Research Article

On the Energy Efficiency of Multicell Massive MIMO with Antenna Selection and Power Allocation

Liping Du,1,2 Ying Tan,1 Yiming Li,3 and Yueyun Chen1

1School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China
2Shunde Graduate School of University of Science and Technology Beijing, Foshan 528000, China
3State Radio Monitoring Center (State Radio Spectrum Management Center), No. 80 Beilishi Road Xicheng District, Beijing, China

Correspondence should be addressed to Liping Du; dlp2001@ies.ustb.edu.cn

Received 30 September 2021; Revised 4 March 2022; Accepted 21 March 2022; Published 22 April 2022

Academic Editor: Muhammad Inam Abbasi

Copyright © 2022 Liping Du et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The energy consumption of massive multiple-input multiple-output (MIMO) systems increases with the number of antennas. Optimizing the energy efficiency (EE) of massive MIMO systems is one of the ways to achieve green communication. This paper proposes an EE optimization method that genetic algorithm-based antenna selection and power allocation (GA-AS+PA) for the downlink of a multicell massive MIMO system under the restriction of the users’ sum-rate. First, we use the genetic algorithm to determine the active transmitting antenna of each base station (BS). Then, the transmission power for each user is allocated using the convex optimization method. Finally, the EE of the system is optimized under the achieved optimum BS’s transmit power and the number of active antennas. From the simulation results, the GA-AS+PA method can improve the EE of the system while meeting user sum-rate requirements, which achieves better performance compared with random antenna selection+equal power allocation method (RAS+EPA), random antenna selection+power allocation method (RAS+PA), the antenna selection method based on genetic algorithm+equal power allocation method (GA-AS+EPA), and equal power allocation (EPA) these four methods. The EE of the proposed GA-AS+PA method is improved by 33.3% compared to the EPA method.

1. Introduction

With the rapid growth of the number of mobile users and high-speed data service applications worldwide, the energy consumption of information and communication systems continues to increase. Green communications have gradually begun to gain widespread attention. How to improve the energy efficiency (EE) of the system is an urgent problem to be solved. Massive multiple-input multiple-output (MIMO), as one of the key technologies of 5G, has the characteristics of high spectrum efficiency and high transmission rate, which attracts many researchers’ attention [1–4]. It employs a very large-scale antenna array at the base station (BS) [5]. However, with lots of antennas and associated radio frequency (RF) chains, massive MIMO faces some challenges including high hardware complexity and system power consumption. To reduce the cost and hardware complexity while retaining the benefits brought by the large number of antennas, EE optimization is an essential problem in massive MIMO systems. Therefore, optimizing the EE of massive MIMO systems has become an important research direction in the field of wireless communication [6, 7]. At present, researchers have studied the optimization of the EE of the massive MIMO system by selecting the antenna, adjusting transmission power and multiparameter joint optimization [8].

