Maimaiti *et al. EURASIP Journal on Wireless Communications and Networking* (2019) 2019:208
https://doi.org/10.1186/s13638-019-1529-7

EURASIP Journal on Wireless Communications and Networking

RESEARCH

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A low-complexity algorithm for the joint antenna selection and user scheduling in multi-cell multi-user downlink massive MIMO systems

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Abstract

The massive MIMO (multiple-input multiple-output) technology plays a key role in the next-generation (5G) wireless communication systems, which are equipped with a large number of antennas at the base station (BS) of a network to improve cell capacity for network communication systems. However, activating a large number of BS antennas needs a large number of radio-frequency (RF) chains that introduce the high cost of the hardware and high power consumption. Our objective is to achieve the optimal combination subset of BS antennas and users to approach the maximum cell capacity, simultaneously. However, the optimal solution to this problem can be achieved by using an exhaustive search (ES) algorithm by considering all possible combinations of BS antennas and users, which leads to the exponential growth of the combinatorial complexity with the increasing of the number of BS antennas and active users. Thus, the ES algorithm cannot be used in massive MIMO systems because of its high computational complexity. Hence, considering the trade-off between network performance and computational complexity, we proposed a low-complexity joint antenna selection and user scheduling (JASUS) method based on Adaptive Markov Chain Monte Carlo (AMCMC) algorithm for multi-cell multi-user massive MIMO downlink systems. AMCMC algorithm is helpful for selecting combination subset of antennas and users to approach the maximum cell capacity with consideration of the multi-cell interference. Performance analysis and simulation results show that AMCMC algorithm performs extremely closely to ES-based JASUS algorithm. Compared with other algorithms in our experiments, the higher cell capacity and near-optimal system performance can be obtained by using the AMCMC algorithm. At the same time, the computational complexity is reduced significantly by combining with AMCMC.

Keywords: 5G, Massive MIMO systems, Antenna selection, User scheduling, Adaptive Markov chain Monte Carlo algorithm

1 Introduction

In order to satisfy the rapidly increasing requirements for high data rate in current wireless communication systems, a new massive MIMO (multiple-input multiple-output) technology was introduced in [1–3]. Massive MIMO technique plays a key role to enhance the cell capacity without increasing system bandwidth or base station (BS) transmission power for the 5G network systems [4]. The key idea of the massive MIMO technique is to install a large amount of transmit antennas at the BS of a cellular and provide services for several users sharing the same spectrum resources. However, as the number of BS antennas and users increases, the combination complexity and hardware cost also increase dramatically. Therefore, when the numbers of BS transmit antenna and active users are extremely large, the joint antenna selection and user scheduling (JASUS) algorithm [5–8] can be adopted as an approach to decide the radio frequency (RF) chain configuration to improve the cell capacity in multi-cell massive multi-user MIMO systems.

In a practical network, one of the key challenges in multi-cell multi-user massive MIMO systems is the

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hardware cost and power consumption because the element of each antenna needs a complete RF chain that consists of RF amplifiers and analog-to-digital converters, which are very pricey and are the main elements of the power consumption at the BS [9]. Different schemes were used in many types of research, such as hybrid precoding and spatial modulation, to reduce the cost of the hardware and the power consumption of the system [10]. One of the best schemes to solve this problem is to applying antenna selection [11–13] to decide optimal subset of BS transmit antennas for decreasing the required number of high pricey RF chains while decreasing the resulting network performance loss.

However, in multi-cell multi-user massive MIMO systems, only a limited number of transmit antennas are selected to provide services for active users scheduled. Hence, if the number of users exceeds, the number of selected transmit antennas, user scheduling must be performed because different wireless channels have different properties. High cell capacity can be obtained by scheduling users with the high channel quality. Therefore, the research of JASUS method for multi-cell multi-user massive MIMO systems is necessary.

Recently, only a few types of research have studied a low complexity JASUS for downlink massive multi-user MIMO systems. Benmimoune et al. [14] proposed a two-step JASUS scheme for downlink multi-user massive MIMO systems. It successively closed unnecessary antennas and removes undesired users which contribute little to system performance. However, due to the high computational complexity, this algorithm can only be employed to the scenarios with a smaller number of candidate antennas and user sets. Thus, using this algorithm in practical multi-cell multi-user massive MIMO system scenarios is difficult. Olyaee et al. [15] proposed a JASUS method based on zero-forcing (ZF) precoding algorithm for single-cell multi-user massive MIMO downlink systems. Though the ZF precoding method has a high system performance, it also has a very high computational complexity. For distributed downlink multi-user massive MIMO system, a JASUS method was proposed in [16] by Xu. et al. It successively obtains the majority of gain with limited backhaul capacity. Lee et al. [17] proposed a random antenna selection algorithm, the algorithm can provide significant capacity efficiency gain, but it is difficult to use for multi-cell multi-user massive MIMO systems. However, the above researches focused on single-cell multi-user massive MIMO systems. Thus, the research of JASUS method for multi-cell multi-user massive MIMO systems remains a largely open area. Therefore, the novel JASUS algorithm with considered multi-cell interference, which causes no or only a few decreases of system performance, represents a new promising research topic.

In this paper, we consider the problem of JASUS in multi-cell multi-user massive MIMO downlink system operating with TDD mode. Considering the trade-off between cell capacity and complexity, we proposed a low-complexity algorithm for JASUS method based on AMCMC. In our proposed method, only a small subset of BS transmit antennas is selected to serve predetermined active users, thus reduces the number of RF chains, avoids uneconomical hardware costs, and reduces power consumption caused by the selection of unnecessary transmit antennas to provide the required services. The main contributions of our work are as follows.

1. A low complexity JASUS method based on AMCMC algorithm is proposed for downlink multi-cell multi-user massive MIMO systems. AMCMC algorithm is helpful for selecting combination subset of antennas and users to approach the maximum cell capacity while decreasing the resulting network performance loss.
2. In this paper, we proposed updating rules for the selection probability of each base station transmit antenna and the scheduling probability for each user. In addition, we also proposed a new projection strategy to satisfy the constraints of antenna and user selection.
3. Performance analysis and simulation results show that our proposed algorithm produced promising results. Compared with ES-based JASUS algorithm, the proposed algorithm achieved comparable performance with low complexity. In addition, the AMCMC-based JASUS algorithm outperforms greedy-based JASUS and norm-based JASUS methods in terms of cell capacity and SER (symbol error rate) performance.

Notation: Symbol $\mathbb{C}$ denotes the set of complex numbers, vectors are denoted by using lower-case bold letters, matrices are denoted by using bold letters, $|.|$ denotes the absolute value of a scalar, $\|\cdot\|_F$ denotes the Frobenius norm function, and (.) represents the binomial coefficient.

The remaining content is organized as follows. In Section 2, the system model and capacity maximize problem formulation are described. In Section 3, we formulate the problem of JASUS method based on AMCMC in multi-cell multi-user massive MIMO systems. Section 4 presents the simulation setup and assumption. In Section 5, we discuss the simulation results and analyze the complexity; finally, this work is concluded in Section 6.

2 System model and problem formulation

In this part, we simply give the system model for multi-cell massive multi-user

MIMO downlink systems with the system capacity formulation model with consideration of the multi-cell interference.

2.1 System model

As shown in Fig. 1, the considered scenario is a multi-cell multi-user massive MIMO downlink system operating in TDD mode, and the cell capacity maximizing problem is studied with consideration of the inter-cell interference. The system is composed of B hexagonal cells. All B BSs, where $B = \{1, 2, \ldots, B\}$ are installed with M antennas and serves U $(M \geq U \geq 1)$ single-antenna users in each cell. The block-fading channel model is assumed. We assume that BS can select N transmit antennas among the M transmit antennas and schedule $K(K \leq N)$ users among the U users within the cell to be served simultaneously. The channel vector $\mathbf{g}_{iju} \in \mathbb{C}^M$ from the jth BS and user u in cell i can be expressed as

$$\mathbf{g}_{iju} = \sqrt{\beta_{iju}}\mathbf{h}_{iju} \tag{1}$$

where β_{iju} denotes the large scale channel fading between jth BS and user u in cell i, including shadowing and path loss. $\mathbf{h}_{iju}$ is the small-scale fading vector, and $\mathbf{h}_{iju} = [h_{iju1}, h_{iju2}, \ldots, h_{ijuM}]^T \in \mathbb{C}^M$. Then, the overall downlink transmission matrix $\mathbf{G}_{ij} \in \mathbb{C}^{M \times U}$ between the BS in cell j and all users in cell i can be expressed as

$$\mathbf{G}_{ij} = \left[\mathbf{g}_{ij1}, \mathbf{g}_{ij2}, \ldots, \mathbf{g}_{ijU}\right] = \mathbf{H}_{ij}\mathbf{D}_{ij}^{\frac{1}{2}} \in \mathbb{C}^{M \times U} \tag{2}$$

where $\mathbf{H}_{ij} = [\mathbf{h}_{ij1}, \mathbf{h}_{ij2}, \ldots, \mathbf{h}_{ijU}] \in \mathbb{C}^{M \times U}$ is the overall small-scale fading matrix and $\mathbf{D}_{ij} = \mathrm{diag}(\beta_{ij1}, \beta_{ij2}, \ldots, \beta_{ijU})$.

