with a number of antennas based on available channel gains.

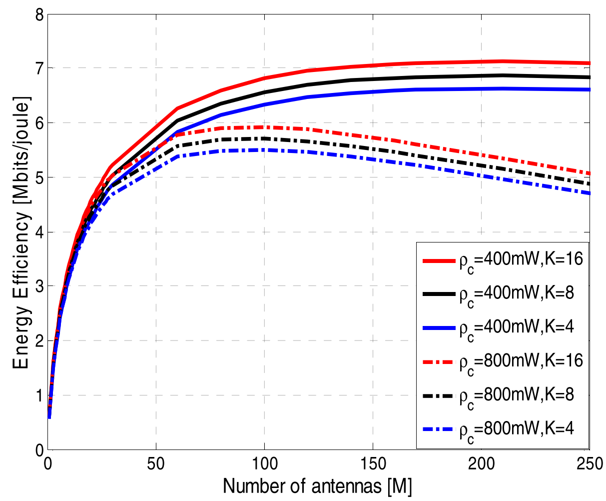

FIGURE 5. Unconstrained EE for number of antennas for different p_c.

Figure 5 shows the relation between the EE corresponding to the number of transmitting antennas with different RF chain circuits and the proposed low-complexity algorithm. However, these EEs start to decrease when the number of antennas becomes larger only when circuit power consumption is considered. Looking at the number of RF chains for the activated antenna, the EE starts to increase and then decreases when the number of antennas increases due to increase power consumption, and RF chains start to impact on EE. When the circuit power consumption $p_c = 800$mW, the number of antennas increases to $M = 100$, the EE decreases more because the RF switches. The resulting resolution is not fine enough, which limits transmission and increases costs and power consumption. Both the number of antenna selection and optimal EE decreases when the RF chain circuit power increases.

Figure 5 shows the energy-efficient low-complexity algorithm, the maximum EE = (7.2, 6.8, 6.5) Mbits/joule, the number of transmission antennas, $M = 200$ with $(K) = (16, 8, 4)$. When the circuit power $p_c = 400mW$, EE becomes constant as the power dissipates because of the amplifier efficiency for every antenna. The performance of the proposed power allocation algorithm in terms of EE is compared with [10], as shown in Fig.2. EE starts increasing to a maximum value of EE $=$ (11, 14, 12) Kbits/J, based on the number of antennas $= 200$, when the number of distributed UEs $=$ (20, 10, 5), and the total transmitted power $= 0.01$mW.

In the proposed approach in [5], the impact of circuit power consumption was not considered at the BS of massive MIMO systems. Similar to [5], Fig. 3 is based on no knowledge of the circuit power consumption, the maximum EE $=$ 42 Mbits/joule, when the number of antennas $= 180$, and the circuit power consumption $=$ 160 mW. As per [22], Fig.1, based on advanced binary search (ABS) for transmission antenna selection and transmitted power allocation, the maximum EE $=$ 4 Kbits/joule, when the number of antennas $=$ 20, and the circuit power consumption $=$ 160 mW. However, when the circuit power consumption increases to, $p_c = 800mW$, the maximum EE $=$ (5.9, 5.7, 5.5) Mbits/joule, which decreases the number of activated antennas to, $M = 80$. According to the proposed EELCA, the EE starts to decrease because of large circuit power consumption and becomes higher than the total transmitted power, which leads to the use of all available RF chains regardless of transmitted power. When the total transmitted power is higher than the circuit power consumption, the maximum EE is achieved based on a selected number of antennas.

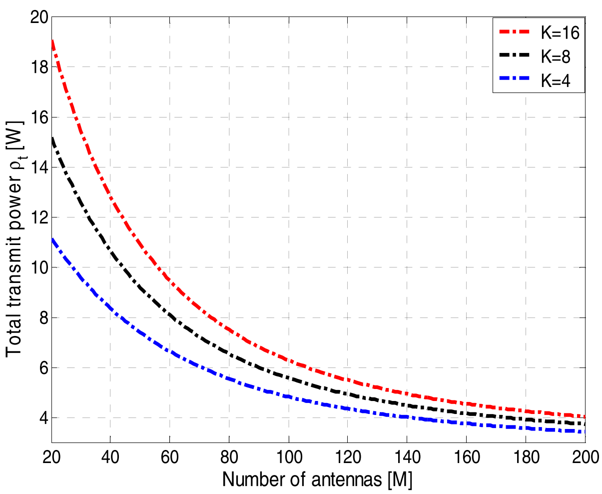

FIGURE 6. Total transmit power p_t versus number of antennas for different users.

Figure 6 shows the total transmitted power corresponding to the number of antennas per BS for different number of users distributed in a circular cell. The optimal transmitted power value for users $\mathscr{P}_k^*$ is directly estimated using the available channel gains with the requirement of the transmitted power allocated to other equivalent channels. The figure shows that the total transmitted power decreased with an increasing number of antennas in a single cell, where the power consumption increased because of RF chains consumed a lot of power at the BS.

The figure shows that the total transmitted power increased with more distributed users, and total transmitted power increased faster than linearly with a distributed number of users and reduced linearly with an increasing number of antennas. The range of total transmitted power values was (19.2–11.2) W, with 20 BS antennas that decreased radically to (4–2) W, with 200 BS antennas because of a large RF chain loss and based on the distributed number of users $K = (16, 8, 4)$, respectively. The proposed EELCA provided more transmitted power when the number of distributed users is large; and when the number of users is small, the total transmitted power decreased because of a small RF chain loss, which decreased the cost of power consumption. Compared with [10], Fig.5, total transmitted power decreased with a large number of antennas, the range of total transmitted power value $p_t = (2-0.5)$ mW, based on the number of antennas $= 200$, when the number of distributed UEs $=$ (20, 10, 5).

V. CONCLUSION

This paper discussed the problem associated with power allocation and joint user association for a DL single-cell massive MIMO system to optimize EE based on Newton's methods. EE was maximized with maximum transmitted power and minimal data rate constraints using EELCA. The unconstrained EE was obtained by finding the root of the first derivative of the EE based on differentiating the instantaneous power allocation. To solve this problem, the study proposed an EELCA, which maximizes the DL EE under an explicit power allocation, joint user association and rate constrained with perfect channel estimation. The simulation results produced maximum EE, transmitted high amount of power coupled with a large RF chain loss, which increased circuit power consumption cost. The EELCA was used to compare the number of activated antennas to satisfy the transmitted power requirement to save energy when the users' needed more power. The results were also compared with other research, and showed that EELCA maximized EE with transmission across a number of antennas compared to [5], and [10]. Future research to increase network EE needs to be explored. These include joint optimal antenna selection, and optimal transmitted power allocation through minimizing the reuse of pilot sequences based on hybrid beamforming for millimeter wave.

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