As for EE optimization of single-cell massive MIMO system, the energy consumption generated by multiple antennas is one of the main reasons for the high energy consumption of the massive MIMO system. Therefore, many researchers use antenna selection techniques to improve the EE of massive MIMO systems. The principle of this technology is to activate a part of the antenna for transmission. In [9], the number of antennas that provide the maximum EE is obtained according to a new power consumption model proposed. The model considers the transmit power on the power amplifier, the power consumed by
the analog equipment, and the residual loss factor in the BS. Based on the proposed power consumption model, it is concluded that as the number of antennas increases, EE is a quasi-concave function of the number of antennas. In [10], the number of antennas can adaptively be selected analyzing the input-output mutual information by applying Jensen’s inequality. Only 30% of antennas is active and 90% of the ergodic rate achieved by full complexity can be achieved, which can significantly improve EE. The authors in [11] proposed an antenna selection scheme to maximize the EE of the massive MIMO system by fixing the transmit power and derived a closed expression for the optimal number of transmit antennas. In order to achieve green communication, the use of reasonable power allocation is also one of the ways to improve system EE. The principle of this method is to allocate different transmission powers to different users. A method of uplink power allocation for multiuser MIMO systems is proposed in [12], which is to turn off the antennas of certain users to maximize the EE of the system. In [13], it assumes that the efficiency of the power amplifier changes with the output power and studies the EE of a single-cell downlink massive MIMO system under ideal channel state information. For the multiuser MIMO downlink, the authors in [14] proposed a fair power allocation algorithm, which takes into account the EE of the edge users of the cell and the average EE of the cell. In [15], the rate limitation and more general signal-to-interference-and-noise ratio (SINR) representation are considered, and a power allocation method based on fractional programming is proposed. The method uses Dinkelbach algorithm to solve the optimal power allocation scheme. In recent years, researchers have begun to consider using multiple parameters to jointly optimize the EE of massive MIMO systems. In [16], it proposed a joint pilot and data power allocation algorithm to maximize the minimum EE using a gradient-based adaptive method. In [17], for the uplink of a multiuser massive MIMO system, EE is optimized by jointly adjusting the number of transmit antennas at the BS and the user’s transmit power. The algorithm can obtain performance close to the exhaustive EE resource allocation algorithm with lower computational complexity. In [18], the resource allocation based on EE is analyzed in the downlink of frequency division duplex (FDD) massive MIMO system. Under the constraints of the total transmission energy and the minimum transmission rate requirements of the user, the system EE is maximized by optimizing the pilot transmission length, pilot transmission power, and data power. The system spectral efficiency (SE) and EE by optimizing the BS transmit power and time switching ratio are improved in [19].

As for EE optimization of multiecell massive MIMO systems, at present, many studies on the EE of massive MIMO systems are focused on a single cell, in other words, only the intracell interference is considered. For a multiecell massive MIMO system, there still exists intercell interference, which will also cause the user’s communication quality to decrease. A dynamic resource allocation strategy under the effect of intercell interference is suggested in [20], which exploits the advantage of user location distribution (ULD) variations to attain a more energy-efficient design. The program can save up to 36% to 50% of energy consumption. In [21], an average sum-rate optimization scheme is presented for the uplink of the multiecell massive MIMO system by varying power scaling factor. This method exploits variations in the average channel gains in multiecell massive MIMO systems to improve sum-rate and power consumption. In [22], the authors develop an efficient antenna selection scheme using genetic algorithms (GAs), which reaches the same throughput as the exhaustive search-based optimal approach, with substantially less implementation complexity. Considering the channel estimation error and pilot pollution, the closed-form expression of the maximum EE of the downlink of the multiecell massive MIMO system is derived and analyzed the scaling law of the antenna at each BS in [23]. The research results in the above literature have shown that the optimization of EE or SE can be achieved by power allocation, but in many cases, the system EE is improved at the cost of decreasing system SE in the research of multiecell massive MIMO system, and vice versa. The authors in [24] have investigated joint beamforming and power allocation in multiecell multiple-input single-output (MISO) downlink networks. This algorithm can improve both SE and EE at the same time, especially in the middle-high transmit power region. The authors in [25] have investigated the trade-off between EE and SE for downlink massive MIMO with respect to the power allocation and the number of antennas, while considering intra- and intercell interference. From [24, 25], it is necessary to consider the balance between EE and SE of system as well as the influence of antenna factor and transmission power for multiecell massive MIMO.

In this paper, we propose an EE optimization method based on antenna selection and power allocation while meeting the sum-rate limit for the downlink of a multiecell massive MIMO system. To maximize the total EE of the system, we first optimize the antenna selection matrix of each BS under different antenna numbers, and then allocate the transmit power to each user, and finally select the optimum antenna number. The contribution of the paper lies in the following:

(i) For the downlink of the multiecell massive MIMO system, we have established a new EE optimization model by adapting antennae selection matrix, power allocation, and the number of antennae under sum rate constraint in order to ensure the user’s communication quality

