

Energy Efficiency Optimization for MIMO Distributed Antenna Systems

Hong Ren, Nan Liu, Cunhua Pan, Chunlong He

Abstract

In this paper, we propose a transmit covariance optimization method to maximize the energy efficiency (EE) for a single-user distributed antenna system, where both the remote access units (RAUs) and the user are equipped with multiple antennas. Unlike previous related works, both the rate requirement and RAU selection are taken into consideration. Here, the total circuit power consumption is related to the number of active RAUs. Given this setup, we first propose an optimal transmit covariance optimization method to solve the EE optimization problem under a fixed set of active RAUs. More specifically, we split this problem into three subproblems, i.e., the rate maximization problem, the EE maximization problem without rate constraint, and the power minimization problem, and each subproblem can be efficiently solved. Then, a novel distance-based RAU selection method is proposed to determine the optimal set of active RAUs. Simulation results show that the performance of the proposed RAU selection is almost identical to the optimal exhaustive search method with significantly reduced computational complexity, and the performance of the proposed algorithm significantly outperforms the existing EE optimization methods.

Index Terms

Distributed antenna system, multiple antennas, energy efficiency, rate constraints, RAU selection

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I. INTRODUCTION

Recently, distributed antenna system (DAS) has been regarded as a promising technique to meet the increasing demand for high spectral efficiency (SE, bit/s/Hz) and good coverage [1]–[3]. Unlike the conventional centralized antenna system (CAS), several distributed RAUs with one or more antennas are geographically separated over the cell in DAS. Each RAU is connected to the central processing unit (CPU) via a high-speed error-free low-latency wired channel such as optical fiber links. **In DAS, all the baseband processing is processed at the CPU, and RAUs only have the basic functionalities of signal processing and reception. Hence, they can be densely deployed with low operational cost. Then, the average access distance for each user can be significantly reduced.** Thus, the DAS has the great potential to improve the SE and coverage, especially for the cell-edge users. On the other hand, large-scale multiple-input and multiple-output (MIMO) has attracted extensive interests due to its advantage of providing tremendous SE for wireless communications [4]. Placing a large number of antennas in different locations can also reduce the correlations of antennas [5], thus improving the SE of the system.

The SE of the DAS system has been extensively studied in the past few years [6]–[9]. Specifically, [6] derived the downlink capacity of a DAS under two cases: unknown channel state information (CSI) and know CSI. In the considered DAS, both the RAUs and the users are equipped with only one antenna. For the case of known CSI, the authors provided one optimal solution for the transmit covariance matrices. However, the property of the optimal solution was not characterized. Then, in [7], the authors solved a relaxed problem by replacing the original positive semi-definite constraint with a 2×2 matrix minor condition, and showed that the optimal phases of the beam weights at the RAUs should be matched to the phases of the channel coefficients, and the amplitudes are determined by the power constraints. Similar method and result can be found in [8] for a DAS system with multiple antennas at each RAU and one antenna for each user. The optimal beam direction for each RAU should be matched to its channel vector and each RAU should use full power to transmit. In [10], the author considered the precoding design to maximize the sum-rate for a multiuser MIMO DAS system. Block diagonalization method was applied to eliminate the multiuser interference and the system is reduced to a multiple parallel single-user MIMO DAS system. However, the rate requirement was not considered in the paper.

On the other hand, energy efficiency (EE) has attracted extensive interests [11], [12] due to energy shortage and the greenhouse effect, and it will be one of the main concerns for the fifth generations (5G) mobile networks [13]. The EE is defined as the ratio of the rate to the total power consumption, representing the number of bits that can be successfully transmitted with per Joule energy consumption. In general, the SE maximization solution for the DAS may not be the EE maximization solution of the DAS since the former always activates all RAUs and uses full power to transmit. Hence, there have been some literatures studying the EE maximization problem for the DAS [14]–[18]. In [14], the authors designed a power allocation method for single-user DAS systems. By solving the Karush-Kuhn-Tucker conditions, the optimal solution can be obtained in closed form. The EE power allocation for the frequency-selective fading DAS was studied in [15], where a numerical search method was proposed. [16] extended the work of [14] to a more general DAS where each RAU has multiple antennas by considering both beamforming and power allocation. The authors showed that the optimal beam direction for the EE maximization should be matched to the channel vector as in [8], and the optimal power allocation can be obtained in closed form by the same method in [14]. However, all of these works do not consider the user’s quality of service such as the rate requirements, and thus the attained rate could be fairly low. **In addition, RAU selection or antenna selection are not taken into account in these papers. The densely deployed RAUs will incur considerable power consumption. Fortunately, it was shown in [19] that the data traffic varies substantially over both time and space due to the changing locations of the user and varying channel state. Hence, significant power savings can be achieved by shutting off some unnecessary RAUs with light load, while guaranteeing the user’s rate requirement. Thus, we should jointly optimize the EE transmission and RAU selection to additionally improve the EE of DAS.** Also, the above papers focused on the DAS where the user is equipped with only one antenna. Due to the fast development in antenna technology [20], multiple antennas may be packed in each user’s terminal. In this case, the multiple-antenna RAUs can transmit multiple streams to the user to enhance the SE of the DAS. To the best of our knowledge, there is few works studying the EE maximization problem for this more general single-user MIMO DAS [17], [18]. In [17], the authors obtained an approximate EE expression for this general scenario based on the assumption of the high SNR approximation. Then, a more tight closed-form approximation of the EE-SE trade-off over the Rayleigh fading channel was derived in [18]. However, the above works studied the EE of

the MIMO DAS from the performance analysis point of view and did not provide any insights on how to design the optimal transmit strategy. In the MIMO DAS, the beam directions and power allocation over the beams should be jointly optimized, and the beam directions cannot be obtained in the closed form as in the MISO case [16]. Some iterative methods should be developed to find the optimal beam direction.

In this paper, we study the EE maximization problem for the single-user downlink MIMO DAS, where both the RAUs and the user are equipped with multiple antennas. Both the rate requirement and the RAU selection are taken into consideration. We propose an iterative optimization method to alternatively optimize the transmit covariance matrices and the set of active RAUs.

Under given active RAUs, the optimization problem is a pseudo-concave maximization problem, which can be solved by the standard convex optimization techniques such as the interior point method [21]. Although the interior point method has only polynomial complexity, it cannot reveal the structural of the precoding matrix. Hence, it is of interest to develop efficient algorithms to give more insights into the structure of the precoding matrix, and additionally reduce the computational complexity. The approach we take in this paper is to divide the optimization problem into three subproblem, i.e., the rate maximization problem, the EE maximization problem without rate constraint and the power minimization problem. For the rate maximization problem with per-RAU power constraint, we devise an efficient algorithm by resorting to the dual-decomposition based method and the closed-form expression of the transmit covariance matrix can be derived. If the obtained maximum rate satisfies the rate requirement, we then attempt to solve the EE maximization problem without rate constraint, which can be easily solved by fractional programming. If the obtained solution satisfies the rate requirement, it is the optimal solution of the optimization problem given the set of active RAUs. Otherwise, we need to solve the power minimization problem with the rate constraint, which can be effectively solved by the bisection search method. In addition, we analyze the complexity to solve each subproblem, and show that our proposed algorithm yields a much lower complexity than the standard convex optimization techniques.

Next, a novel distance-based RAU selection procedure is proposed to determine the optimal set of active RAUs. This selection method is reasonable since user's channel gain is mainly determined by the distance, and in general there are great differences among the distances from the user to the RAUs of the DAS. This method has a lower complexity compared with the

channel-norm based antenna selection method in [22], as the calculation of channel-norms incurs additional computation complexity. Moreover, the search procedure will stop once the current achieved EE is lower than the previous highest EE, and the set of active RAUs achieving the previous highest EE will be the output of our algorithm. Simulation results show that the proposed distance-based RAU selection and transmit covariance optimization scheme yields almost the same EE performance as the exhaustive RAU selection, and significantly outperforms the existing EE optimization method.

The rest of this paper is organized as follows. In Section II, we introduce the system model and problem formulation. Section III develops the optimal transmit covariance optimization method to deal with the EE maximization problem under a given set of active RAUs. Section IV presents the novel low-complexity distance-based RAU selection method. Simulation results are given in Section V to evaluate the performance of the proposed RAU selection method. Finally, Section VI concludes this paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a downlink single cell DAS with I RAUs and one user, where RAU i is equipped with M_i antennas and the user is equipped with N antennas, $i = 1, 2, \dots, I$, as shown in Fig. 1. We assume that all the RAUs are connected to the central processing unit (CPU) through the high speed fiber-optic cable. Moreover, it is assumed that all the RAUs are fully controlled by the CPU.