Our objective is to find optimum combinations subset of BS antennas and users to approach the maximum cell capacity while decreasing the resulting network performance loss. Furthermore, we will decrease the number of expensive RF chains and avoid the uneconomic costs of the hardware and decrease power consumption caused by selecting undesired antennas to provide the requirement of service.

2.2 Problem formulation

In the downlink system, the signal received by users in cell i can be written as

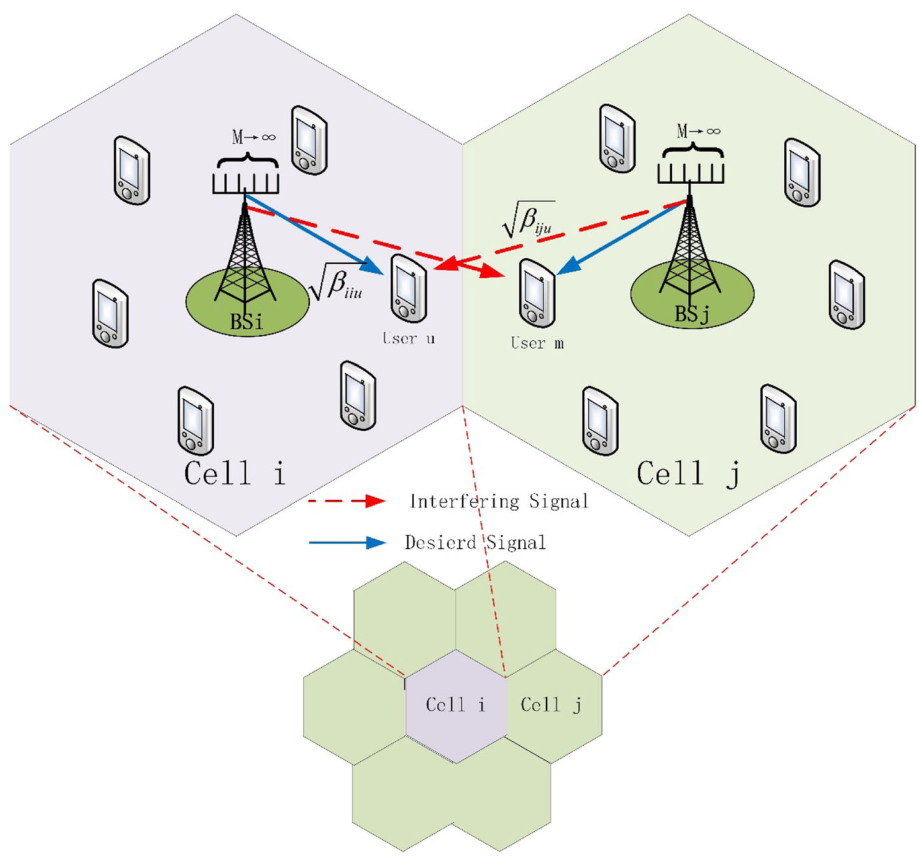

Fig. 1. Illustration of the downlink multi-cell multi-user massive MIMO network transmission model

$$\mathrm{r}_i = \sqrt{p_t}\sum_{j=1}^{\mathrm{B}} \mathbf{G}_{ij}^H \mathbf{W}_j s_j + \mathbf{n}_i \tag{3}$$

where p_t denotes the transmitted power, $\mathbf{s}_j = [\mathrm{s}_{j1}, \mathrm{s}_{j2}, \ldots, \mathrm{s}_{jU}]^T \in \mathbb{C}^U$ is the transmit signals for users in cell j, $\mathbf{W}_j \in \mathbb{C}^{M\times U}$ is the precoding matrix of BS in cell j, and $\mathbf{n}_i = [n_{i1}, n_{i2}, \ldots, n_{iu}]^T \in \mathbb{C}^U$ is the noise vector at the uth user in cell i. The downlink signal received by user u in cell i can be written as

$$r_{iu} = \underbrace{\sqrt{p_t}\mathbf{g}_{iiu}^H \mathbf{w}_{iu} s_{iu}}_{\text{desired signal}} + \underbrace{\sqrt{p_t}\sum_{b\neq u} \mathbf{g}_{iib}^H \mathbf{w}_{ib} s_{ib}}_{\text{intra-cell interference}} + \underbrace{\sqrt{p_t}\sum_{j\neq i}\sum_{b=1}^{U} \mathbf{g}_{iju}^H \mathbf{w}_{jb} s_{jb}}_{\text{inter-cell interference}} + n_{iu} \tag{4}$$

where $\mathbf{w}_{jb}$ is the bth column of precoding matrix $\mathbf{W}_j$. Formula (4) including the desired signal for the user u in cell i, intra-cell interference signal (comes from other users in the same cell), and inter-cell interference signal (comes from other cells), respectively.

Since we used the zero-forcing (ZF) methods and supposing that the channel state information (CSI) is perfectly known at the BS, the intra-cell interference signal (second term) in function (4) drops to zero according to prevenient works [14, 18–20]. Therefore, function (4) becomes

$$r_{iu} = \underbrace{\sqrt{p_t}\mathbf{g}_{iiu}^H \mathbf{w}_{iu} s_{iu}}_{\text{desired signal}} + \underbrace{\sqrt{p_t}\sum_{j\neq i}\sum_{b=1}^{U} \mathbf{g}_{iju}^H \mathbf{w}_{jb} s_{jb}}_{\text{inter-cell interference}} + n_{iu} \tag{5}$$

We assume that BS can choose N transmit antennas among the M transmit antennas, and schedule $K (K \leq N)$ users among the U users within the cell to be served simultaneously. For convenience, we give the selected subset of the antenna and scheduled subset of user indicator functions are $\boldsymbol{\omega}$ and $\overline{\boldsymbol{\varpi}}$,

$$\boldsymbol{\omega} = \{\omega_m\}_{m=1}^{M} \tag{6}$$

$$\overline{\boldsymbol{\varpi}} = \{\varpi_u\}_{u=1}^{U} \tag{7}$$

where $\boldsymbol{\omega}$ and $\overline{\boldsymbol{\varpi}}$ are binary vectors that include two values 0 and 1 to indicate if a given antenna or a given user is selected. (e.g., 1 → selected, 0 → unselected).

For making an easy description, we will define to two indicator functions, which are $I_m(\boldsymbol{\omega}) \triangleq \omega_m \in \{0, 1\}$ and $I_u(\overline{\boldsymbol{\varpi}}) \triangleq \varpi_u \in \{0, 1\}$, respectively. We use these to indicate whether the mth BS antenna and the uth user are selected or not, respectively. $\mathbf{s}_{i\{\overline{\boldsymbol{\varpi}}\}} \in \mathbb{C}^K$ denotes transmit signal vector, sub-block channel matrix of corresponding denotes by $\mathbf{G}_{ij\{\overline{\boldsymbol{\varpi}},\, \boldsymbol{\omega}\}} \in \mathbb{C}^{N\times K}$ and $\mathbf{n}_{i\{\overline{\boldsymbol{\varpi}}\}} \in \mathbb{C}^K$ is noise vector, respectively. Finally, in order to denote the joint antenna and user selection, we employ the 2-tuple $\boldsymbol{\Omega} \triangleq (\overline{\boldsymbol{\varpi}}; \boldsymbol{\omega})$. In order to have an easy explanation, we will interchangeably use $\boldsymbol{\Omega}$ and $(\overline{\boldsymbol{\varpi}}; \boldsymbol{\omega})$ for the following part. After using antenna selection and user scheduling method, function (5) becomes

$$\begin{aligned} \mathrm{r}_{i\{\varpi_u\}} = {} & \sqrt{p_t}\mathbf{g}_{ii\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}^H \mathbf{w}_{i\{\varpi_u\}} s_{i\{\varpi_u\}} \\ & + \sqrt{p_t}\sum_{j\neq i}\sum_{b=1}^{U} \mathbf{g}_{ij\{\overline{\boldsymbol{\varpi}},\omega\}}^H \mathbf{w}_{j\{\varpi_b\}} s_{j\{\varpi_b\}} \\ & + n_{i\{\varpi_u\}} \end{aligned} \tag{8}$$

where $\mathbf{w}_{j\{\varpi_b\}}$ is bth column of precoding matrix $\mathbf{W}_{j\{\overline{\boldsymbol{\varpi}},\, \boldsymbol{\omega}\}} \in \mathbb{C}^{N\times K}$ and $n_{i\{\varpi_u\}}$ is the noise at the uth user in cell i.