(ii) Due to the couple between antenna selection matrix and the number of antennae, the original nonconvex problem is resolved into three subproblems: antenna selection matrix optimization, power allocation optimization, and the number of antenna optimization. We proposed genetic algorithm-based antenna selection and power allocation method (GA-AS+PA). The GA are used to select the transmitting antenna of each BS, and the antennas matrix under different candidate antenna number that contributes the most to the sum-rate of the system are selected. Since highly nonconvex objective function and constraints
exist in the power allocation optimization subproblem, we convert them into equivalent and more tractable forms by utilizing the first-order Taylor approximation method and achieve the power allocation under candidate antenna number. Based on the optimal antenna select matrix and power allocation, the antenna number that maximize EE under the sum rate constraint is decided.

The rest of the paper is organized as follows. In Section 2, we review the multicell massive MIMO system model and the problem formulation of EE optimization. The proposed method is discussed in Section 3. The simulation results are shown in Section 4. Section 5 concludes the paper.

The symbols used in this paper are defined as follows: the matrices and the vectors are represented by upper and lower bold letters. \( (A)^T, (A)^*, \) and \( (A)^H \) represent the transpose, conjugate, and conjugate transpose of matrix \( A \). 

\( N \times N \) identity matrix is denoted as \( I_N \).

### 2. System Model and Problem Formulation

#### 2.1. System Model

In the paper, we consider a multicell massive MIMO system model, which is shown in Figure 1. There are \( L \) hexagonal cells in the cellular network, and each cell includes one BS equipped with \( M \) antennas, serving \( K (M \gg K) \) single antenna users.

The channel quality is determined by the large-scale fading coefficient and the small-scale fading coefficient. \( H_{lj} \in \mathbb{C}^{M \times K} \) is the channel matrix between all users in the \( j \)th \((1 \leq j \leq L)\) cell and the BS of \( l \)th \((1 \leq l \leq L)\) cell, denoted as

\[
H_{lj} = G_{lj} \sqrt{D_{lj}},
\]

where \( G_{lj} \in \mathbb{C}^{M \times K} \) is the channel matrix of small-scale fading coefficients, and \( D_{lj} \in \mathbb{C}^{K \times K} \) is diagonal matrix. The elements of \( D_{lj} = [\beta_{lj1}, \beta_{lj2}, \ldots, \beta_{ljK}] \) are the large-scale fading coefficient between the \( k \)th \((1 \leq k \leq K)\) user in the \( j \)th cell and the \( l \)th BS

\[
\beta_{ljk} = \frac{z_{ljk}}{r_{ljk}^\kappa},
\]

where \( \kappa(\kappa > 2) \) is the path loss index, and \( R \) is the radius of the cell. \( r_{ljk} \) is the distance between the \( k \)th user in the \( j \)th cell and the \( l \)th BS. \( z_{ljk} \) represents the shadow fading and possesses a lognormal distribution \( (10 \log(z_{ljk}) \sim \mathcal{CN}(0, \sigma_{\text{shadow}}^2)) \).

All elements of \( G_{lj} \in \mathbb{C}^{M \times K} \) are independent identical distribution (i.i.d). \( g_{ljm} \) is the small-scale fading coefficient between the \( k \)th user in the \( j \)th cell and the \( m \)th antenna of the \( l \)th BS

All antennas have the same large-scale fading coefficient for a specific terminal because the distance between the antenna array is negligible compared with the distance between the users and the BS.

We assume that the system uses time division duplex (TDD) mode. For the uplink of the massive MIMO system, it is assumed that the pilot sequence transmitted by all users in the \( j \)th cell is \( \phi_j = [\theta_{j1}, \theta_{j2}, \ldots, \theta_{jK}]^T \), while pilot length \( \tau K \) and \( \phi_j\phi_j^H = I_K \). The training information received by the BS of the \( l \)th cell is

\[
Y_l = \sqrt{p_p} \sum_{j=1}^{L} H_{lj} \phi_j + N_l,
\]