If we activate more RAUs, the transmit power consumption can be reduced due to the beamforming gain. However, the circuit power consumption of the RAUs will become considerable. Hence, the system may suffer EE performance loss. On the other hand, if we activate less RAUs, more transmit power should be consumed to guarantee the user's rate requirement although the circuit power consumption is reduced. Sometimes less RAUs may not be able to support the rate requirement of the user. Hence, selecting a suitable subset of RAUs may be a good option in terms of the EE performance. Denote $\mathbb{S} \subseteq \{1, 2, \dots, I\}$ as the set of the selected RAUs to transmit signals to the user with the number of RAUs $A \triangleq |\mathbb{S}|$. The subset \mathbb{S} is given as $\mathbb{S} = \{s_1, s_2, \dots, s_A\}$, whose elements represent the RAU indices and are arranged in increasing order, i.e., $s_1 < s_2 < \dots < s_A$. When the selected active RAU set is \mathbb{S} , the downlink transmission

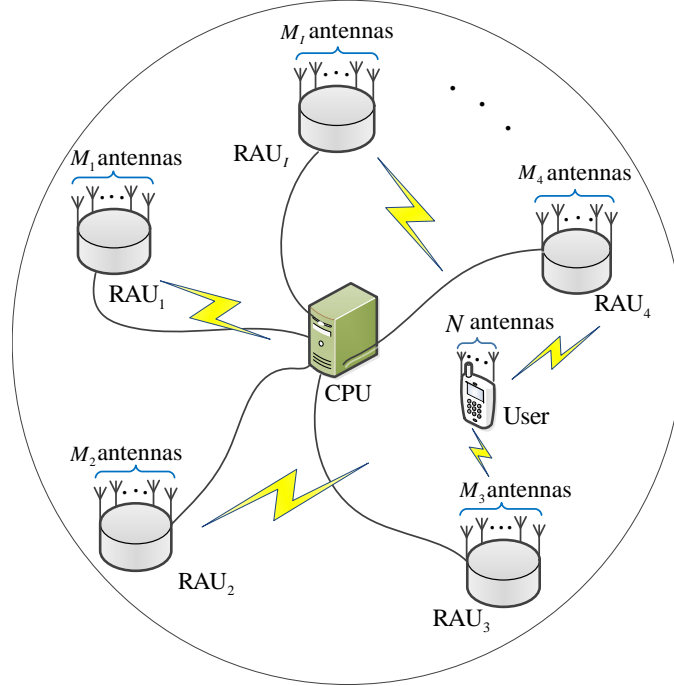


Fig. 1. Structure of DAS with I distributed antenna RAUs.

can be modeled as a single user MIMO with M_A transmitting antennas and N receiving antennas, where $M_A = \sum_{i=1}^A M_{s_i}$ denotes the total number of active antennas.

Let $\mathbf{H}_{s_i} \in \mathbb{C}^{N \times M_{s_i}}$, $s_i \in \mathbb{S}$ be the channel matrix from RAU s_i to the user, and $\mathbf{H}_{\mathbb{S}} = [\mathbf{H}_{s_1}, \mathbf{H}_{s_2}, \dots, \mathbf{H}_{s_A}] \in \mathbb{C}^{N \times M_A}$ be the overall channel matrix from the selected RAUs in \mathbb{S} to the user. Hence, the received signal at the user from all RAUs is given by

$$\mathbf{y}_{\mathbb{S}} = \mathbf{H}_{\mathbb{S}} \mathbf{x}_{\mathbb{S}} + \mathbf{z} \quad (1)$$

where $\mathbf{x}_{\mathbb{S}} \in \mathbb{C}^{M_A \times 1}$ and $\mathbf{y}_{\mathbb{S}} \in \mathbb{C}^{N \times 1}$ denote the transmit and receive signals for the user, respectively, and $\mathbf{z} \in \mathbb{C}^{N \times 1}$ denotes the receiver noise at the user. For simplicity, we assume that $\mathbf{z} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$. It is also assumed that the CPU can acquire perfect channel state information (CSI), and the channels are in block-fading and change sufficiently slowly such that they can be treated as fixed during the considered transmission period.

Denote $\mathbf{Q}_{\mathbb{S}} = \mathbb{E}\{\mathbf{x}_{\mathbb{S}} \mathbf{x}_{\mathbb{S}}^H\}$ as the transmit covariance matrix for the user, with $\mathbf{Q}_{\mathbb{S}} \in \mathbb{C}^{M_A \times M_A}$ and $\mathbf{Q}_{\mathbb{S}} \succeq \mathbf{0}$. Then, the spectral efficiency (SE) (bps/Hz) for the user is [23]

$$R_{\mathbb{S}} = \log_2 \left| \mathbf{I} + \mathbf{H}_{\mathbb{S}} \mathbf{Q}_{\mathbb{S}} \mathbf{H}_{\mathbb{S}}^H \right|. \quad (2)$$

In order to impose the per-RAU power constraint, we introduce a set of matrices, $\mathbf{B}_i, i = 1, \dots, A$, as follows

$$\mathbf{B}_i \triangleq \text{Diag} \left(\underbrace{0, \dots, 0}_{\sum_{l=1}^{i-1} M_{s_l}}, \underbrace{1, \dots, 1}_{M_{s_i}}, \underbrace{0, \dots, 0}_{\sum_{l=i+1}^A M_{s_l}} \right), i = 1, \dots, A. \quad (3)$$

Then, the per-RAU power constraint can be expressed as

$$\text{tr}(\mathbf{B}_i \mathbf{Q}_{\mathbb{S}}) \leq P_{s_i}, i = 1, \dots, A, \quad (4)$$

where P_{s_i} denotes the transmit power constraint for RAU s_i .

To consider the energy-efficiency design, the total power consumption should be considered: the power for reliable data transmission and the circuit power consumption, which is the power consumed by mixers, filters and digital-to-analog converters, digital signal processing (DSP), RF chains, etc. Hence, the total power consumption can be modeled as [24]

$$P_{\text{total}} = \text{tr}(\mathbf{Q}_{\mathbb{S}}) + M_{AP} p_c + A p_0, \quad (5)$$

where p_c denotes the RF chain power consumption corresponding to one antenna, and p_0 is the static power consumption for each RAU. For simplicity, define $P_{C,\mathbb{S}} \triangleq M_{AP} p_c + A p_0$.

The EE (bits/Joule) is defined as the ratio of the the number of bits to the total power consumption. Our objective is to find a selected active RAU set $\mathbb{S} \subseteq \{1, 2, \dots, I\}$ and optimize the corresponding transmit covariance matrix $\mathbf{Q}_{\mathbb{S}}$ to maximize the EE of the DAS system, subject to both the per-RAU power constraint and the rate requirements. Formally, this problem can be formulated as

$$\begin{aligned} (\mathbf{P0}) \quad & \max_{\mathbb{S}, \mathbf{Q}_{\mathbb{S}} \succeq \mathbf{0}} \frac{W \log_2 |\mathbf{I} + \mathbf{H}_{\mathbb{S}} \mathbf{Q}_{\mathbb{S}} \mathbf{H}_{\mathbb{S}}^H|}{\text{tr}(\mathbf{Q}_{\mathbb{S}}) + P_{C,\mathbb{S}}} \\ & \text{s.t.} \quad \text{tr}(\mathbf{B}_i \mathbf{Q}_{\mathbb{S}}) \leq P_{s_i}, \quad \forall i = 1, \dots, A, \\ & \quad \quad W \log_2 |\mathbf{I} + \mathbf{H}_{\mathbb{S}} \mathbf{Q}_{\mathbb{S}} \mathbf{H}_{\mathbb{S}}^H| \geq R_{\min}, \end{aligned} \quad (6)$$

where W is the channel bandwidth and R_{\min} denotes the minimum rate requirements.

For Problem **(P0)**, it is difficult to jointly optimize the selected RAU set \mathbb{S} and the transmit covariance matrix $\mathbf{Q}_{\mathbb{S}}$ since both the channel matrices and the total power consumption depend on \mathbb{S} . Fortunately, given \mathbb{S} , the numerator and denominator of the objective function in (6) are concave and affine respectively, and both of them are **differentiable**. Hence, the objective function in (6) is pseudo-concave. Moreover, the feasible set in Problem **(P0)** is convex. **Thus, the optimization Problem (P0) under given \mathbb{S} is a fractional program [25], which can be efficiently**

solved by the theory fractional programming. In the following two sections, we first optimize the transmit covariance matrix under given \mathbb{S} and then provide several techniques to determine \mathbb{S} , respectively.

III. EE OPTIMIZATION FOR GIVEN RAU SET

In this section, we optimize the transmit covariance matrix to maximize EE under given \mathbb{S} . This problem can be solved through the standard convex optimization method such as the interior-point method [26], which has a polynomial complexity. However, it is of interest to develop efficient methods that additionally reduce the computational complexity, which will be the aim of this section. For notational simplicity, we omit \mathbb{S} in the subscript in this section. Define \mathcal{W} as

$$\mathcal{W} = \{ \mathbf{Q} \in \mathbb{C}^{M_A \times M_A} : \mathbf{Q} \succeq \mathbf{0}, \text{tr}(\mathbf{B}_i \mathbf{Q}) \leq P_{s_i}, \forall i \}. \quad (7)$$

Then, by discarding the constant W , we can rewrite the problem as follows

$$\begin{aligned} \max_{\mathbf{Q} \in \mathcal{W}} \quad & \frac{\log_2 |\mathbf{I} + \mathbf{H} \mathbf{Q} \mathbf{H}^H|}{\text{tr}(\mathbf{Q}) + P_C} \\ \text{s.t.} \quad & \log_2 |\mathbf{I} + \mathbf{H} \mathbf{Q} \mathbf{H}^H| \geq \tilde{R}_{\min}. \end{aligned} \quad (8)$$

where $\tilde{R}_{\min} = R_{\min}/W$.