2.3 Capacity of massive MIMO

According to the aforementioned discussion, the received signal-to-interference-plus-noise ratio (SINR) for the user $u \in U$ (which is connected to cell i) with a selected channel vector $\mathbf{g}_{ij\{\overline{\boldsymbol{\varpi}},\, \boldsymbol{\omega}\}}$ can be written as

$$\mathrm{SINR}_{i\{\varpi_u\}} = \frac{p_t \left|\mathbf{g}_{ii\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}^H \mathbf{w}_{i\{\varpi_u\}}\right|^2}{\sum_{j\neq i} p_t \left|\mathbf{g}_{ij\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}^H \mathbf{w}_{j\{\varpi_u\}}\right|^2 + \left|n_{i\{\varpi_u\}}\right|^2} \tag{9}$$

Considering the inter-cell interference, the formula of sum capacity for cell i can be expressed as

$$C_{\mathrm{sum}}^i\left(\mathbf{G}_{\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}\right) = \log_2\left(\det\left(I + \frac{p_t\left|\mathbf{G}_{ii\{\overline{\boldsymbol{\varpi}},\omega\}}^H \mathbf{W}_{i\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}\right|^2}{\sum_{j\neq i} p_t \left|\mathbf{G}_{ij\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}^H \mathbf{W}_{j\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}\right|^2 + \mathbf{n}_{i\{\overline{\boldsymbol{\varpi}}\}}\mathbf{n}_{i\{\overline{\boldsymbol{\varpi}}\}}^H}\right)\right) \tag{10}$$

Our target is to jointly select the optimal combination sets of BS transmit antenna and active user to approach the maximum cell capacity while decreasing the computational complexity. Hence, the problem of JASUS can be written as

$$\Phi_C = \underset{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}}{\text{maximize}}\; C_{\mathrm{sum}}^i\left(\mathbf{G}_{\{\overline{\boldsymbol{\varpi}},\boldsymbol{\omega}\}}\right) \tag{11}$$

subject to

$$\sum_{u=1}^{U} I_u(\overline{\boldsymbol{\varpi}}) = K \tag{12}$$

$$\sum_{m=1}^{M} I_m(\boldsymbol{\omega}) = N \tag{13}$$

Addressing the aforementioned problem by employing an ES method needs to evaluating the cell capacity of

$\phi \triangleq C_M^N \times C_U^K$ joint antenna and user combinations, where C_M^N and C_U^K are the binomial coefficient. This fact indicates that the ES method cannot be used in current the massive MIMO systems where U and M are very numerous, it leads to high computational complexity. Thus, a low complexity algorithm for JASUS is needed in order to obtain the best network performance with low computational complexity.

Obviously, formula (11) serves as the target function in this study. Therefore, address the problem (11) in multi-cell multi-user massive MIMO systems, we need to solve the following three main problems:

1. Inter-cell interference: the first problem is the inter-cell interference coming from other cells. In order to solve this problem, cells can adjust their precoding matrices, thus can eliminate or decrease the interference from all users. In order to make better use of the coordinated massive MIMO technology, a group of users in the cells should be scheduled so that each group of users in the cell has the biggest spatial separation with the interference channels of users in neighboring cells.
2. Computational complexity: the second problem is how to obtain the best combination subset of antenna and user in each cell with lower computational complexity so as to decrease or eliminate the inter-cell interference and maximize the sum capacity of all cells. We know that in multi-cell massive MIMO systems, the various path loss between the antennas coming from neighboring cells and users coming from target cell also bring to much computational complexity same to the antenna selection and user scheduling. Thus, the computational complexity of the ES algorithm becomes very large than of a single-cell JASUS.
3. CSI feedback cost: for massive MIMO systems, the perfect CSI feedback depends mainly on the number of active antennas and the users they support. Hence, in order to centralize processing for selecting antennas and scheduling users across cells, the BS needs to exchange the overall CSI of overall combined subset antennas and users at each scheduling period, it brings more burden for BS. In addition, when the number of BS antennas and users in each cell increases, the cost of CSI increases accordingly.

On the base of the aforementioned discussion, a low complexity scheme is needed from the practical point of view for JASUS in multi-cell multi-user massive MIMO scenarios to reduce the complexity of function (11) while decreasing the cost of the CSI feedback.

3 Joint antenna selection and user scheduling algorithm

In this part, we presented two suboptimal iterative algorithms for JASUS before a discussion of the proposed AMCMC method.

3.1 Norm-based JASUS algorithm

Firstly, we presented a norm-based JASUS method for addressing the objective function (10). The norm-based JASUS scheme maximizes $\|\mathbf{G}_{\{\overline{\boldsymbol{\omega}},\,\boldsymbol{\omega}\}}\|_F$, where $\|.\|_F$ is the Frobenius norm function. Let $C_{\text{sum}}^{\text{NB}}(\mathbf{G}_{\{\overline{\boldsymbol{\omega}},\,\boldsymbol{\omega}\}}) = \|\mathbf{G}_{\{\overline{\boldsymbol{\omega}},\,\boldsymbol{\omega}\}}\|_F$. This scheme including initialization step and iterative updating step, respectively. This both steps use the vector norm as criteria which considerably decrease each iterative computation complexity. The norm-based JASUS problem is modeled as

$$\omega_{\text{NB}} = \underset{\overline{\boldsymbol{\omega}},\boldsymbol{\omega}}{\arg\max} \quad C_{\text{sum}}^{\text{NB}}\left(\mathbf{G}_{\{\overline{\boldsymbol{\omega}},\boldsymbol{\omega}\}}\right) \tag{14}$$

where ω_{NB} is the combination selection indicator. Nevertheless, it has still a problem that when performing transmit antenna selection and user scheduling simply based on the F-norm criteria, it would sacrifice some cell capacity. In sum, the norm-based JASUS method has extremely low complexity, but it cannot guarantee a high sum capacity performance.

3.2 Greedy-based JASUS algorithm

In order to enhance the cell capacity over norm-based JASUS, we presented a greedy-based JASUS algorithm. Unlike to the norm-based JASUS algorithm, the greedy-based JASUS algorithm maximizes the cell capacity in each step. This method also includes initialization step and iterative updating step. The greedy-based JASUS problem is modeled as

$$\omega_{\text{GR}} = \underset{\overline{\boldsymbol{\omega}},\boldsymbol{\omega}}{\arg\max} \quad C_{\text{sum}}^{\text{GR}}\left(\mathbf{G}_{\{\overline{\boldsymbol{\omega}},\boldsymbol{\omega}\}}\right) \tag{15}$$

where ω_{GR} is the combination selection indicator. Compared with the norm-based JASUS algorithm, this method has a good capacity performance, but it has high computational complexity.

3.3 AMCMC-based JASUS algorithm

Although the greedy-based JASUS method improved the cell capacity, it ignores the computational complexity of all system. For the actual network communication system, it will not have commercial value or attraction. Hence, considering the trade-off between cell capacity and complexity, we proposed a low-complexity JASUS method based on AMCMC algorithm and its description is as follows.

MCMC [21] is a method of generating random samples, which is often used to calculate statistical estimation, marginal probability, and conditional probability. MCMC algorithms depend on (Markov) sequences with limit distributions corresponding to interest distributions. In the past decades, it has been widely used in many fields such as engineering and statistics [22]. The key idea of the MCMC method is that Markov chains are simulated in state space X, and the stable distribution of the chains is the target distribution π [23].

In order to address our objection problem in (11), we must tackle tow essential issues when applying AMCMC algorithm. The first problem is how to provide a proposal distribution of candidate samples L_{MCMC}. The second problem is how to design the most suitable updating rule for the proposal distribution.

3.3.1 Derivation of the candidate sampling distribution for the MCMC method

The biggest advantage of the MCMC method is that it can search the "elite samples" instead of exhaustively searching the whole samples. At iteration t, the samples $\{\boldsymbol{\Omega}_{\ell,t}=\{\overline{\boldsymbol{\omega}}_{\ell,t},\boldsymbol{\omega}_{\ell,t}\}\}_{\ell=1}^{L_{\mathrm{MCMC}}}$ from an MCMC method can be employed to estimate the maximum value of the target function $C_{\mathrm{sum}}^{i}(\mathbf{G}_{\{\overline{\boldsymbol{\omega}},\,\boldsymbol{\omega}\}})$

$$\Phi_C^* = \underset{\boldsymbol{\Omega}_{\ell,t}\triangleq\left(\overline{\boldsymbol{\omega}}_{\ell,t};\boldsymbol{\omega}_{\ell,t}\right);\quad \ell=1,2,\ldots,L_{\mathrm{MCMC}}}{\arg\max} C_{\mathrm{sum}}^{i}\left(\mathbf{G}_{\left\{\overline{\boldsymbol{\omega}}_{\ell,t},\boldsymbol{\omega}_{\ell,t}\right\}}\right) \tag{16}$$

where L_{MCMC} denotes the total number of samples, and Φ_C^* is the estimated value of formula (11).

Given that scheduled of per user ϖ_u and selection of each antenna ω_m are binary variables, we use the Boltzmann distribution of the objective function $C_{\mathrm{sum}}^{i}(\mathbf{G}_{\{\overline{\boldsymbol{\omega}}_{\ell,t},\boldsymbol{\omega}_{\ell,t}\}})$ with a suitable temperature τ

$$\underset{\boldsymbol{\Omega}_{\ell,t}\triangleq\left(\overline{\boldsymbol{\omega}}_{\ell,t},\boldsymbol{\omega}_{\ell,t}\right)}{\pi\left(\boldsymbol{\Omega}_{\ell,t}\right)} = \frac{\exp\left\{\left(C_{\mathrm{sum}}^{i}\left(\boldsymbol{\Omega}_{\ell,t}\right)/\tau\right)\right\}}{\Gamma} \tag{17}$$

where $\Gamma=\sum_{\boldsymbol{\Omega}_{\ell,t}\triangleq(\overline{\boldsymbol{\omega}}_{\ell,t},\boldsymbol{\omega}_{\ell,t})}\exp\{(C_{\mathrm{sum}}^{i}(\boldsymbol{\Omega}_{\ell,t})/\tau)\}$ is a normalization constant in the MCMC method that can be neglected. Thus, maximizing $C_{\mathrm{sum}}^{i}(\boldsymbol{\Omega}_{\ell,t})$ is equivalent to maximizing $\pi(\boldsymbol{\Omega}_{\ell,\ t})$, and $\pi(\boldsymbol{\Omega}_{\ell,\ t})$ is the target distribution.