where \( p_p \) is the pilot transmit power. \( N_l \) is the additive white Gaussian noise in the \( l \)th cell. Based on the channel reciprocity criterion, the channel information can be estimated according to the uplink pilot transmitted by the users. With the least square (LS) channel estimation, the estimation of channel state information (CSI) of the BS in the \( l \)th cell to the users is shown as

\[
\hat{H}_l = \frac{1}{\sqrt{p_p}} Y_l \phi_l^H = \frac{1}{\sqrt{p_p}} \left( \sum_{j=1}^{L} H_{lj} \sqrt{p_p} \phi_j + N_l \right) \phi_l^H
\]

\[
= H_l + \left( \sum_{j=1,j \neq l}^{L} H_{lj} \phi_j \right) \phi_l^H + \frac{1}{\sqrt{p_p}} N_l \phi_l^H.
\]
We define the error matrix as \( \Delta \mathbf{H}_{il} = \mathbf{\hat{H}}_{il} - \mathbf{H}_{il} \), and \( \Delta \mathbf{h}_{il} \) is the \( k \)th column of \( \Delta \mathbf{H}_{il} \in \mathbb{C}^{M \times K} \).

For the downlink of the multicell massive MIMO system in the TDD mode, the received signal \( y_{lk} \) of the \( k \)th user in the \( l \)th cell can be expressed as

\[
y_{lk} = \sum_{j=1}^{L} \sum_{n=1}^{K} \sqrt{p_{jn}} \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{jn} \sqrt{p_{jn}} \mathbf{x}_{jn} + n_{lk},
\]

(6)

where \( \mathbf{P}_{j} \triangleq \text{diag}(p_{j1}, p_{j2}, \cdots, p_{jK}) \) and \( p_{jn} \) is the transmit power of the BS of the \( j \)th cell to the \( n \)th user of this cell. \( x_{jn} \) is the data sent by the BS of the \( j \)th cell to the \( n \)th user in this cell. \( n_{lk} \) is the additive white Gaussian noise with zero mean and unit variance, \( n_{lk} \sim \mathcal{CN}(0, 1) \). \( \mathbf{W}_{j} \) is the precoding matrix of the \( j \)th cell, and \( \mathbf{w}_{jn} \) is the \( n \)th column of \( \mathbf{W}_{j} \in \mathbb{C}^{M \times K} \). We use zero-forcing (ZF) precoding at the BSs; then, the precoding matrix of the \( j \)th cell is \( \mathbf{W}_{j} = \mathbf{H}_{lj}^{*} (\mathbf{H}_{lj} \mathbf{H}_{lj}^{*})^{-1} \), and \( \text{tr}(\mathbf{W}_{j}^{H} \mathbf{W}_{j}) = K \). We assume \( \mathbf{\hat{h}}_{il} \mathbf{w}_{lk} = \delta_{ki} \). Then, \( \delta_{ki} = 0 \), when \( k \neq i \). \( \mathbf{S}_{j} \in \mathbb{C}^{M \times M} \) is the antenna selection matrix of the \( l \)th BS. It can be expressed as

\[
\mathbf{S}_{j[\ell]} = \begin{cases} 1, & \text{the } i \text{th antenna is activated,} \\ 0, & \text{the } i \text{th antenna is not activated.} \end{cases}
\]

(7)

Therefore, the received signal of the \( k \)th user in the \( l \)th cell can be expressed as (8), where the first item is the expected signal, and the other items represent intercell interference, channel estimation error, intracell interference, and Gaussian white noise.

\[
y_{lk} = \sum_{j=1}^{L} \sum_{n=1}^{K} \sqrt{p_{jn}} \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{jn} \mathbf{x}_{jn} + n_{lk} = \sum_{n=1}^{K} \sqrt{p_{jn}} \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{jn} \mathbf{x}_{jn} + \sum_{j=1,j \neq l}^{L} \sum_{n=1}^{K} \sqrt{p_{jn}} \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{jn} \mathbf{x}_{jn} + n_{lk}
\]