Before solving this problem, we introduce three auxiliary subproblems

$$\mathbf{(P1)} \quad \mathbf{Q}_{(P1)}^* = \arg \max_{\mathbf{Q} \in \mathcal{W}} \log_2 |\mathbf{I} + \mathbf{H} \mathbf{Q} \mathbf{H}^H|, \quad (9)$$

$$\mathbf{(P2)} \quad \mathbf{Q}_{(P2)}^* = \arg \max_{\mathbf{Q} \in \mathcal{W}} \frac{\log_2 |\mathbf{I} + \mathbf{H} \mathbf{Q} \mathbf{H}^H|}{\text{tr}(\mathbf{Q}) + P_C}, \quad (10)$$

$$\mathbf{(P3)} \quad \mathbf{Q}_{(P3)}^* = \arg \min_{\mathbf{Q} \in \mathcal{W}, \log_2 |\mathbf{I} + \mathbf{H} \mathbf{Q} \mathbf{H}^H| = \tilde{R}_{\min}} \text{tr}(\mathbf{Q}). \quad (11)$$

Due to the rate constraint, the problem in (8) may be infeasible as shown in [27]. Hence, we need to check the feasibility of the problem in (8), which can be accomplished by checking whether the maximum SE under all RAUs' power constraints can satisfy the rate requirement. The rate maximization problem under all RAUs' power constraints is given in Problem **(P1)**. If the optimal solution to Problem **(P1)**, denoted as $\mathbf{Q}_{(P1)}^*$, can satisfy the rate constraint, this problem is feasible. Otherwise, it is infeasible. When this problem is feasible, we continue to solve the EE optimization problem without the rate constraint, which is given in Problem **(P2)**. Denote the optimal solution to Problem **(P2)** as $\mathbf{Q}_{(P2)}^*$. If $\log_2 |\mathbf{I} + \mathbf{H} \mathbf{Q}_{(P2)}^* \mathbf{H}^H| \geq \tilde{R}_{\min}$ holds,

$\mathbf{Q}_{(P2)}^*$ is the optimal solution to the problem in (8) since Problem **(P2)** is a relaxed version of the problem in (8). Otherwise, the rate constraint are met with equality at the optimum. Hence, the problem in (8) reduces to the power minimization problem given in Problem **(P3)**. Denote the optimal solution to Problem **(P3)** as $\mathbf{Q}_{(P3)}^*$, which is the optimal solution to the problem in (8).

In summary, the algorithm to solve the problem in (8) is given in Algorithm 1. The remaining task is to solve Problems **(P1)**, **(P2)** and **(P3)**, respectively. The details of solving these subproblems are given in the following subsections.

Algorithm 1 Solving EE optimization problem under fixed \mathbb{S}

1. Solve Problem **(P1)** to obtain the optimal solution $\mathbf{Q}_{(P1)}^*$. If $\log_2 \left| \mathbf{I} + \mathbf{H}\mathbf{Q}_{(P1)}^* \mathbf{H}^H \right| \geq \tilde{R}_{\min}$, go to Step 2; Otherwise, declare that the problem is infeasible and terminate.
 2. Solve Problem **(P2)** to obtain the optimal solution $\mathbf{Q}_{(P2)}^*$. If $\log_2 \left| \mathbf{I} + \mathbf{H}\mathbf{Q}_{(P2)}^* \mathbf{H}^H \right| \geq \tilde{R}_{\min}$, the optimal solution to the problem in (8) is $\mathbf{Q}_{(P2)}^*$, terminate; Otherwise, go to Step 3.
 3. Solve Problem **(P3)** to obtain the optimal solution $\mathbf{Q}_{(P3)}^*$, which is the optimal solution to the problem in (8).
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*A. Algorithm to solve Problem **(P1)***

When the user is equipped with only one antenna, the sum-rate maximization problem **(P1)** has been solved recently in [28], in which the optimal beamforming is obtained by solving a relaxed problem by replacing the positive semi-definite constraint with a 2×2 matrix minor condition. The authors in [28] shows that the optimal solution takes a form of maximum ratio transmission per each RAU with full power. However, the method in [28] is not applicable for the MIMO case considered here and a new method needs to be developed.

Obviously, Problem **(P1)** is a convex problem and thus can be solved using standard convex optimization techniques, e.g., the interior point method. However, our interest is to design an algorithm for solving Problem **(P1)** via its dual problem due to the zero gap between Problem **(P1)** and its dual problem. Note that this method has been extensively used to develop efficient beam-vectors and precoding matrices [10], [27], [29]–[31].

We first derive the Lagrangian function of **(P1)** with respect to all RAUs' power constraints, given by

$$L(\mathbf{Q}, \{\lambda_i\}) = \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H| + \sum_{i=1}^A \lambda_i (P_i - \text{tr}(\mathbf{B}_i\mathbf{Q})), \quad (12)$$

where $\{\lambda_i \geq 0, \forall i\}$ are the corresponding Lagrangian dual variables. Therefore, the dual function is

$$g(\{\lambda_i\}) = \max_{\mathbf{Q} \succeq \mathbf{0}} L(\mathbf{Q}, \{\lambda_i\}). \quad (13)$$

Then the dual problem is given by

$$\min_{\{\lambda_i \geq 0, \forall i\}} g(\{\lambda_i\}). \quad (14)$$

To solve its dual problem in (14), we should solve the problem in (13) with fixed $\{\lambda_i\}$, then update the Lagrangian dual variables $\{\lambda_i\}$ by solving the dual problem in (14). Iterate the above two steps until convergence.

1) *Solving the dual function of (13)*: For given $\{\lambda_i, \forall i\}$, solving the dual function is the same as solving the following optimization problem

$$\max_{\{\mathbf{Q} \succeq \mathbf{0}\}} \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H| - \text{tr}(\mathbf{B}\mathbf{Q}), \quad (15)$$

where $\mathbf{B} = \sum_{i=1}^A \lambda_i \mathbf{B}_i$. We then have the following lemma.

Lemma 1: For the problem in (15) to have a bounded objective value, matrix \mathbf{B} should be positive definite.

Proof: Obviously, $\mathbf{B} \succeq \mathbf{0}$. We prove this lemma by contradiction. Suppose that \mathbf{B} is not a full-rank matrix. We can always find a vector $\mathbf{q} \in \mathbb{C}^{M_A \times 1}$ such that $\mathbf{B}\mathbf{q} = \mathbf{0}$ and $\mathbf{H}\mathbf{q} \neq \mathbf{0}$ due to the independent generations of channel elements. Suppose the solution is $\mathbf{Q}^* = p\mathbf{q}\mathbf{q}^H$ with $p \geq 0$. Substituting this solution into the objective function of Problem (15) yields

$$\log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}^*\mathbf{H}^H| - \text{tr}(\mathbf{B}\mathbf{Q}^*) = \log_2 |\mathbf{I} + p\mathbf{H}\mathbf{q}\mathbf{q}^H\mathbf{H}^H| = \log_2 (1 + p\mathbf{q}^H\mathbf{H}^H\mathbf{H}\mathbf{q}). \quad (16)$$

Since $\mathbf{q}^H\mathbf{H}^H\mathbf{H}\mathbf{q} > 0$, the objective value is unbounded as p grows to infinity. Therefore, we conclude that the presumption is not correct. Thus, $\mathbf{B} \succ \mathbf{0}$ holds. \square

According to Lemma 1, \mathbf{B} can be written as $\mathbf{B} = \mathbf{B}^{1/2}\mathbf{B}^{1/2}$. Let $\tilde{\mathbf{Q}} = \mathbf{B}^{1/2}\mathbf{Q}\mathbf{B}^{1/2}$, we can get $\mathbf{Q} = \mathbf{B}^{-1/2}\tilde{\mathbf{Q}}\mathbf{B}^{-1/2}$. Inserting it into (15) yields

$$\max_{\tilde{\mathbf{Q}} \succeq \mathbf{0}} \log_2 \left| \mathbf{I} + \tilde{\mathbf{Q}}\mathbf{B}^{-\frac{1}{2}}\mathbf{H}^H\mathbf{H}\mathbf{B}^{-\frac{1}{2}} \right| - \text{tr}(\tilde{\mathbf{Q}}). \quad (17)$$

To solve this problem, we first write the eigenvalue decomposition (EVD) of $\mathbf{B}^{-1/2}\mathbf{H}^H\mathbf{H}\mathbf{B}^{-1/2}$ as

$$\mathbf{B}^{-\frac{1}{2}}\mathbf{H}^H\mathbf{H}\mathbf{B}^{-\frac{1}{2}} = \mathbf{U}\mathbf{D}\mathbf{U}^H, \quad (18)$$

where \mathbf{U} is a semi-unitary matrix of the eigenvectors with

$$r \triangleq \text{rank}\left(\mathbf{B}^{-\frac{1}{2}}\mathbf{H}^H\mathbf{H}\mathbf{B}^{-\frac{1}{2}}\right), \quad (19)$$

and \mathbf{D} is a diagonal matrix with $\mathbf{D} = \text{diag}\{d_1, \dots, d_r\}$ being the eigenvalues.

Then, the solution to the problem in (17) is given by

$$\tilde{\mathbf{Q}} = \mathbf{U}\Lambda\mathbf{U}^H, \quad (20)$$

where $\Lambda = \text{diag}\{q_1, \dots, q_r\}$ represents the power allocation on all subchannels with

$$q_m = \left[\frac{1}{\ln 2} - \frac{1}{d_m}\right]^+, m = 1, \dots, r, \quad (21)$$

where $[x]^+ = \max\{0, x\}$.