In order to prove the MCMC method for searching the distribution $\pi(\boldsymbol{\Omega}_{\ell,\ t})$, we use a MIS (metropolized independence sampler) [23], which is a generic MCMC method. The step is as follow. An initial value $\boldsymbol{\Omega}_{[0],\ t}$ is chosen randomly. Given the current sample $\boldsymbol{\Omega}_{[\ell],\ t}$,

- A candidate sample $\boldsymbol{\Omega}_{[\mathrm{new}],\ t}$ is drawn from proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,\ t}; \mathbf{R}_{t-1})$.
- Simulate u uniform[0, 1], and according to the accepting probability $\alpha(\boldsymbol{\Omega}_{[\ell],\ t}, \boldsymbol{\Omega}_{[\mathrm{new}],\ t})$, let

$$\boldsymbol{\Omega}_{[\ell+1],t} = \begin{cases} \boldsymbol{\Omega}_{[\mathrm{new}],t} & \text{if} \quad u\le\alpha\left(\boldsymbol{\Omega}_{[\ell],t},\boldsymbol{\Omega}_{[\mathrm{new}],t}\right) \\ \boldsymbol{\Omega}_{[\ell],t} & \text{otherwise} \end{cases} \tag{18}$$

Where

$$\alpha\left(\boldsymbol{\Omega}_{[\ell],t},\boldsymbol{\Omega}_{[\mathrm{new}],t}\right) = \min\left\{1,\frac{\pi\left(\boldsymbol{\Omega}_{[\mathrm{new}],t}\right)/\Psi\left(\boldsymbol{\Omega}_{[\mathrm{new}],t}\right)}{\pi\left(\boldsymbol{\Omega}_{[\ell],t}\right)/\Psi\left(\boldsymbol{\Omega}_{[\ell],t}\right)}\right\} \tag{19}$$

After L_{MCMC} iterations, we can achieve a set of samples $\left\{\boldsymbol{\Omega}_{[0],t},\boldsymbol{\Omega}_{[1],t},\ldots,\boldsymbol{\Omega}_{[L_{\mathrm{MCMC}}],t}\right\}$, which is subjected to distribution $\pi(\boldsymbol{\Omega}_{\ell,\ t})$.

3.3.2 Derivation of updating rule for the AMCMC algorithm

In this part, we provide updating rule for the proposal distribution. For the AMCMC method, the joint proposal distribution is proportional to the product of Bernoulli distributions, namely

$$\Psi\left(\boldsymbol{\Omega}_{\ell,t};\mathbf{R}_{t-1}\right)\triangleq\underbrace{\frac{\prod_{u=1}^{U}p_{u,t-1}^{I_u\left(\overline{\boldsymbol{\omega}}_{\ell,\ t}\right)}\left(1-p_{u,t-1}\right)^{1-I_u\left(\overline{\boldsymbol{\omega}}_{\ell,\ t}\right)}}{\Gamma'}}_{\triangleq\Psi\left(\overline{\boldsymbol{\omega}}_{\ell,\ t};\mathbf{P}_{t-1}\right)} \times\underbrace{\frac{\prod_{m=1}^{M}g_{m,t-1}^{I_m\left(\boldsymbol{\omega}_{\ell,\ t}\right)}\left(1-g_{m,t-1}\right)^{1-I_m\left(\boldsymbol{\omega}_{\ell,\ t}\right)}}{\Gamma'}}_{\triangleq\Psi\left(\boldsymbol{\omega}_{\ell,\ t};\mathbf{g}_{t-1}\right)} \tag{20}$$

where p_u denotes the probability of the uth user being selected for communicating with the BS. That is, $\varpi_u \sim \mathrm{Ber}(p_u)$ for $u = 1, 2, \ldots,$ U, and g_m is the probability of the mth BS antenna being selected. That is, $\omega_m \sim \mathrm{Ber}(\mathrm{g}_m)$ for $m = 1, 2, \ldots,$ M. We use the indicator functions $I_m(\boldsymbol{\omega}_{\ell,\ t})$ and $I_u(\overline{\boldsymbol{\omega}}_{\ell,t})$ to indicate whether the mth BS antenna and the uth user are selected or not, respectively. $\mathbf{R}_{t-1} \triangleq \{\mathbf{P}_{t-1}, \mathbf{g}_{t-1}\}$, where $\mathbf{P}_t=\{p_{u,t}\}_{u=1}^{U}$, $\mathbf{g}_t=\{\mathrm{g}_{m,t}\}_{m=1}^{M}$, and Γ' is a normalization constant that can be ignored in the AMCMC. The adaptation scheme is employed to adjust the parameterized proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,\ t}; \mathbf{R}_{t-1})$ and minimize the Kullback-Leibler divergence [24, 25] between the target distribution $\pi(\boldsymbol{\Omega}_{\ell,\ t})$ and the proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,\ t}; \mathbf{R}_{t-1})$, namely

$$D\left[\pi\left(\boldsymbol{\Omega}_{\ell,t}\right)\middle\|\Psi\left(\boldsymbol{\Omega}_{\ell,t};\mathbf{R}_{t-1}\right)\right] = \sum_{\ell=1}^{L_{\mathrm{MCMC}}}\pi\left(\boldsymbol{\Omega}_{\ell,t}\right)\times\log\left(\frac{\pi\left(\boldsymbol{\Omega}_{\ell,t}\right)}{\Psi\left(\boldsymbol{\Omega}_{\ell,t};\mathbf{R}_{t-1}\right)}\right) \tag{21}$$

It is observed that $\tilde{D} = \pi(\boldsymbol{\Omega}_{\ell,t}) \times \log\pi(\boldsymbol{\Omega}_{\ell,t}) - D[\pi(\boldsymbol{\Omega}_{\ell,t}) \| \Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1})]$ is a convex function [26]. Hence, the minimization of the Kullback-Leibler divergence $D[\pi(\boldsymbol{\Omega}_{\ell,t}) \| \Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1})]$ w.r.t. $\mathbf{R}$ can be achieved when $\partial\tilde{D}/\partial\mathbf{R} = 0$. Thus, $\tilde{D}$ can be written as

$$\tilde{D} = \sum_{\ell=1}^{L_{\mathrm{MCMC}}} \pi\left(\boldsymbol{\Omega}_{\ell,t}\right) \times \log\Psi\left(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1}\right) \tag{22}$$

We set the partial derivative of (22) to zero with respect to $\mathbf{R}$. Then, the Eq. (22) can be written as

$$\frac{\partial}{\partial\mathbf{R}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} \pi\left(\boldsymbol{\Omega}_{\ell,t}\right) \times \log\Psi\left(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1}\right) = 0 \tag{23}$$

where the partial derivatives of $\log\Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1})$ with respect to p_u and g_m are respectively given by

$$\frac{\partial}{\partial p_u} \log\Psi\left(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1}\right) = \frac{I_u\left(\overline{\boldsymbol{\omega}}_{\ell,t}\right) - p_{u,t-1}}{\left(1 - p_{u,t-1}\right)p_{u,t-1}} \tag{24}$$

$$\frac{\partial}{\partial g_m} \log\Psi\left(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1}\right) = \frac{I_m\left(\boldsymbol{\omega}_{\ell,t}\right) - g_{\mathrm{m},t-1}}{\left(1 - g_{\mathrm{m},t-1}\right)g_{\mathrm{m},t-1}} \tag{25}$$

By substituting (24) and (25) into (23), we obtain

$$\sum_{\ell=1}^{L_{\mathrm{MCMC}}} \pi\left(\boldsymbol{\Omega}_{\ell,t}\right) \times \frac{I_u\left(\overline{\boldsymbol{\omega}}_{\ell,t}\right) - p_{u,t-1}}{\left(1 - p_{u,t-1}\right)p_{u,t-1}} = 0 \quad \text{for} \quad u = 1, 2, \ldots, U \tag{26}$$

$$\sum_{\ell=1}^{L_{\mathrm{MCMC}}} \pi\left(\boldsymbol{\Omega}_{\ell,t}\right) \times \frac{I_m\left(\boldsymbol{\omega}_{\ell,t}\right) - g_{\mathrm{m},t-1}}{\left(1 - g_{\mathrm{m},t-1}\right)g_{\mathrm{m},t-1}} = 0 \quad \textit{for} \quad m = 1, 2, \ldots, M \tag{27}$$