(8)

\[
\begin{align*}
\text{SINR}_{lk} &= \frac{\mathbf{p}_{lk} \mathbf{S}_{j} \mathbf{w}_{lk}^{T} \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{lk}}{|n_{lk}|^2 + \sum_{n \neq k}^{K} |\mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{ln}|^2 + \sum_{n=1}^{K} p_{ln} |\Delta \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{ln}|^2 + \sum_{j' \neq l}^{L} \sum_{n=1}^{K} p_{jn} |\mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{jn}|^2}.
\end{align*}
\]

(9)

From which, we can obtain the SINR of the \( k \)th user in the \( l \)th cell in (9). According to Jensen’s inequality, the lower bound of the sum-rate of the \( k \)th user in the \( l \)th cell is

\[
R_{lk} \log \{1 + E(\text{SINR}_{lk})\}. 
\]

(10)

Substituting (9) into (10), the sum-rate of system can be expressed as (11)

\[
R_{lk} = \log \left\{ 1 + E \left( \frac{\mathbf{p}_{lk} \mathbf{S}_{j} \mathbf{w}_{lk}^{T} \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{lk}}{\sum_{n \neq k}^{K} |\mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{ln}|^2 + \sum_{n=1}^{K} p_{ln} |\Delta \mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{ln}|^2 + \sum_{j' \neq l}^{L} \sum_{n=1}^{K} p_{jn} |\mathbf{h}_{ljk}^{T} \mathbf{S}_{j} \mathbf{w}_{jn}|^2} \right) \right\}.
\]

(11)

where \( P_{\text{total}} \) is the total power consumed by the system. \( P_{j} \) is transmission power of the \( l \)th the BS. \( \alpha \) is the power amplifier coefficient. \( p_{c} \) is the power consumption of each antenna at the BS, and \( p_{u} \) is the power consumption of the user.

This paper considers the influence of the antenna number \( M_{S} \), the antenna selection matrix \( \mathbf{S} \), and the transmit power \( \mathbf{P} \) on EE of system. When the sum-rate satisfies the
minimum limit, we take the system EE maximization as the optimization goal. Therefore, the problem can be expressed as

\[
\max_{\mathbf{S}, \mathbf{P}, \mathbf{M}_k} \eta_{EE}
\]

\[s.t. \sum_{k=1}^{K} R_{lk} R_{\text{ms}_{lk}}, l = 1, 2 \cdots L \tag{13a}\]

\[\sum_{k=1}^{K} \left| p_{lk} \mathbf{S}[\mathbf{w}_{lk}] \right|^2 = p_{\text{max}}, l = 1, 2 \cdots L, k = 1, 2 \cdots K \tag{13b}\]

\[p_{lk}, l = 1, 2 \cdots L, k = 1, 2 \cdots K \tag{13c}\]

\[tr(S_l) = M_S, l = 1, 2 \cdots L \tag{13d}\]

where (13a) gives that the sum-rate of each cell is greater than the minimum limit \(R_{\text{ms}}\). The (13b) shows that the total power of each BS is lower than the maximum limit \(p_{\text{max}}\). The (13c) indicates that the transmit power is nonnegative. The (13d) is the number of antennas, where \(M_S\) is the number of antennas activated at each BS.

3. Proposed Solution

It is easy to understand that the above problem is nonconvex in the optimization variables, and therefore, it is difficult to find the globally optimal solution. In order to solve the above problem, we decompose this problem into multiple subproblems.

3.1. Optimal Antenna Selection Matrix. According to formula (12), when the antenna selection matrix is determined, the \(\eta_{EE}\) changes with the molecule \(\sum_{l=1}^{L} \sum_{k=1}^{K} R_{lk}\). So, we first maximize the sum rate of the system. It assumes that the transmission power of the BS to each user is equal (i.e., \(p_{in} = p_{in}, \forall i, k\)). The GA are used to select the transmitting antenna of each BS, and the antennas that contribute the most to the sum-rate of the system are selected.