Hence, the optimal \mathbf{Q} is given by

$$\mathbf{Q} = \mathbf{B}^{-\frac{1}{2}}\mathbf{U}\Lambda\mathbf{U}^H\mathbf{B}^{-\frac{1}{2}}. \quad (22)$$

2) *Solving the dual problem* (14): To solve the dual problem (14), we utilize the subgradient method, which is a simple method to deal with the nondifferentiable objective function [32]. The subgradient is required by the subgradient method at each iteration. According to [32], the subgradient of $g(\cdot)$ at $\lambda^{(k)} = [\lambda_1, \dots, \lambda_I]$ in the k th iteration is given by [32]

$$s_i^{(k)} = P_i - \text{tr}(\mathbf{B}_i\mathbf{Q}), i = 1, \dots, I. \quad (23)$$

Then the Lagrangian dual variables can be updated as

$$\lambda_i^{(k+1)} = \left[\lambda_i^{(k)} - u^{(k)}s_i^{(k)}\right], \forall i. \quad (24)$$

where $u^{(k)}$ is the step in the k th iteration. The subgradient method is guaranteed to converge if $u^{(k)}$ satisfies $\lim_{k \rightarrow \infty} u_k = 0$ and $\sum_{k=1}^{\infty} u_k = \infty$ [33].

In summary, the algorithm to solve Problem **(P1)** is given in Algorithm 2.

Remark 1: For the special case of $N = 1$, the channel matrix \mathbf{H} reduces to a vector \mathbf{h} and the semi-unitary matrix \mathbf{U} in (18) reduces to a vector, given by

$$\mathbf{u} = \frac{\mathbf{B}^{-1/2}\mathbf{h}}{\|\mathbf{B}^{-1/2}\mathbf{h}\|}. \quad (25)$$

Also, diagonal matrix \mathbf{D} reduces to a scalar q and only one subchannel is used to transmit information, that is power allocation matrix Λ reduces to a scalar q . Hence, according to (22), the optimal transmit covariance matrix is given by

$$\mathbf{Q} = \frac{q}{\|\mathbf{B}^{-1/2}\mathbf{h}^H\|^2} \mathbf{B}^{-1}\mathbf{h}^H\mathbf{h}\mathbf{B}^{-1}. \quad (26)$$

Since \mathbf{B} is a diagonal matrix, the optimal transmission strategy should be the maximum ratio transmission, which is consistent with the analysis in [28]. Here, we have extended the result in [28] to the more general case with multiple antennas at the receiver.

Algorithm 2 Solving Problem **(P1)**

Initialize: Iteration number $k = 0$, $\lambda^{(0)} = [\lambda_1, \dots, \lambda_A]$, such that $\mathbf{B} \succ \mathbf{0}$.

Repeat

1. Compute $\mathbf{Q}(\lambda) = \mathbf{B}^{-\frac{1}{2}}\mathbf{U}\Lambda\mathbf{U}^H\mathbf{B}^{-\frac{1}{2}}$ with fixed $\lambda^{(k)}$ using (22);
2. Compute the subgradient $s_i^{(k)}, \forall i$, using (23);
3. Update $\lambda_i^{(k+1)}$ using (24), increase k by 1;

Until convergence

B. Algorithm to solve Problem (P2)

Since the numerator and denominator in the objective function of Problem **(P2)** are concave and affine in \mathbf{Q} respectively, the objective function is a pseudo-concave function [34]. In addition, the available power region is a convex set. Hence, Problem **(P2)** can be efficiently solved by using the following lemma, the proof of which can be found in [35].

Lemma 2: Define function $G(\eta)$ as

$$G(\eta) \triangleq \max_{\mathbf{Q} \in \mathcal{W}} \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H| - \eta (\text{tr}(\mathbf{Q}) + P_C), \quad (27)$$

For a fixed η , the solution to the problem in (27) is denoted as $\mathbf{Q}^*(\eta)$. Then solving Problem **(P2)** is equivalent to finding the root of the equation η^* , which satisfies

$$G(\eta^*) = \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}^*(\eta^*)\mathbf{H}^H| - \eta^* (\text{tr}(\mathbf{Q}^*(\eta^*)) + P_C) = 0. \quad (28)$$

Lemma 2 gives us insights to solve Problem **(P2)**. We should firstly solve the problem in (27) for a fixed η , and then utilize the Dinkelbach method [35] to update η . For a fixed η , the solution to the problem in (27) can be obtained by the same method as the one used to solve Problem **(P1)**, except that \mathbf{B} is replaced by $\tilde{\mathbf{B}} = \eta\mathbf{I} + \sum_{i=1}^A \lambda_i \mathbf{B}_i$.

After solving the problem in (27), we utilize the Dinkelbach method [35] to update η as follows

$$\eta^{(n+1)} = \frac{\log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}^*(\eta^{(n)})\mathbf{H}^H|}{\text{tr}(\mathbf{Q}^*(\eta^{(n)})) + P_C}, \quad (29)$$

where n is the iteration index.

Based on the above analysis, we provide Algorithm 3 to solve Problem **(P2)**.

Algorithm 3 The Dinkelbach method to solve Problem **(P2)**

Initialize: $\eta^{(0)}$ satisfying $G(\eta^{(0)}) \geq 0$, iteration number $n = 0$;

Repeat

1. Compute the optimal solution $\mathbf{Q}^*(\eta^{(n)})$ with fixed $\eta^{(n)}$ by using Algorithm 2 except that \mathbf{B} is replaced by $\tilde{\mathbf{B}} = \eta\mathbf{I} + \sum_{i=1}^A \lambda_i \mathbf{B}_i$.

2. Update $\eta^{(n+1)}$ according to (29), and set $n \leftarrow n + 1$;

Until convergence

If the optimal solution to Problem **(P2)** does not satisfy the rate requirement, save the obtained η^* from Algorithm 3, which will be used to solve Problem **(P3)** as shown in the next subsection.

C. Algorithm to solve Problem **(P3)**

Problem **(P3)** is non-convex due to the rate *equality* constraint. However, it is straightforward to see that the solution is equal to the following convex problem

$$\begin{aligned} \min_{\mathbf{Q} \in \mathcal{W}} \quad & \text{tr}(\mathbf{Q}) \\ \text{s.t.} \quad & \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H| \geq \tilde{R}_{\min}, \end{aligned} \quad (30)$$

Thus, it can be solved by the Lagrangian dual method.

The dual function is given by

$$g(\lambda) = \min_{\mathbf{Q} \in \mathcal{W}} \text{tr}(\mathbf{Q}) + \lambda \left(\tilde{R}_{\min} - \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H| \right). \quad (31)$$

Then the dual problem is

$$\max_{\lambda \geq 0} g(\lambda). \quad (32)$$

Now, we solve the problem in (31) for a given λ . If $\lambda = 0$, the optimal \mathbf{Q} should be the zero matrix. In this case, the rate becomes zero, which cannot be the optimal dual variable. Hence, λ should be positive. Denote $\mu = 1/\lambda > 0$, the problem in (31) can be equivalently expressed as

$$\max_{\mathbf{Q} \in \mathcal{W}} \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H| - \mu \text{tr}(\mathbf{Q}). \quad (33)$$

Note that for a fixed μ , the problem in (33) is the same as the problem in (27), and thus can be solved by the same method as the one used to solve Problem **(P1)**. Denote the optimal solution of the problem in (33) as $\mathbf{Q}^*(\mu)$. According to the complementary slackness condition [26], we should find the optimal μ^* such that $\log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}^*(\mu^*)\mathbf{H}^H| = \tilde{R}_{\min}$. In the following lemma, we show that the optimal μ^* should be smaller than the η^* obtained in Algorithm 3.

Lemma 3: The optimal μ^* that leads to $\log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}^*(\mu^*)\mathbf{H}^H| = \tilde{R}_{\min}$ is smaller than the η^* obtained in Algorithm 3.

proof: See Appendix A. □

Based on Lemma 3, we can use the bisection search method to find the optimal μ^* with the upper bound given by η^* .

D. Complexity Analysis

In this subsection, we provide the complexity analysis for the EE optimization problem (8) for a fixed \mathbb{S} . Since this problem is divided into three subproblems, we should provide the complexity for each of these subproblems. We assume that $M_A \geq N$. For Algorithm 2 to solve Problem **(P1)**, the main complexity lies in step 1, where the EVD operation in (18) is performed. According to [26], this operation incurs the complexity of $2M_A^2N + 2N^3/3$ flops. Hence, the total computational complexity of Algorithm 2 involves $T_{\text{alg2}}(2M_A^2N + 2N^3/3)$ flops, where T_{alg2} is the average number of iterations required to converge. The simulation results show that Algorithm 2 converges fast with the proper choice of the step size. For Problem **(P2)**, the Dinkelbach method is used, in which the problem in (27) is solved in each iteration that has a similar complexity as that of the Problem **(P1)**. Hence, the total complexity of Algorithm 3 involves $T_{\text{alg3}}T_{\text{alg2}}(2M_A^2N + 2N^3/3)$ flops, where T_{alg3} is the number of iterations required for Algorithm 3 to converge. **Since Algorithm 3 is Dinkelbach's algorithm, it has super-linear convergence**

rate [36]. The simulation results in Section V that only a few number of iterations are enough for Algorithm 3 to converge. As for Problem (P3), the bisection search method is employed which involves solving the problem in (33) in each iteration that has a similar complexity as that for (P1). Thus, the total complexity to solve (P3) involves $T_{\text{bis}}T_{\text{alg2}}(2M_A^2N + 2N^3/3)$ flops, where T_{bis} denotes the average number of iterations for the bisection search method to converge. According to Lemma 3, the upper bound of μ^* is η^* . Hence, the maximum value of T_{bis} is given by $\log_2(\eta^*/\varepsilon)$, where ε is the accuracy of the bisection search method. Simulation results show that T_{bis} is very small. Hence, the total complexity to solve the problem in (8) involves at most $(T_{\text{alg3}} + T_{\text{bis}} + 1)T_{\text{alg2}}(2M_A^2N + 2N^3/3)$ flops.