Given a number of samples $\{\boldsymbol{\Omega}_{\ell,t} = \{\overline{\boldsymbol{\omega}}_{\ell,t}, \boldsymbol{\omega}_{\ell,t}\}\}_{\ell=1}^{L_{\mathrm{MCMC}}}$ drawn from target distribution $\pi(\boldsymbol{\Omega}_{\ell,t})$, the Monte Carlo estimate of $\partial\tilde{D}/\partial p_u$ and $\partial\tilde{D}/\partial g_m$ are

$$\frac{1}{L_{\mathrm{MCMC}}} \left[\frac{1}{\left(1 - p_{u,t-1}\right)p_{u,t-1}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} I_u\left(\overline{\boldsymbol{\omega}}_{\ell,t}\right) - p_{u,t-1} \right] \tag{28}$$

$$\frac{1}{L_{\mathrm{MCMC}}} \left[\frac{1}{\left(1 - g_{\mathrm{m},t-1}\right)g_{\mathrm{m},t-1}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} I_m\left(\boldsymbol{\omega}_{\ell,t}\right) - g_{\mathrm{m},t-1} \right] \tag{29}$$

Applying the Robbins-Monro stochastic approximation scheme [26], we can achieve the recursive update function to close to the root of $\partial\tilde{D}/\partial p_u = 0$ and $\partial\tilde{D}/\partial g_m = 0$, namely

$$p_{u,t} = p_{u,t-1} + \frac{r_t}{\left(1 - p_{u,t-1}\right)p_{u,t-1}} \times \left(\frac{1}{L_{\mathrm{MCMC}}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} I_u\left(\overline{\boldsymbol{\omega}}_{\ell,t}\right) - p_{u,t-1} \right) \tag{30}$$

$$g_{\mathrm{m},t} = g_{\mathrm{m},t-1} + \frac{r_t}{\left(1 - g_{\mathrm{m},t-1}\right)g_{\mathrm{m},t-1}} \times \left(\frac{1}{L_{\mathrm{MCMC}}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} I_m\left(\boldsymbol{\omega}_{\ell,t}\right) - g_{\mathrm{m},t-1} \right) \tag{31}$$

where r_t denotes the sequence of decreasing step sizes [27]. In addition, we can simplify formulas (30) and (31), because $(1 - p_{u,\ t-1})p_{u,\ t-1}$ and $(1 - g_{\mathrm{m},\ t-1})g_{\mathrm{m},\ t-1}$ has no significant impact on the convergence of (30) and (31). Hence, Eqs. (30) and (31) becomes

$$p_{u,t} = p_{u,t-1} + r_t \times \left(\frac{1}{L_{\mathrm{MCMC}}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} I_u\left(\overline{\boldsymbol{\omega}}_{\ell,t}\right) - p_{u,t-1} \right) \tag{32}$$

$$g_{\mathrm{m},t} = g_{\mathrm{m},t-1} + r_t \times \left(\frac{1}{L_{\mathrm{MCMC}}} \sum_{\ell=1}^{L_{\mathrm{MCMC}}} I_m\left(\boldsymbol{\omega}_{\ell,t}\right) - g_{\mathrm{m},t-1} \right) \tag{33}$$

The updated proposal distribution Eqs. (32) and (33) are iteratively used with the objective to close to the target distribution.

3.4 Constraints for the AMCMC-based JASUS problem

For the JASUS problem, the vectors $\overline{\boldsymbol{\omega}}$ and $\boldsymbol{\omega}$ are subject to constraint functions (12) and (13), respectively. However, employing functions (32) and (33) with MIS to generate samples, but we cannot ensure that the samples meet the constraints (12) and (13). In order to ensure that the samples drawn from (32) and (33) meet the constraints (12) and (13), we propose a new projection strategy. For convenience, we only introduce the proposed projection strategy for $\boldsymbol{\omega}$ because the similar projection strategy can be used to $\overline{\boldsymbol{\omega}}$.

Assume the sample $\boldsymbol{\omega}_{\ell,\ t}$ drawn from $\Psi(\cdot; \mathbf{g}_{t-1})$ at the tth iteration. We define the two sets, which are $\phi_0 = \{\mathrm{m} : I_m(\boldsymbol{\omega}_{\ell,\ t}) = 0\}$ and $\phi_1 = \{\mathrm{m} : I_m(\boldsymbol{\omega}_{\ell,\ t}) = 1\}$, respectively. We use these to collect the indices for the unselected and selected BS antennas, respectively. The following projection strategy is applied if $\sum_{m=1}^{M} I_m\left(\boldsymbol{\omega}_{\ell,t}\right) \neq N$:

- If $\sum_{m=1}^{M} I_m\left(\boldsymbol{\omega}_{\ell,t}\right) < N$, then the proposed projection strategy sequentially selects the BS antenna with the biggest probability from the set ϕ_0 to the set ϕ_1 until

$|\phi_1| = N$, where ϕ_1 is the number of elements of the set ϕ_1.

- If $\sum_{m=1}^{M} I_m(\boldsymbol{\omega}_{\ell,t}) > N$, then the BS antennas with the smallest probability in the set ϕ_1 are closed sequentially according to the proposed projection strategy until $|\phi_1| = N$.

3.5 Convergence analysis for the AMCMC-based JASUS algorithm

In order to obtain a higher convergence rate, the probability parameters $\mathbf{R}_{t-1}$ of the proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1})$ are adjusted. In this paper, we use literature [28] to explain the convergence problem, because our proposed method gives a similar description of the convergence problem and proves the effectiveness of the method through analysis. Besides, the complexity of the MCMC algorithm has been proved to be only related to sample size L_{MCMC} in [22]. The proposed adaptive strategy requires less sample size and iteration times, which can significantly improve the convergence speed of the MCMC algorithm.

3.6 Constrained AMCMC-based JASUS algorithm

On the base of the aforementioned discussion, we can be written the proposed AMCMC-based JASUS algorithm by the following steps. At iteration t, L_{MCMC} samples $\{\boldsymbol{\Omega}_{\ell,t} = \{\overline{\boldsymbol{\omega}}_{\ell,t}, \boldsymbol{\omega}_{\ell,t}\}\}_{\ell=1}^{L_{\text{MCMC}}}$ from the MCMC method are can be generated by employing MIS according to proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1})$. Then, the new proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_t)$ will be updated by the Kullback-Leibler divergence until it approach the target distribution $\pi(\boldsymbol{\Omega}_{\ell,t})$. The detailed AMCMC-based JASUS algorithm is described as follows.

Algorithm 1 : AMCMC-based JASUS algorithm

Step1: initialize $\mathbf{R}_0 \triangleq \{\mathbf{P}_0, \mathbf{g}_0\}$. Then, let $\boldsymbol{\Omega}_{[0],\text{t}} = \max\limits_{\boldsymbol{\Omega}_{\ell,t} \triangleq (\overline{\boldsymbol{\omega}}_{\ell,t}; \boldsymbol{\omega}_{\ell,t})} C_{sum}^{i}(\boldsymbol{\Omega}_{\ell,t})$, after that, let $\Phi_C^* = \boldsymbol{\Omega}_{[0],\text{t}}$ and set $\mathbf{P}_0 = \{\text{p}_{u,0}\}_{u=1}^{U}$ with $\text{p}_{u,0} = 1/2$ and set $\mathbf{g}_0 = \{\text{g}_{m,0}\}_{m=1}^{M}$, where $g_{\text{m},0} = 1/2$ for density function $\Psi(\boldsymbol{\Omega}_{\ell}; \mathbf{R}_{[0]})$, respectively. Set t :=1.

Step2: we use proposal distribution $\Psi(\boldsymbol{\Omega}_{\ell,t}; \mathbf{R}_{t-1})$ to draw a small set of samples $\{\boldsymbol{\Omega}_{\ell,t} = \{\overline{\boldsymbol{\omega}}_{\ell,t}, \boldsymbol{\omega}_{\ell,t}\}\}_{\ell=1}^{L_{MCMC}}$ from the target function $\pi(\boldsymbol{\Omega}_{\ell,t})$ and guarantee that each sample $\boldsymbol{\Omega}_{\ell,t} = \{\overline{\boldsymbol{\omega}}_{\ell,t}, \boldsymbol{\omega}_{\ell,t}\}$ is feasible by using the our proposed projection strategy introduced in Section 3.4.

Step3: update $\mathbf{R}_t = \{\mathbf{P}_t, \mathbf{g}_t\}$, where $\mathbf{P}_t = \{p_{u,t}\}_{u=1}^{U}$ and $\mathbf{g}_t = \{\text{g}_{\text{m},t}\}_{m=1}^{M}$ via formula (32) and (33).

Step4: if $\pi(\boldsymbol{\Omega}_{\ell,t}) > \pi(\Phi_C^*)$ for $\ell = 1, 2, ..., \text{L}_{MCMC}$, then $\Phi_C^* = \Phi_C^{(\ell)}$.

Step5: stop this simulation when the predefined maximum number of iterations is satisfied; otherwise, set $t := t + 1$, and go back to Step 2.

4 Simulation configuration

In this section, the simulation configuration and simulation parameters are described. The considered scenario is a multi-cell multi-user massive MIMO downlink system operating in TDD mode with $B = 7$, as shown in Fig. 2. The simulation is done with a static network simulator. The key simulation parameters are summarized in Table 1. In this simulation, we assume that the CSI is perfectly known at the transmitter, the total power is uniformly allocated among the transmit antennas. The system composed of B hexagonal cells. All B BSs, where $B = \{1, 2, \ldots, B\}$ are installed with M antennas and serve U single-antenna users in each cell. Each BS is located at the cell center while U single-antenna users are randomly located in the cell. There is no user movement and handover during the simulation process.