The optimization problems P1 is

\[P1 : \max_{\mathbf{S}} \sum_{l=1}^{L} \sum_{k=1}^{K} R_{lk} \tag{14}\]

\[s.t. \sum_{k=1}^{K} \left| p_{lk} \mathbf{S}[\mathbf{w}_{lk}] \right|^2 = p_{\text{max}}, l = 1, 2 \cdots L, k = 1, 2 \cdots K \tag{14a}\]

\[p_{lk}, l = 1, 2 \cdots L, k = 1, 2 \cdots K \tag{14b}\]

\[tr(S_l) = m, l = 1, 2 \cdots L, m = K, K + 1, \cdots, M \tag{14c}\]

The details of the antenna selection algorithm are given in Algorithm 1.

3.2. Optimal Transmission Power. After solving the P1 to obtain the antenna selection matrix \([\mathbf{S}[\mathbf{i}], \mathbf{S}[\mathbf{i}+1], \cdots, \mathbf{S}[\mathbf{M}]\]\), we further optimize the transmission power. So, the optimization problem can be expressed as

\[P2 : \max_{\mathbf{P}} \sum_{l=1}^{L} \sum_{k=1}^{K} R_{lk} \tag{15}\]

\[s.t. \sum_{k=1}^{K} \left| p_{lk} \mathbf{S}_m[\mathbf{w}_{lk}] \right|^2 = p_{\text{max}}, l = 1, 2 \cdots L, k = 1, 2 \cdots K, \tag{15a}\]

\[m = K, K + 1, \cdots, M \]
\[ p_{ik}^m, l = 1, 2 \cdots L, k = 1, 2 \cdots K \] (15b)

Since this problem is a nonconvex problem, we use the following method to transform it into a convex problem. First, \( R_{ik} \) is expressed as (16).

\[
R_{ik} = \log \left\{ \sum_{n=1}^{K} p_{in}^m h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{n=1}^{K} p_{in}^m \Delta h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m h_{ik}^T S_{jljn}^m w_{jn}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m \Delta h_{ik}^T S_{jljn}^m w_{jn}^m \right\}^2
\] (16)

Let

\[
e^{\text{eik}} = \sum_{n=1}^{K} p_{in}^m h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{n=1}^{K} p_{in}^m \Delta h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m h_{ik}^T S_{jljn}^m w_{jn}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m \Delta h_{ik}^T S_{jljn}^m w_{jn}^m
\] (17)

\[
e^{\text{eik}} = \sum_{n=1}^{K} p_{in}^m h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{n=1}^{K} p_{in}^m \Delta h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m h_{ik}^T S_{jljn}^m w_{jn}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m \Delta h_{ik}^T S_{jljn}^m w_{jn}^m
\] (18)

P3: \[
\text{max}_{P, u_{ik}, d_{ik}} \sum_{l=1}^{K} \sum_{k=1}^{K} (u_{ik} - d_{ik})
\] (19)

s.t. \[
\sum_{n=1}^{K} p_{in}^m h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{n=1}^{K} p_{in}^m \Delta h_{ik}^T S_{iln}^m w_{ln}^m
\] + \[
\sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m h_{ik}^T S_{jljn}^m w_{jn}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m \Delta h_{ik}^T S_{jljn}^m w_{jn}^m
\] (19a)

\[= 1, 2 \cdots K, m = K, K + 1, \cdots, M
\]

\[
\tilde{d}_{ik} = \log \left( \sum_{n=1}^{K} p_{in}^m h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{n=1}^{K} p_{in}^m \Delta h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m h_{ik}^T S_{jljn}^m w_{jn}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m \Delta h_{ik}^T S_{jljn}^m w_{jn}^m \right),
\] (20)

\[l = 1, 2 \cdots L, k = 1, 2 \cdots K, m = K, K + 1, \cdots, M.
\]