On the other hand, the complexity of the interior point method [26] is $(m + 1)^{1/2}n(n^2 + \sum_{i=1}^m k_i^3 + n \sum_{i=1}^m k_i^2)$ flops [37], where n is the number of unknown variables, m is the number of constraints, and k_i is the constant length in the i th constraint [37]. For the problem in (8), $n = M_A^2$, $m = A + 1$ and $k_i = 1, \forall i$. In general, the number of receive antennas at the user is much smaller than that of the active antennas, i.e., $N \ll M_A$. Hence, our algorithm yields a much lower computational complexity than the interior point method.

IV. ACTIVE RAU SELECTION

In this section, we study the active RAU selection scheme. Obviously, the optimal RAU selection can be obtained by exhaustive search. Specifically, we compute the EE for all possible RAU selection sets $\mathbb{S} \subseteq \{1, 2, \dots, I\}$ based on the algorithms developed in Section III. Then, we select the best RAU set which has the best EE performance¹. However, the complexity of exhaustive search is too high to implement in practice. Hence, a more efficient RAU selection scheme is required.

In [22], the authors proposed a norm-based antenna selection scheme for the centralized antenna system. It can be extended to the RAU selection here. In particular, we need to calculate the norms of the channel matrices from all RAUs to the user and sort them in decreasing order. Then, the RAU is added in the active RAU set one after another based on the sorted order.

However, in the DAS, the distances from the user to the RAUs are different and the channel norm is mainly determined by the distance. Based on these facts, we only need to obtain the

¹If problem (8) is infeasible, we set the corresponding EE to be zero. If there is no feasible set, we activate all transmit antennas to achieve the best sum rate performance.

distance information² and sort them in increasing order instead of calculating the channel norms. This method can reduce the computational complexity. It will be shown in Section V that the EE performance of these two selection schemes are almost the same. Denote the distance from the i th RAU to the user as d_i , the distance-based RAU selection scheme is given in Algorithm 4.

Algorithm 4 Distance-Based RAU Selection Scheme

Initialize: Set $EE_{\text{opt}} = 0$, feasibility mark $\text{flag} = 0$, the optimal RAU set $\mathbb{S}_{\text{opt}} = \emptyset$, the number of active RAUs $A = 1$. Sort the distances d_i s in increasing order, i.e, $d_{\pi(1)} \leq \dots \leq d_{\pi(I)}$, where $\pi(i)$ represents the index of the user that has the i th smallest distance.

- 1) Set $\mathbb{S}_a = \{\pi(1), \dots, \pi(A)\}$ and the channel matrix from the selected RAUs as $\mathbf{H}_{\mathbb{S}_a} = [\mathbf{H}_{\pi(1)}, \mathbf{H}_{\pi(2)}, \dots, \mathbf{H}_{\pi(A)}]$.
 - 2) Solve the EE optimization problem in (8) by using Algorithm 1 based on the active RAU set \mathbb{S}_a . If it is infeasible, set $EE_{\mathbb{S}_a} = 0$. Otherwise, set $\text{flag} = 1$ and compute the achieved EE $EE_{\mathbb{S}_a}$.
 - 3) If $EE_{\text{opt}} \leq EE_{\mathbb{S}_a}$, set $EE_{\text{opt}} = EE_{\mathbb{S}_a}$ and $\mathbb{S}_{\text{opt}} = \mathbb{S}_a$; Otherwise, terminate.
 - 4) If $A < I$, set $A = A + 1$ and go to Step 1); Otherwise, go to Step 5),
 - 5) If $\text{flag} = 0$, set $\mathbb{S}_{\text{opt}} = \{1, \dots, I\}$, solve the rate maximization problem with Algorithm 2 based on \mathbb{S}_{opt} , compute the corresponding EE EE_{opt} , and terminate; Otherwise, terminate.
-

Compared with the antenna selection algorithm in [22], our proposed algorithm does not need to solve the EE optimization problem I times. It will be terminated as long as the current achieved EE is smaller than the previous highest EE as seen in step 3) of Algorithm 4. This can significantly reduce the search complexity especially when the number of RAUs is large. This is also reasonable, because if adding one more RAUs in the selection RAU set decreases the EE, the remaining RAUs will also degrade the EE since their distances are much larger and the corresponding channel gains are much smaller. The simulation results will demonstrate this statement.

²According to [38], the distance information can be easily calculated through the GPS or other similar methods.

We compare the complexity of our proposed algorithm with the exhaustive search. In the exhaustive search, the size of the set of RAU candidates \mathbb{S} is given as $2^I - 1$, and thus the problem in (8) should be solved $2^I - 1$ times, which increases exponentially with the RAU number I . On the other hand, for our proposed RAU selection algorithm, i.e., Algorithm 4, we solve the problem in (8) at most I times. For example, for $I = 20$, 1048575 RAU selection sets are required for the exhaustive search, while at most 20 candidates are required in our proposed selection scheme, which account for only 0.19‰ of the complexity of the exhaustive search.

V. SIMULATION RESULT

In this subsection, we evaluate the performance of the proposed RAU selection and transmit covariance optimization scheme, i.e., Algorithm 4, through simulations. We assume the user is uniformly distributed in the circular cell centered at $(0, 0)$ with radius R . According to [39] and [40], if the number of RAUs I is smaller than 6, the location of the j -th RAU is $(r \cos(2\pi(j-1)/I), r \sin(2\pi(j-1)/I))$ for $j = 1, \dots, I$, where $r = 2R \sin(\pi/I)/(3\pi/I)$. Otherwise, the first RAU is located at the cell center $(0, 0)$, and the other $I - 1$ RAUs are located at $(r \cos(2\pi(j-2)/(I-1)), r \sin(2\pi(j-2)/(I-1)))$ with $j = 2, \dots, I$. The channel modeled considers large-scale pathloss [41], shadow fading and independent Rayleigh fading. More specifically, the shadow fading follows the log-normal distribution with the standard deviation $\delta_{sh} = 8\text{dB}$. For simplicity, we assume each RAU has the same number of antennas $M_j = M, j = 1, \dots, I$ and the same power constraints $P_j = P_{\max}, j = 1, \dots, I$. Unless otherwise specified, the other main system parameters are given in Table I. The following results are obtained by averaging over 500 independent channel generations.

A. Convergence behavior of the proposed algorithms

We first study the convergence behaviors of the proposed algorithms: Algorithm 2 to solve Problem **(P1)**, Algorithm 3 to solve Problem **(P2)** and the bisection method to solve Problem **(P3)**. Since we only consider the convergence behaviours for these algorithms, we do not consider RAU selection in this subsection and all RAUs are turned on.

Fig. 2 illustrates the maximum rate achieved by Algorithm 2 versus the number of iterations under three different configurations: the DAS network with $I = 2$, $I = 6$ and $I = 10$. The step is set as $u^{(k)} = 1/(30k)$, where k is the iteration index. It can be seen from Fig. 2 that

TABLE I
MAIN SIMULATION PARAMETERS

Parameters	Value
Channel bandwidth W	20 MHz
Cell radius R	1000 m
Number of transmit antennas M	4
Number of receiver antennas N	4
Noise power spectral density	-174 dBm/Hz
RF chain power consumption p_c	1 W
Static power consumption p_0	1 W
Tolerance ε	$10^{(-5)}$
Maximum transmit power P_{\max}	10 W
Channel path loss model	$38.46 + 35\log_{10}(d)$ [41]

the maximum rate monotonically increases during the iterative procedure of Algorithm 2 and converges rapidly (within 50 iterations for all considered configurations). On the other hand, from Fig. 2, it can be seen that the maximum rate performance is significantly affected by the number of the antennas: a larger I corresponds to a higher rate.

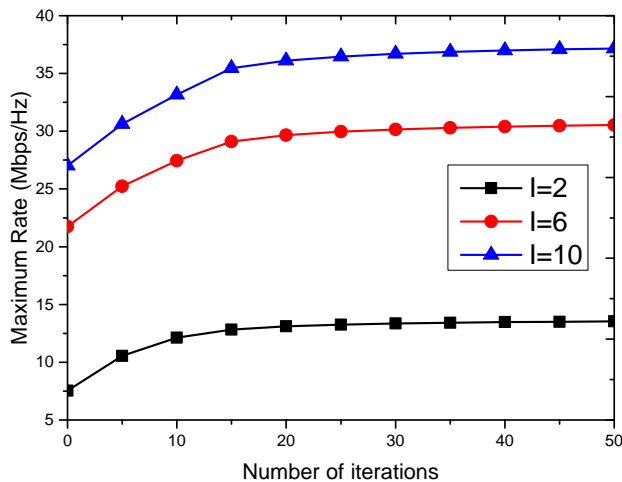


Fig. 2. Convergence behaviors of Algorithm 2 to solve Problem (P1) under different number of RAUs.