5 Simulation results and analysis

In this section, we provide numerical results and computational complexity analysis of the proposed algorithm by simulative evaluation.

5.1 Performance evaluation

As can be seen the result from Fig. 3, the multi-cell multi-user massive MIMO downlink system using different JASUS method at various SINR. We find that the sum capacity of the AMCMC-based JASUS algorithm is very close to the maximum capacity result obtained by the ES-based JASUS algorithm with a wide range of SINRs. For example, when the SINR is 20 dB, the achieved values of cell capacity by using ES and AMCMC algorithms are

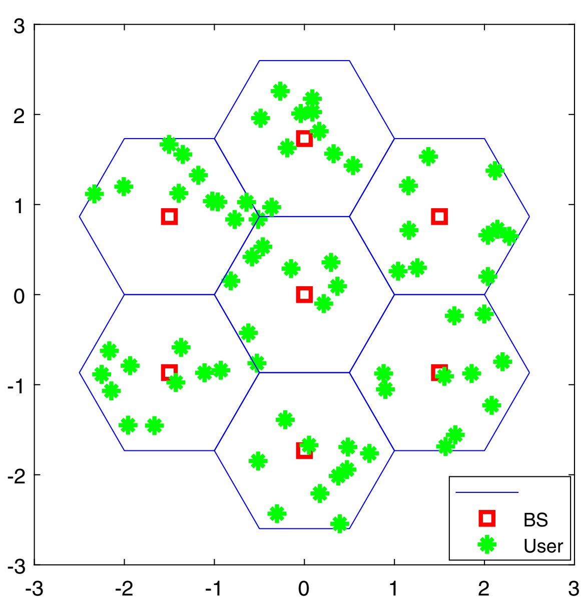

Fig. 2 Multi-cell multi-user massive MIMO system with $B = 7$ and $K = 10$

Table 1 Simulation parameters setting

Parameters	Values
No. of cells in the simulation B	7
Average no. of UEs in one cell	$2 \leq U \leq 50$
Number of BS antennas M	$10 \leq M \leq 64$
Inter-site distance	500 m
Cell radius	295 m
Path loss	$128.1 + 37.6 \times \log_{10}$(distance(km))[dB]
Each BS transmission power	10 dB
Shadowing standard derivation	7 dB
Noise spectral density	− 174 dBm/Hz
Users' speed	0
System bandwidth	20 MHz

50.7 and 49.9 b/s/Hz, respectively. Ninety-eight percent of the optimal capacity is obtained by our proposed method. The result shows that the AMCMC-based JASUS method has a good performance compared to the greedy-based JASUS method with the wide range of SINRs, both AMCMC-based JASUS and greedy-based JASUS methods have better capacity performances compared to the norm-based JASUS algorithm. This simulation result shows that, when the SINR is 30 dB, ES, AMCMC, and greedy algorithms enhanced cell capacity of approximately 9.1, 8.2, and 5.8 b/s/Hz, respectively.

Figure 4 shows the increase of sum cell capacity during each iteration for AMCMC-based JASUS algorithm with SINR = 20 dB. As can be seen from Fig. 4, we find that the AMCMC-based JASUS converges after about $t = 30$ iterations. As expected, the sum cell capacity obtained by AMCMC-based JASUS strictly monotonically increased with a number of iteration.

Now, the assumed scenario is a multi-cell multi-user massive MIMO downlink system with 50 active users ($U = 50$) at SINR = 20 dB, and we assume a different number of transmit antenna, M, from 16 to 60. Sixteen antennas ($N = 16$) were selected to be used by the transmitter and ten users ($K = 10$) were served. As can be seen in the result from Fig. 5, the cell capacity difference between the ES-based JASUS and AMCMC-based JASUS scheme is relatively small, and the cell capacity achieved by the aforementioned algorithms slightly grows with M. In summary, when numbers of the selected BS antennas (N) and scheduled users (K) are confirmed, the increase of the number of transmitting antennas (M) has little effect on the system capacity performance. Thus, it can be proven from the result that activation of more transmit antennas at the BS side is unnecessary.

A cell capacity performance comparison of each JASUS algorithms with various numbers of the selected antennas at SINR = 20 dB is shown in Fig. 6. The various

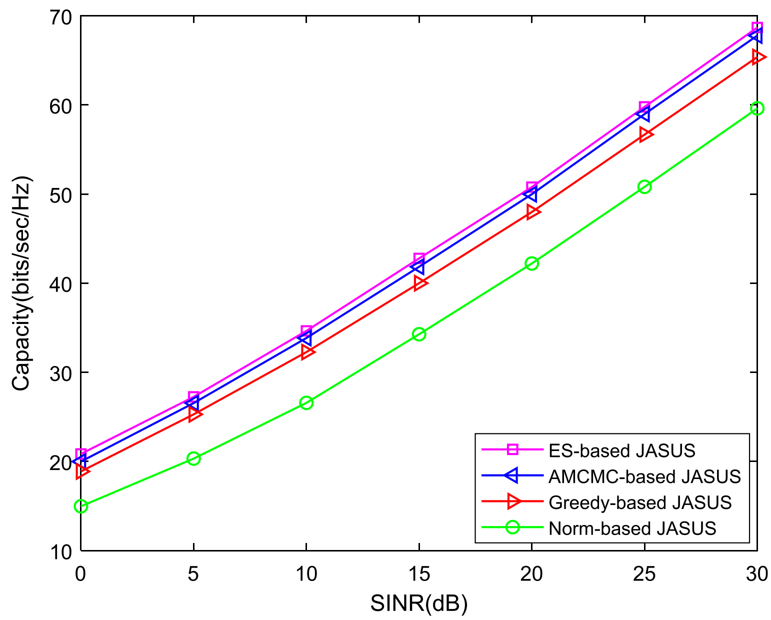

Fig. 3 Ergodic capacity versus SINR with $B = 7$, $M = 64$, $U = 50$, $N = 16$, and $K = 10$

numbers of the selected antennas ($12 \leq N \leq 24$) correspond to the different maximum cell capacity of the networks. Compared with the norm-based JASUS, the JASUS algorithms, which are ES, AMCMC, and greedy, had more significant enhancement for the system performance. For example, the maximum cell capacity enhancements, which are approximately 2.5, 2.2, and 1.7 b/s/Hz at SINR = 20 dB, are achieved when 18 ($N = 18$) BS antennas are selected. From the figure, it can be observed, when $N > 18$, the cell capacity achieved by the JASUS algorithms is slightly growing when the number of selected antenna goes large. Thus, it can be proven from the result that when numbers of the scheduled users K are confirmed, the system capacity sequentially increases until the numbers of selected BS antenna close to the $N = 18$, when $N > 18$, the increasing number of selected antennas has no significant effect on the system capacity performance. Therefore, the results show that more antenna selection is unnecessary at the base station. Thus, the proposed algorithm is demonstrated to be effective. In addition, we considerably decreased system cost and power consumption while approach the maximum cell capacity by selected suitable transmit antennas at BS side.

Figure 7 shows that the cell capacity different K at SINR = 20 dB, for user scheduling and with transmit antenna selection. It can be observed that the cell sum capacity increases with increasing of user K. The different numbers of the scheduled users ($2 \leq K \leq 16$) correspond to the different maximum cell capacity of the networks. Compared with the norm-based result, ES, AMCMC, and greedy algorithms enhanced the system performance. For example, the maximum cell capacity enhancement, which are approximately 6.2,

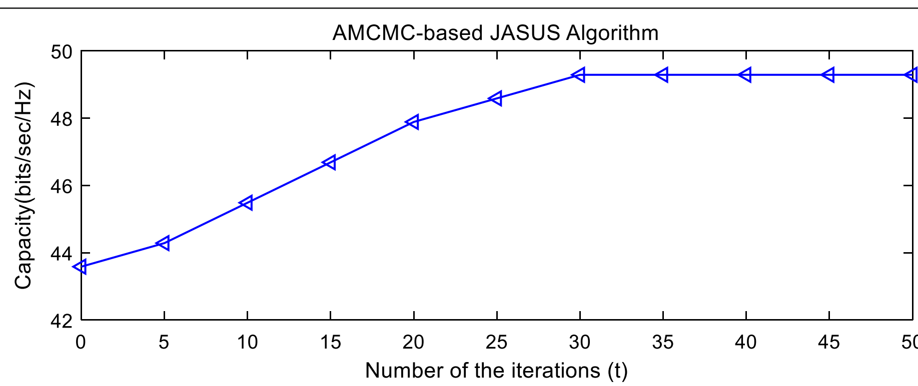

Fig. 4 Ergodic capacity achieved in iterative by AMCMC-based JASUS with $B = 7$, $M = 64$, $U = 50$, $N = 16$, $K = 10$, and SINR = 20 dB