P4: \[
\text{max}_{P_{ik}, u_{ik}, d_{ik}} \sum_{l=1}^{K} \sum_{k=1}^{K} (u_{ik} - d_{ik})
\] (21)

s.t. \[
\sum_{n=1}^{K} p_{in}^m h_{ik}^T S_{iln}^m w_{ln}^m + \sum_{n=1}^{K} p_{in}^m \Delta h_{ik}^T S_{iln}^m w_{ln}^m
\] + \[
\sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m h_{ik}^T S_{jljn}^m w_{jn}^m + \sum_{j \neq l}^{L} \sum_{n=1}^{K} p_{jn}^m \Delta h_{ik}^T S_{jljn}^m w_{jn}^m
\] (21a)

\[= 1, 2 \cdots K, m = K, K + 1, \cdots, M
\]
Finally, we maximize the value is obtained based on the equal power allocation criterion. The initial nonconvex problem (13). In the subproblems P1, the genetic algorithm-based antenna selection method is used to select the optimal antenna subset by comparing the fitness values after IAS evolutionary generation, and the complexity of the antenna selection part is $O(IAc)$. In the subproblems P2, assuming that the maximum number of iterations for calculating a power solution using CVX is $I_p$, and the outer loop of the power distribution algorithm is iterated $T$ times, the maximum complexity of the power distribution part is $O(TI_p)$. In the subproblems P5, therefore, the total complexity of the proposed algorithm is $O(TI_{Ac}I_p) + O(M)$.

4. Simulation Results

In this work, as shown in Figure 1, we consider a massive MIMO system consisting of seven hexagonal cells each with a radius of 500 m, where one central cell is surrounded by six cells [17]. In cell $j$, the $j$th BS is equipped with $M$ transmit antennas and serves $K$ single antenna users. We will study the performance of the proposed scheme through Monte Carlo simulation. The system parameters are given in Table 1, some of which are taken from [18, 26]. The following comparison methods are used: the proposed GA-AS+PA method, random antenna selection+equal power allocation method (RAS+EPA), random antenna selection+power allocation method (RAS+PA) [21], the antenna selection method based on genetic algorithm+equal power allocation
method (GA-AS+EPA) \[22\], and equal power allocation method (EPA).

In Figure 2, the achievable sum-rate of the five above methods is shown with the changing of the number of active antennas. The number of users in each cell is 10. The average SNR is 10 dB. The simulation results show that the achievable sum-rate of the proposed GA-AS+PA method, RAS+EPA method, RAS+PA method, and GA-AS+EPA method all increase as the number of antennas increases. We can also observe that our proposed GA-AS+PA method achieves higher sum-rate performance than the benchmark schemes. The GA-AS+PA method optimized both the antenna selection matrix and transmit power to improve the sum-rate. When the number of active antennas of the BS is small, the achievable sum-rate of the proposed method is close to the GA-AS+EPA method. With the increase in the number of antennas, the GA-AS+PA method has more obvious advantages than the GA-AS+EPA method and is close to the RAS+PA method. In other words, the effect of power allocation is more obvious when the number of antennas increases. When \( M_s = 180 \), the speed of the proposed method exceeds the EPA method. In general, the achievable sum-rate of system rate can increase by jointly optimizing the antenna selection matrix and transmit power allocation optimizing, and it is better than optimizing one of the variables alone.

Figure 3 shows the EE of the system of the five methods when the numbers of antennas increase. The number of users in each cell is 10. The average SNR is 10 dB. Except EPA, the EE of the rest four methods increases first and then decreases with the increasing of antennas number. And the proposed method is higher than the RAS+EPA method, RAS+PA method, and GA-AS+EPA method. It is known that the more antennas are activated, the more energy the system consumes. At the same time, it can be seen from Figure 2, the acceleration of the increase in the achievable sum-rate of the system will gradually slow down as the number of antennas increases. Therefore, the EE of the system shows a trend of first increasing and then decreasing, and there is a maximum EE. In addition, when \( M_s = 40 \), the EE of these four methods is higher than the EPA method.