Fig. 3 shows the convergence behaviour of Algorithm 3 for different number of antennas with $I = 2$, $I = 6$ and $I = 10$. It can be seen from this figure that several iterations are enough for Algorithm 3 to converge. In addition, a larger I does not guarantee a higher EE due to more circuit power consumption. For example, the EE corresponding to $I = 6$ is higher than the EE for the other two scenarios ($I = 4$ and $I = 10$). Hence, to achieve the highest EE, it is necessary to choose the appropriate set of active RAUs.

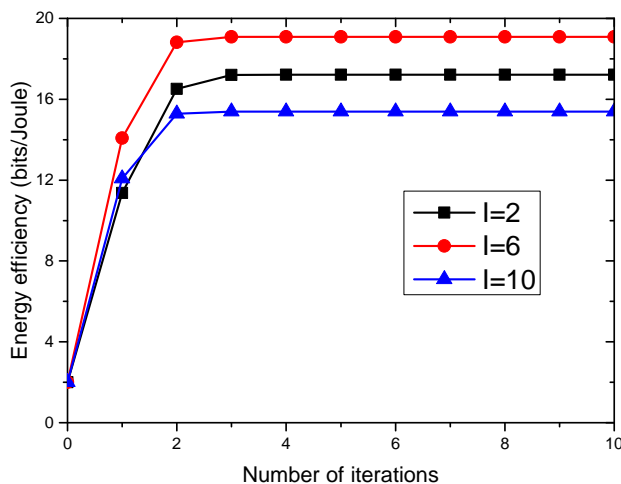


Fig. 3. Convergence behaviors of Algorithm 3 to solve Problem (P2) under different number of RAUs.

The convergence behaviour of the bisection method to solve Problem (P3) is given in Fig. 4. Denote R_{\max} and R_{frac} as the maximum rates achieved by solving Problem (P1) and Problem (P2), respectively. In Problem (P3), the rate constraint is set as $R_{\min} = (R_{\max} + R_{\text{frac}})/2$. It can be seen from Fig. 4 that the achievable rate converges rapidly (within 10 iterations for all considered configurations).

B. Performance comparison

In this subsection, We compare our proposed RAU selection and transmit covariance optimization algorithm, i.e., Algorithm 4, with the following algorithms: exhaustive search which examines all possible RAU selection set (labeled as “Exhaustive search”), norm-based RAU selection algorithm (labeled as “Prop norm-based alg.”) which is the same as Algorithm 4 except that we sort the channel norms in decreasing order, EE maximization without RAU selection

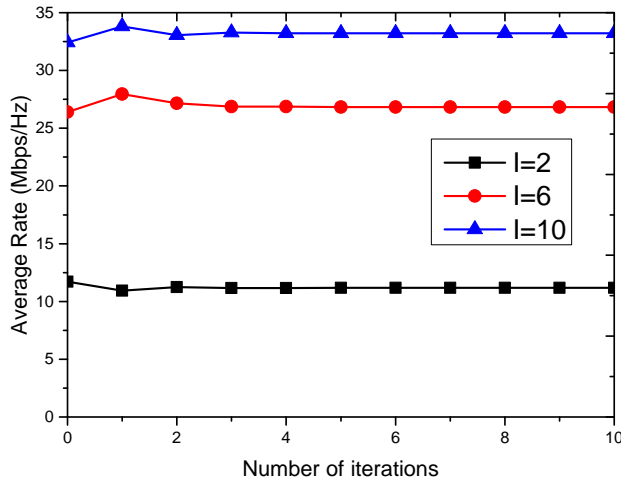


Fig. 4. Convergence behaviors of the bisection method to solve Problem (P3) under different number of RAUs.

and all available RAUs are active (labeled as “EE without RAU sel.”) and SE maximization activating all available RAUs (labeled as “SE maximization”). We also show the performance of the EE maximization proposed in [22] for the centralized antenna system (CAS) where all antennas are placed at the center of the cell. For a fair comparison, we assume that the maximum transmit power for CAS is set to be IP_{\max} and the base station is equipped with IM antennas. Moreover, the total circuit power consumption of CAS is defined as $Ip_c + IMp_0$.

The effects of the rate constraint on the EE of the DAS are studied in Fig. 5, the corresponding rate and the number of active RAUs are shown in Fig. 6 and Fig. 7, respectively. The total number of RAUs is set as $I = 4$. As expected, the EE achieved by all algorithms decreases with the rate constraint. The reason is that, more RAUs need to be active to ensure that the rate requirement can be satisfied, which incurs more circuit power consumption. Note that both the exhaustive search method and the channel-norm-based search method provide marginal gains over our proposed RAU selection method, and our proposed algorithm yields the least computational complexity. In addition, we observe that our proposed algorithm significantly outperforms the other schemes in terms of the EE, especially in the low rate constraint regime. The superiority of the proposed algorithm over the “EE without RAU sel.” comes from the RAU selection procedure. It means that turning off some RAUs can save significant amount of circuit power consumption when the rate requirement is satisfied, and thus improves the EE of the DAS. It is interesting to find

that the EE performance of the DAS is much higher than that of the CAS. This observation is meaningful: to achieve the best EE performance, RAUs should be placed in a distributed manner rather than in a centralized manner. Moreover, the rate maximization algorithm has the worst EE performance since it aims at improving the throughput of the DAS, implying that all RAUs should be activated and each RAU uses full power to transmit.

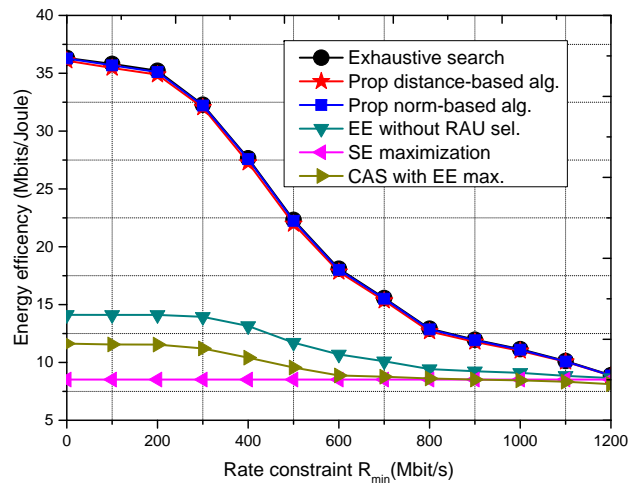


Fig. 5. EE under different rate constraints, where $I = 4$.

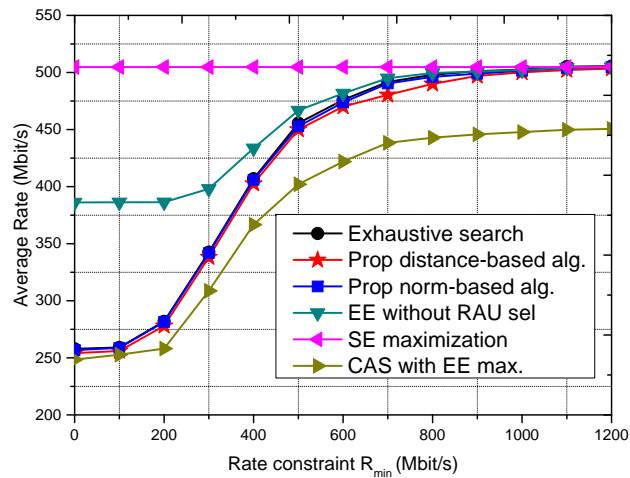


Fig. 6. Corresponding rate under different rate constraints, where $I = 4$.

As expected, Fig. 6 shows that the rates achieved by all methods increase with the rate

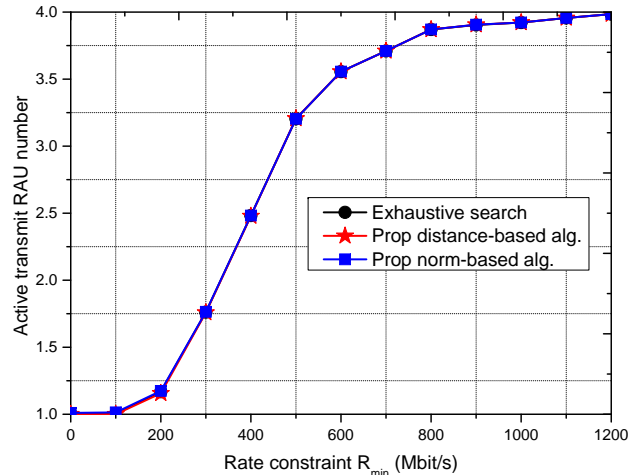


Fig. 7. Corresponding number of active RAUs under different rate constraints, where $I = 4$.

constraint and finally keep constant at 504 Mbit/s. In this case, all RAUs should be active and full transmit power is used. When the rate constraint is beyond 504 Mbit/s, the original problem is infeasible, which can be checked by the first step of Algorithm 1. It can be seen from Fig. 7 that the number of active RAUs for different RAU selection methods are almost the same and increases with the rate constraint, which is consistent with the analysis for Fig. 5.