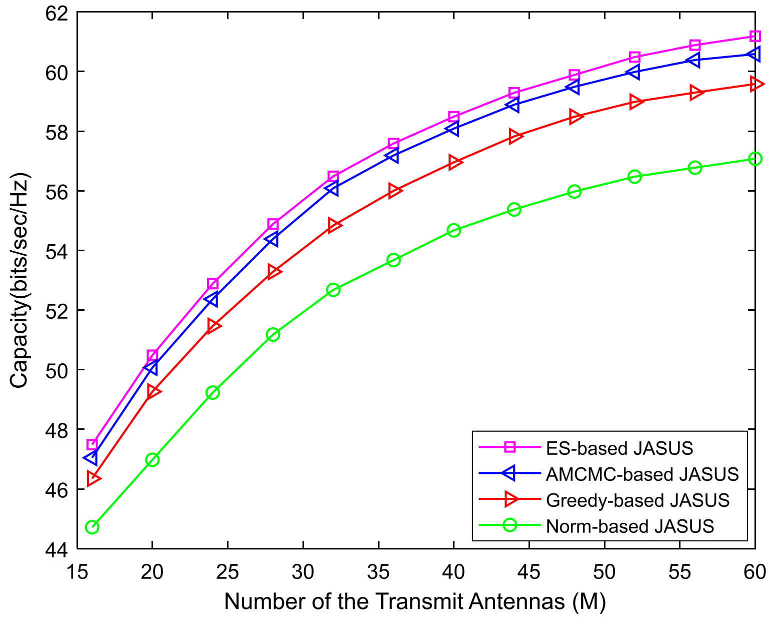

Fig. 5 Ergodic capacity of different algorithms with versus transmit antenna numbers with $B = 7$, $U = 50$, $N = 16$, $K = 10$, and SINR = 20 dB

5.5, and 4.0 b/s/Hz at SINR = 20 dB, are achieved when ten ($K = 10$) users are scheduled. From the figure, it can be observed that when $K > 10$, the cell capacity achieved by the aforementioned algorithms slightly grows when the number of the scheduled user goes large. This result proves that the behavior of JASUS algorithm does not change drastically when the scheduled user number becomes large.

Finally, we discuss on SER of different JASUS algorithms. A 16-QAM scheme is used with a ZF receiver. The SER performance of the linear ZF receiver system is shown in Fig. 8. Compared with the results of norm-based JASUS algorithm, ES, AMMC, and greedy algorithms improved the SER of the system. Same to the case of the cell capacity performance, the system SER of the AMCMC-based JASUS algorithm is close to that of

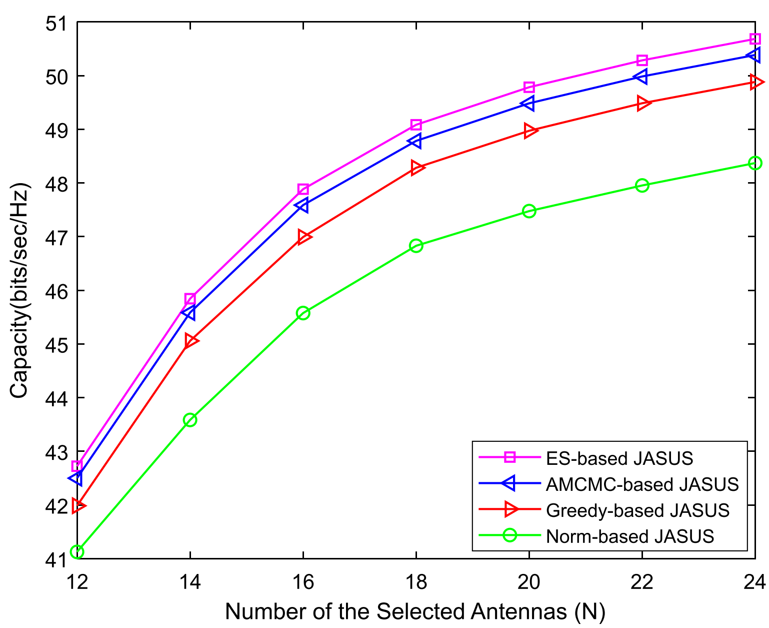

Fig. 6 Ergodic capacity of different algorithms with different numbers of the selected antennas with $B = 7$, $M = 64$, $U = 50$, $K = 10$, and SINR = 20 dB

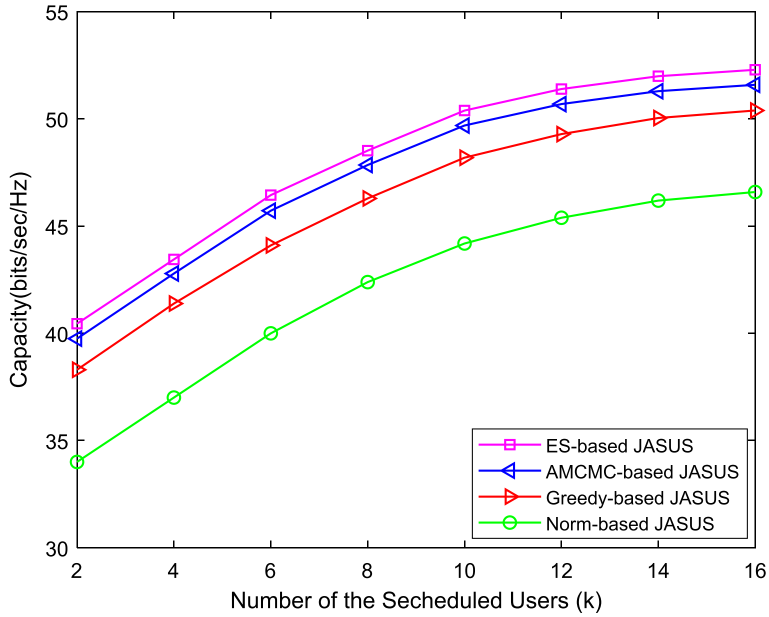

Fig. 7 Ergodic capacity of different algorithms with different scheduled number of users with $B = 7$, $M = 64$, $U = 50$, $N = 16$, and SINR = 20 dB

the ES-based JASUS algorithm. At the same time, we find that ES-based JASUS and AMMC-based JASUS have better SER performance than greedy-based JASUS and norm-based JASUS, especially the SINR to high. When the SINR is 20 dB, the SER performances of the ES-based JASUS, AMCMC-based JASUS, greedy-based JASUS, and norm-based JASUS algorithms are approximately 3.5×10^{-2}, 3.9×10^{-2}, 4.9×10^{-2}, and 6.8×10^{-2}, respectively.

5.2 Computational complexity analysis

The computational complexities of the introduced different JASUS algorithm are analyzed in this section. Table 2 summarizes the computational complexity of our proposed algorithm along with the complexity of another algorithm. The asymptotic notations, which reflect the computational complexity, was used to evaluation how the scheme responds to changes of parameters which are M, N, U, and K. From Table 2, we can easily observe the

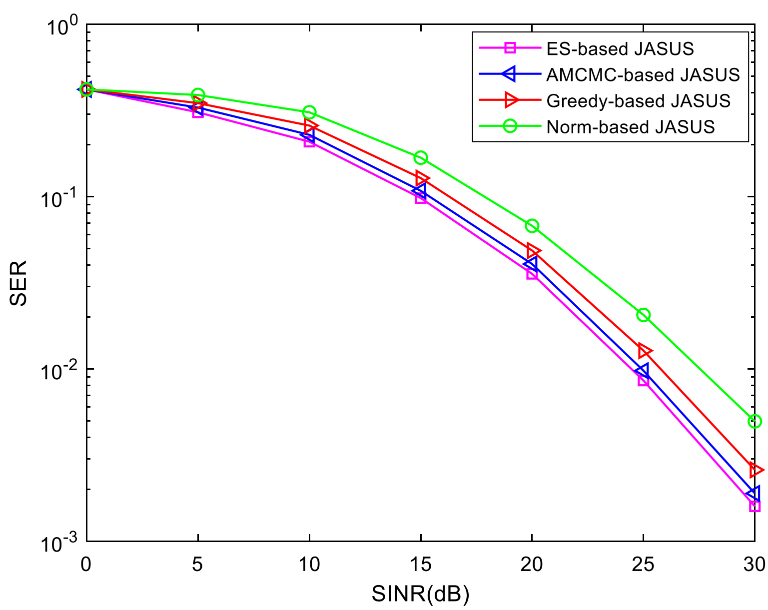

Fig. 8 SER versus SINR with $B = 7$, $M = 64$, $U = 50$, $N = 16$, and $K = 10$

Table 2 Computational complexity analysis

Algorithms	General case	$M = 64$, $N = 16$, $U = 50$, $k = 10$
ES-based JASUS	$O(C_M^N C_U^K N^3)$	2.1×10^{28}
AMCMC-based JASUS	$O(N^3 t L_{MCMC})$	2.8×10^7
Greedy-based JASUS	$tO(MUN^3)$	3.9×10^8
Norm-based JASUS	$O(MU) + tO(N^3)$	1.3×10^5
Number of iterations t	$1 \le t \le 50$	$t = 30$
Constant δ	0.5/1/1.5/2/2.5	$\delta = 2$
Number of promising samples L_{MCMC}	$L_{MCMC} = \delta \times (M + U)$	$L_{MCMC} = 228$

Notes: $\delta = 2$ is the best value in our experiments, because when δ is larger than 2, the cell capacity performance improvement is no longer significant

computational complexity gap between the four methods. Note that C_M^N denotes the binomial coefficient, and the matrix inverse operation [29–32] makes the computational complexity of per sample up to $O(N^3)$. Thus, the overall complexity of our proposed Algorithm 1 for the problem of (11) is $O(N^3 t L_{MCMC})$, where $t \times L_{MCMC}$ is the total number of target function evaluations. Ultimately, we can be observed from Table 2 that our proposed algorithm has a very low computational complexity compared to ES-based JASUS and greedy-based JASUS algorithms. However, the norm-based JASUS algorithm has a very low computational complexity compared to our proposed algorithm, but it also has a very low cell capacity. This result shows that our proposed algorithm is suitable for practical multi-cell multi-user massive MIMO system.