Figure 4 shows the number of antennas required of the proposed GA-AS+PA method, RAS+EPA, RAS+PA, and GA-AS+EPA methods when the number of users \( K \)
increases. The average SNR is 10 dB. The simulation results show that the RAS+EPA method needs to activate the most antennas under the condition of the minimum achievable sum-rate limit of the system. Then, it follows the RAS+PA method and the GA-AS+EPA method. The number of active antennas required by these two methods is basically the same. Compared with the previous three methods, the proposed GA-AS+PA method has the least active antenna number. In other words, the proposed method activates fewer antennas under the same constraint conditions, thereby reducing energy consumption of system and improving the EE.

Figure 5 shows the EE of different methods relative to the number of user $K$, when the number of antennas required meets the constraints. The average SNR is 10 dB. The simulation results show that the EE of the RAS+PA method and the GA-AS+EPA method are basically the same when the number of users increases. The EE of the proposed GA-AS+PA method is higher than the RAS+EPA, RAS+PA, and GA-AS+EPA. It indicates that under the same constraints, the effect of joint optimization of transmit power and antenna selection matrix is better than optimizing one of the parameters alone. The proposed method can choose to activate a smaller number of antennas, which reduces the energy consumption and improves the EE of the system.

Figure 6 shows the achievable sum-rate of the five methods when the average SNR increases. The number of users in each cell is 10 and $M_5$ is 130. The simulation results show that the achievable sum-rate of these five methods all increase with the average SNR. When the average SNR is low, the achievable sum-rate of the proposed GA-AS+PA method, RAS+EPA method, RAS+PA method, and GA-AS+EPA method is close. As the average SNR increases, the achievable sum-rate of the proposed method is closer to the EPA method and higher than the RAS+EPA method, RAS+PA method, and GA-AS+EPA method. When SNR is 25 dB, the rates of these four methods basically no longer increase.

Figure 7 shows the EE of the five methods changing with the average SNR. The number of users in each cell is 10. $M_5$ is 130. The simulation results show that the system EE of these five methods first increases and then decreases when the average SNR increases. It can be seen from Figure 6 that the rate of increase of the achievable sum-rate will gradually slow down with the average SNR increases. Therefore, the EE shows a trend of first increasing and then decreasing, and there is a maximum EE. When the SNR is small, the EE of the proposed GA-AS+PA method is higher than the RAS+EPA method, RAS+PA method, and GA-AS+EPA method, and EPA method. When SNR > 20 dB, the EE of these five methods is basically the same. Because when the average SNR is large, the main factor affecting EE becomes the transmit power of BS.

Figure 8 shows the EE of the four methods changing with the sum-rate. The number of users in each cell is 10. The average SNR is 10 dB. The results show that the system EE of these four methods first increases and then decreases with the sum-rate. And the proposed method is higher than the RAS+EPA method, RAS+PA method, and GA-AS+EPA method. When the requirement of sum-rate is low, the rate will increase significantly as the number of antennas increases. When the rate becomes larger, more antennas need to be activated, which increases the power consumption of the BS, then reducing EE. So, the EE begins to decrease as the sum-rate increases. In the case of the same sum-rate, the proposed method can activate fewer antennas, reduce the energy consumption of the system, and improve the EE of the system.
From the results of sum-rate and the EE, the advantages of the proposed method are more obvious.

5. Conclusion

This paper proposes a GA-AS+PA method for EE optimization for the downlink of a multicell massive MIMO system under the consideration of the users’ sum-rate. First, the active transmitting antenna of each BS is selected using the GA. Then, the nonconvex constraint is transformed into convex through the Taylor series, and then, the optimal power allocation is obtained using convex optimization method. The result shows an optimal value of EE while changing the sum rate. The proposed GA-AS+PA method can reduce the number of activated antennas while meeting the requirements of the sum-rate when the average SNR is the same, thereby improving the EE of the system. Moreover, the EE of the GA-AS+PA method is improved by 33.3% compared to the EPA method, so the proposed methods can achieve higher EE under the conditions of different numbers of users.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The work is supported by the Science and Technology Innovation Fund Project of Shunde Graduate School, University of Science and Technology Beijing (No. BK20AF004).

References