Fig. 8 studies the effect of the number of RAUs on the EE performance of different methods under two cases: $R_{\min} = 0$ Mbps/Hz and $R_{\min} = 800$ Mbps/Hz. The corresponding rate and number of active RAUs are shown in Fig. 9 and Fig. 10, respectively. Similar to the observations in Fig. 5, the EE performance of the proposed RAU selection is almost the same as exhaustive search and channel-norm-based method, and significantly outperforms the other schemes for both cases. For the case of $R_{\min} = 0$ Mbps/Hz, it can be observed from Fig. 8.(a) that the EE achieved by the proposed RAU selection method increases with the number of RAUs. The reason is that as the number of RAUs increases, the average access distance of the user to the RAUs reduces, and thus the EE of the DAS improves. On the other hand, the EE of the CAS almost stays fixed for all considered number of RAUs. This again confirms the fact that, in order to have a better EE performance, massive number of antennas in 5G networks should be placed spatially separated. It is interesting to see from Fig. 10 that when no rate constraint is incorporated, the number of active RAUs is always equal to one. Note that a similar property

has also been observed in [14] for the single-antenna case.

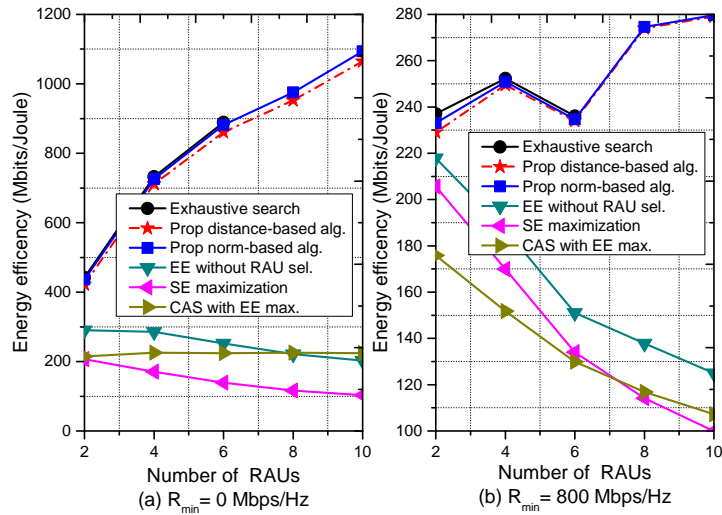


Fig. 8. EE under different number of RAUs with (a) $R_{\min} = 0$ Mbps/Hz and (b) $R_{\min} = 800$ Mbps/Hz.

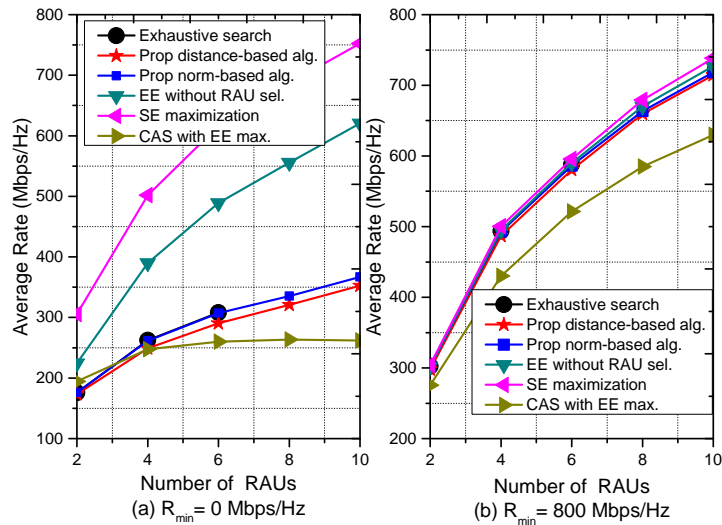


Fig. 9. Corresponding rate under different number of RAUs with (a) $R_{\min} = 0$ Mbps/Hz and (b) $R_{\min} = 800$ Mbps/Hz.

For the case of $R_{\min} = 800$ Mbps/Hz, from Fig. 8 (b), we find that the EE of the CAS, i.e., the EE achieved by “CAS with EE max” decreases dramatically with the number of RAUs. This is due to the fact that more RAUs should be active to support the rate requirement. On the other hand, the EE achieved by our proposed RAU selection method only decreases at $I = 6$.

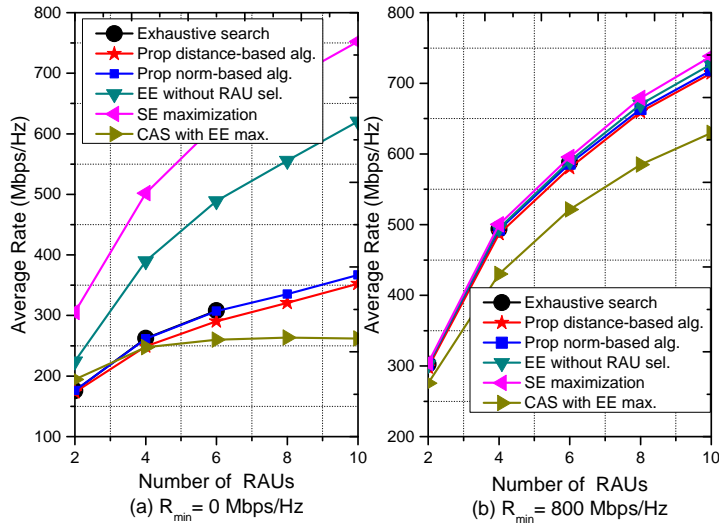


Fig. 10. Corresponding number of active RAUs under different number of RAUs with (a) $R_{\min} = 0$ Mbps/Hz and (b) $R_{\min} = 800$ Mbps/Hz.

Then, with the increase of RAUs, the benefits from the RAU selection diversity dominates the negative effects of the increasing circuit power consumption. It can also be seen from Fig. 9 that the rate achieved by our algorithm is comparable with those achieved by the EE optimization without RAU selection and the rate maximization method. However, it has much better EE performance as seen in Fig. 8 (b). Also, Fig. 10 (b) shows the number of *active* RAUs increases with the number of RAUs, since more RAU should be active for the high rate requirement at $R_{\min} = 800$ Mbps/Hz.

VI. CONCLUSION

In this paper, we have studied the transmit covariance optimization for the EE maximization problem in a multiple-antenna DAS, where both the per-RAU power constraints and the user's rate requirement are incorporated. Given a fixed set of active RAUs, we obtain the optimal transmit covariance matrix by splitting the EE optimization problem into three subproblems, each of which has been solved with low-complexity. Then, we develop a novel distance-based RAU selection method to additionally improve the EE of the DAS with much reduced complexity. Simulation results show that our proposed RAU selection performs as well as the optimal exhaustive RAU search method, and significantly outperforms EE optimization method without

RAU selection and the antenna selection method in the CAS.

APPENDIX A

PROOF OF LEMMA 3

Before proving the lemma, we first study the property of the following function

$$\text{EE}(x) = \max_{\mathbf{Q} \in \mathcal{W}} \frac{\log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}\mathbf{H}^H|}{\text{tr}(\mathbf{Q}) + x}, \quad (34)$$

where $x > 0$. Denote the optimal solution for a given x as $\mathbf{Q}^\circ(x)$ and the corresponding achievable rate as $R(x) = \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}^\circ(x)\mathbf{H}^H|$.

Property 1: As $x \rightarrow +\infty$, $R(x)$ will approach the maximum achievable rate $R_{\max} = \log_2 |\mathbf{I} + \mathbf{H}\mathbf{Q}_{(\mathbf{P1})}^*\mathbf{H}^H|$ achieved by solving the rate maximization problem **(P1)**.

Proof: Given x , function $\text{EE}(x)$ can be obtained by using the Dinkelbach method as shown in Algorithm 3. At any iteration n , $\eta^{(n+1)}$ is updated according to (29), which will approach zero since the numerator is upper bounded by R_{\max} and the denominator approaches infinity. Then, at iteration $n + 1$, the optimal transmit covariance matrix \mathbf{Q} is obtained by solving the problem in (27), where $\eta = \eta^{(n+1)}$ approaches zero. Hence, the optimal solution to the problem in (27) is almost equal to the solution of the rate maximization Problem **(P1)**, which completes the proof.

□

Property 2 [42]: Function $\text{EE}(x)$ is a continuous and strictly decreasing function of x , while its corresponding achievable rate $R(x)$ is a continuous and strictly increasing function of x . □

Based on the above properties, we start to prove the lemma. From (29), we see that $\text{EE}(P_C) = \eta^*$. According to Algorithm 1, we are solving Problem **(P3)** because the achievable rate $R(P_C)$ is less than \tilde{R}_{\min} , i.e., $R(P_C) < \tilde{R}_{\min}$. Moreover, since problem (8) is feasible according to Algorithm 1, we have $R(P_C) < \tilde{R}_{\min} < R_{\max}$. Then, by using Property 1 and Property 2, there must exist some $x = x'$ for which the achievable rate is equal to \tilde{R}_{\min} , i.e., $R(x') = \tilde{R}_{\min}$. Also, $x' > P_C$ means that $\eta^* = \text{EE}(P_C) > \text{EE}(x')$ according to the strictly decreasing nature of $\text{EE}(x)$ specified in Property 2.

According to Lemma 2, $\mathbf{Q}^\circ(x')$ is the optimal solution to the problem in (27) with $\eta = \text{EE}(x')$. By comparing the problem in (33) with the problem in (27) and recalling that $R(x') = \tilde{R}_{\min}$, we can conclude that $\mathbf{Q}^\circ(x)$ is also the optimal solution to the problem in (33), i.e., $\mathbf{Q}^*(\mu^*) = \mathbf{Q}^\circ(x)$, and $\mu^* = \text{EE}(x')$. Hence, we have $\eta^* > \mu^*$.