6 Conclusion

In this paper, we studied the problem of JASUS in a multi-cell multi-user massive MIMO downlink system operating with TDD mode. Considering the trade-off between network performance and computational complexity, we proposed a low-complexity algorithm for JASUS method based on AMCMC algorithm in the downlink multi-cell multi-user massive MIMO systems. AMCMC algorithm has been proven helpful for selecting combination subset of antennas and users to approach the maximum cell capacity with consideration of the inter-cell interference. In our algorithm, the updating rules of the selection probability of each base station antenna and scheduling probability for each user are proposed. In addition, we proposed a new projection strategy to satisfy the constraints of selection. Performance analysis and simulation results show that our proposed algorithm can produce promising results and achieve a good trade-off between complexity and performance. Compared with ES-based JASUS algorithm, the proposed algorithm achieved comparable performance with very low complexity. In addition, we demonstrate that our proposed algorithm outperforms greedy-based JASUS and norm-based JASUS methods in terms of cell capacity and SER performance with under poorly conditioned channels. At the same time, the computational complexity is reduced significantly by combining with the proposed algorithm.

Abbreviations

AMCMC: Adaptive Markov chain Monte Carlo; BS: Base station; CSI: Channel state information; ES: Exhaustive search; JASUS: Joint antenna selection and user scheduling; MIMO: Multiple-input multiple-output; MU: Multi-user; RF: Radio frequency; SINR: Signal-to-interference-plus-noise ratio; TDD: Time division duplexing; ZF: Zero-forcing

Acknowledgements

This work described in this paper was supported by the National Science and Technology Major Project: No. 2018ZX03001029-004.

Authors' contributions

WG conceived and designed the study. SM and KZ performed the simulation experiments. SM and KZ wrote the paper. XL and ZS reviewed and edited the manuscript. All authors read and approved the final manuscript.

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Funding

The funding for the research reported is provided by the National Science and Technology Major Project: No. 2018ZX03001029-004. The funds are mainly used for simulation hardware support.

Competing interests

The authors declare that they have no competing interests.

Received: 10 March 2019 Accepted: 25 July 2019
Published online: 14 August 2019

References

1. T.A. Sheikh, J. Bora, A. Hussain, in *CCTCEEC*. A survey of antenna and user scheduling techniques for massive MIMO-5G wireless system (Mysore, 2017), pp. 578–583. https://doi.org/10.1109/CTCEEC.2017.8455177
2. T.L. Marzetta, Noncooperative cellular wireless with unlimited numbers of base station antennas. IEEE Trans. Wirel. Commun. **9**(11), 3590–3600 (2010)
3. E.G. Larsson, O. Edfors, F. Tufvesson, T.L. Marzetta, Massive MIMO for next generation wireless systems. IEEE Comun. Mag. **52**(2), 186–195 (2014)
4. S. Han, I. Chih-Lin, Z. Xu, C. Rowell, Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G. IEEE Comun. Mag. **53**(1), 186–194 (2015)
5. Y. Dong, Y. Tang, K.Z. Shenzhen, in *IEEE/ACIS International Conference on Computer and Information Science IEEE*. Improved joint antenna selection and user scheduling for massive MIMO systems (2017)
6. M. Torabi, D. Haccoun, Performance analysis of joint user scheduling and antenna selection over MIMO fading channels. IEEE Signal Process. Lett. **18**(4), 235–238 (2011)
7. C. Bandeira, D. Moreira, P. Normando, et al., in *Proc. IEEE Vehicular Technology Conf. (VTC-Spring)*. Performance of joint antenna and user selection schemes for interference alignment in MIMO interference channels (2013)
8. S. Xue, Z. Qian, W. Shao, et al., in *Proc. IEEE International Conf. Computational Electromagnetics (ICCEM)*. Distributed joint antenna and user selection for MIMO broadcast channels (2016)
9. J.-C. Chen, "Joint Antenna Selection and User Scheduling for Massive Multiuser MIMO Systems With Low-Resolution ADCs," IEEE Trans. Veh. Technol. **68**(1) 1019–1024 (2019)

10. X. Gao, L. Dai, A.M. Sayeed, Low RF-complexity technologies to enable millimeter-wave MIMO with large antenna array for 5G wireless communications. IEEE Commun. Mag. **56**(4), 211–217 (2018)
11. T.-H. Tai, W.-H. Chung, T.-S. Lee, "A low complexity antenna selection algorithm for energy efficiency in massive MIMO systems", Proc. IEEE Int. Conf. Data Sci. Data Intensive Syst. 284-289 (2015)
12. X. Gao , O. Edfors, F. Tufvesson, and E. G. Larsson, "Massive MIMO in real propagation environments: Do all antennas contribute equally?," IEEE Trans. Commun. **63**(11) 3917–3928 (2015)
13. B. Makki, A. Ide, T. Svensson, T. Eriksson, M.-S. Alouini, A genetic algorithm-based antenna selection approach for large-but-finite MIMO networks. IEEE Trans. Veh. Technol. **66**(7), 6591–6595 (2016)
14. M. Benmimoune, E. Driouch, W. Ajib, D. Massicotte, in *Proc. IEEE WCNC*. Joint transmit antenna selection and user scheduling for massive MIMO systems (2015), pp. 381–386
15. M. Olyaee, M. Eslami, J. Haghighat, An energy-efficient joint antenna and user selection algorithm for multi-user massive MIMO downlink. IET Commun. **12**(3), 255–260 (2018)
16. G. Xu, A. Liu, W. Jiang, H. Xiang, W. Luo, Joint user scheduling and antenna selection in distributed massive MIMO systems with limited backhaul capacity. China Commun. **11**(5), 17–30 (2014)
17. B.M. Lee, J. Choi, J. Bang, B.-C. Kang, in *IEEE Int. Symp. On Circuits and Systems (ISCAS)*. An energy efficient antenna selection for large scale green MIMO systems (2013), pp. 950–953
18. Q.H. Spencer, A.L. Swindlehurst, M. Haardt, Zero-forcing methods for downlink spatial multiplexing in multiuser MIMO channels. IEEE Trans. Signal Process. **52**(2), 461–471 (2004)
19. G. Dimic, N.D. Sidiropoulos, On downlink beamforming with greedy user selection: performance analysis and a simple new algorithm. IEEE Trans. Signal Process. **53**(10), 3857–3868 (2005)
20. M. Al-Saedy, M. Al-Imari, M. Al-Shuraifi, et al. Joint User Selection and Multi-Mode Scheduling in Multicell MIMO Cellular Networks[J]. IEEE Transactions on Vehicular Technology, 1-1 (2017)
21. J.C. Spall, Estimation via Markov chain Monte Carlo. Control Syst. IEEE **23**(2), 34–45 (2003)
22. W.R. Gilks, S. Richardson, D.J. Spiegelhalter, *Markov Chain Monte Carlo in Practice* (Chapman and Hall, London, 1996)
23. J. Liu, *Monte Carlo Strategies in Scientific Computing* (Springer-Verlag, New York, 2001)
24. S. Kullback, R. Leibler, On information and sufficiency. Ann. Math. Stat. **22**(1), 79–86 (1951)
25. R.Y. Rubinstein, D.P. Kroese, *The Cross-Entropy Method: A Unified Approach to Combinatorial Optimization, Monte-Carlo Simulation and Machine Learning* (Springer-Verlag, Berlin, 2004)
26. H. Robbins, S. Monro, A stochastic approximation method. Ann. Math. Stat. **22**(3), 400–407 (1951)
27. H. Kushner, G. Yin, *Stochastic Approximation Algorithms and Applications*, 2nd edn. (Springer-Verlag, New York, 2003)
28. Y. Liu, Y.Y. Zhang, C.L. Ji, W.Q. Malik, D.J. Edwards, A low complexity receive-antenna-selection algorithm for MIMO-OFDM wireless systems. IEEE Trans. Veh. Technol. **58**(6), 2793–2802 (2009)
29. X. Gao, L. Dai, Y. Ma, Z. Wang, Low-complexity near-optimal signal detection for uplink large-scale MIMO systems. Electron. Lett. **50**(18), 1326–1328 (2014)
30. X. Gao, L. Dai, Y. Hu, Y. Zhang, Z. Wang, Low-complexity signal detection for large-scale MIMO in optical wireless communications. IEEE J. Sel. Areas Commun. **33**(9), 1903–1912 (2015)
31. L. Dai, X. Gao, X. Su, S. Han, I. Chih-Lin, Z. Wang, Low-complexity soft-output signal detection based on Gauss-Seidel method for uplink multiuser large-scale MIMO systems. IEEE Trans. Veh. Technol. **64**(10), 4839–4845 (2015)
32. Z. Wu, C. Zhang, Y. Xue, S. Xu, Z. You, "Efficient architecture for soft-output massive MIMO detection with gauss-seidel method", Proc. IEEE Int. Conf. Circuits Syst. (ISCAS), 1886-1889 (2016)

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