REFERENCES

- [1] X.-H. You, D.-M. Wang, B. Sheng, X.-Q. Gao, X.-S. Zhao, and M. Chen, "Cooperative distributed antenna systems for mobile communications [coordinated and distributed MIMO]," *IEEE Wireless Communications*, vol. 17, no. 3, pp. 35–43, June 2010.
- [2] H. Zhu, "Performance comparison between distributed antenna and microcellular systems," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 6, pp. 1151–1163, 2011.
- [3] J. Wang, H. Zhu, and N. Gomes, "Distributed antenna systems for mobile communications in high speed trains," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 4, pp. 675–683, 2012.
- [4] T. Marzetta, "Noncooperative cellular wireless with unlimited numbers of base station antennas," *IEEE Transactions on Wireless Communications*, vol. 9, no. 11, pp. 3590–3600, November 2010.
- [5] Q. Sun, S. Jin, J. Wang, Y. Zhang, X. Gao, and K.-K. Wong, "On scheduling for massive distributed MIMO downlink," in *Global Communications Conference (GLOBECOM), 2013 IEEE*, Dec 2013, pp. 4151–4156.
- [6] W. Choi and J. Andrews, "Downlink performance and capacity of distributed antenna systems in a multicell environment," *IEEE Transactions on Wireless Communications*, vol. 6, no. 1, pp. 69–73, Jan 2007.
- [7] M. Vu, "MISO capacity with per-antenna power constraint," *IEEE Transactions on Communications*, vol. 59, no. 5, pp. 1268–1274, May 2011.
- [8] S.-R. Lee, S.-H. Moon, H.-B. Kong, and I. Lee, "Optimal beamforming schemes and its capacity behavior for downlink distributed antenna systems," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 2578–2587, June 2013.
- [9] R. Heath, T. Wu, Y. H. Kwon, and A. Soong, "Multiuser MIMO in distributed antenna systems with out-of-cell interference," *IEEE Transactions on Signal Processing*, vol. 59, no. 10, pp. 4885–4899, Oct 2011.
- [10] R. Zhang, "Cooperative multi-cell block diagonalization with per-base-station power constraints," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 9, pp. 1435–1445, 2010.
- [11] D. Feng, C. Jiang, G. Lim, J. Cimini, L.J., G. Feng, and G. Li, "A survey of energy-efficient wireless communications," *IEEE Communications Surveys Tutorials*, vol. 15, no. 1, pp. 167–178, First 2013.
- [12] C. Pan, W. Xu, W. Zhang, J. Wang, H. Ren, and M. Chen, "Weighted sum energy efficiency maximization in ad hoc networks," *IEEE Wireless Communications Letters*, vol. 4, no. 3, pp. 233–236, June 2015.
- [13] J. Andrews, S. Buzzi, W. Choi, S. Hanly, A. Lozano, A. Soong, and J. Zhang, "What will 5G be?" *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1065–1082, June 2014.
- [14] H. Kim, S.-R. Lee, C. Song, and I. Lee, "Optimal power allocation for energy efficiency maximization in distributed antenna systems," in *Communications (ICC), 2013 IEEE International Conference on*, June 2013, pp. 5769–5773.
- [15] X. Chen, X. Xu, and X. Tao, "Energy efficient power allocation in generalized distributed antenna system," *IEEE Communications Letters*, vol. 16, no. 7, pp. 1022–1025, July 2012.
- [16] H. Kim, E. Park, H. Park, and I. Lee, "Beamforming and power allocation designs for energy efficiency maximization in MISO distributed antenna systems," *IEEE Communications Letters*, vol. 17, no. 11, pp. 2100–2103, November 2013.
- [17] C. He, G. Li, F.-C. Zheng, and X. You, "Energy efficiency of distributed MIMO systems," in *Signal and Information Processing (GlobalSIP), 2014 IEEE Global Conference on*, Dec 2014, pp. 218–222.

- [18] O. Onireti, F. Heliot, and M. Imran, "On the energy efficiency-spectral efficiency trade-off of distributed MIMO systems," *IEEE Transactions on Communications*, vol. 61, no. 9, pp. 3741–3753, September 2013.
- [19] L. Correia, D. Zeller, O. Blume, D. Ferling, Y. Jading, I. Godor, G. Auer, and L. Van der Perre, "Challenges and enabling technologies for energy aware mobile radio networks," *IEEE Commun. Mag.*, vol. 48, no. 11, pp. 66–72, 2010.
- [20] S. H. Yeung, A. Garcia-Lamperez, T. Kumar Sarkar, and M. Salazar-Palma, "A thin and compact high gain planar antenna integrated with a CMRC compact filter," in *2014 IEEE International Wireless Symposium (IWS)*, March 2014, pp. 1–4.
- [21] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.
- [22] J. Xu and L. Qiu, "Energy efficiency optimization for MIMO broadcast channels," *IEEE Transactions on Wireless Communications*, vol. 12, no. 2, pp. 690–701, February 2013.
- [23] I. E. Telatar, "Capacity of multi-antenna gaussian channels," *European transactions on telecommunications*, vol. 10, no. 6, pp. 585–595, 1999.
- [24] S. He, Y. Huang, S. Jin, and L. Yang, "Coordinated beamforming for energy efficient transmission in multicell multiuser systems," *IEEE Transactions on Communications*, vol. 61, no. 12, pp. 4961–4971, 2013.
- [25] C. Isheden, Z. Chong, E. Jorswieck, and G. Fettweis, "Framework for link-level energy efficiency optimization with informed transmitter," *IEEE Transactions on Wireless Communications*, vol. 11, no. 8, pp. 2946–2957, August 2012.
- [26] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.
- [27] C. Pan, J. Wang, W. Zhang, B. Du, and M. Chen, "Power minimization in multi-band multi-antenna cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 9, pp. 5056–5069, Sept 2014.
- [28] S.-R. Lee, S.-H. Moon, H.-B. Kong, and I. Lee, "Optimal beamforming schemes and its capacity behavior for downlink distributed antenna systems," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 2578–2587, June 2013.
- [29] W. Yu and T. Lan, "Transmitter optimization for the multi-antenna downlink with per-antenna power constraints," *IEEE Transactions on Signal Processing*, vol. 55, no. 6, pp. 2646–2660, 2007.
- [30] H. Dahrouj and W. Yu, "Coordinated beamforming for the multicell multi-antenna wireless system," *IEEE Transactions on Wireless Communications*, vol. 9, no. 5, pp. 1748–1759, 2010.
- [31] R. Zhang and S. Cui, "Cooperative interference management with miso beamforming," *IEEE Transactions on Signal Processing*, vol. 58, no. 10, pp. 5450–5458, 2010.
- [32] D. P. Palomar and M. Chiang, "A tutorial on decomposition methods for network utility maximization," *IEEE Journal on Selected Areas in Communications*, vol. 24, no. 8, pp. 1439–1451, 2006.
- [33] S. Boyd, L. Xiao, and A. Mutapcic, "Subgradient methods," *lecture notes of EE392o, Stanford University, Autumn Quarter*, vol. 2004, pp. 2004–2005, 2003.
- [34] A. Zappone, P. Cao, and E. A. Jorswieck, "Energy efficiency optimization in relay-assisted mimo systems with perfect and statistical csi," *IEEE Transactions on Signal Processing*, vol. 62, no. 2, pp. 443–457, 2014.
- [35] W. Dinkelbach, "On nonlinear fractional programming," *Management Science*, vol. 13, no. 7, pp. 492–498, 1967.
- [36] C. Isheden, Z. Chong, E. Jorswieck, and G. Fettweis, "Framework for link-level energy efficiency optimization with informed transmitter," *IEEE Transactions on Wireless Communications*, vol. 11, no. 8, pp. 2946–2957, 2012.
- [37] A. Ben-Tal and A. Nemirovski, *Lectures on Modern Convex Optimization: Analysis, Algorithms, and Engineering Applications*. Philadelphia, PA: MPS-SIAM, 2001.

- [38] H. Kim, S.-R. Lee, K.-J. Lee, and I. Lee, "Transmission schemes based on sum rate analysis in distributed antenna systems," *IEEE Transactions on Wireless Communications*, vol. 11, no. 3, pp. 1201–1209, March 2012.
- [39] Y. Qian, M. Chen, X. Wang, and P. Zhu, "Antenna location design for distributed antenna systems with selective transmission," in *Wireless Communications Signal Processing, 2009. WCSP 2009. International Conference on*, Nov 2009, pp. 1–5.
- [40] X. Wang, P. Zhu, and M. Chen, "Antenna location design for generalized distributed antenna systems," *IEEE Communications Letters*, vol. 13, no. 5, pp. 315–317, May 2009.
- [41] S. Assumptions, "Parameters for FDD HeNB RF requirements," in *3GPP TSG-RAN WG4 R4-092042*, 2009.
- [42] C. Pan, W. Xu, J. Wang, H. Ren, W. Zhang, N. Huang, and M. Chen, "Totally distributed energy-efficient transmission in mimo interference channels," *IEEE Transactions on Wireless Communications*, vol. 14, no. 11, pp. 6325–6338, 2015.