Antenna Port Selection in a Coordinated Cloud Radio Access Network

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***Abstract*— We investigate the optimization of antenna port selection in the downlink of a cloud radio access network in which a user terminal can be served by multiple ports. The goal is to maximize the minimum weighted signal-to-interference-plus-noise ratios observed by the users while satisfying their quality-of-service requirements. This optimization is formulated as a mixed integer programming problem and solved using semidefinite relaxation and Gaussian randomization. It is shown that our technique outperforms baseline schemes by 6–8 dB.**

***Index Terms*— Distributed antennas, C-RAN, antenna selection.**

I. Introduction

DISTRIBUTED antenna systems (DAS) offer an effective means for improving the spectral efficiency of wireless communication networks, including those with heterogeneous traffic. In DAS, antennas are not collocated at a base station (BS), but dispersed over the coverage area. A key DAS objective is to improve coverage and capacity of indoor and cellular wireless communication systems [1]–[3]. However, realizing this potential requires proper selection of the antenna ports [4], [5]. Approaches for optimizing this selection include those based on maximizing the sum-rate [6] and maximizing the minimum signal-to-interference-plus-noise ratio (SINR) [7], [8]. To elaborate, in [7] the transmission parameters are optimized in a DAS in which the user terminals (UTs) are restricted to be served by the ports of their respective BSs.

We advance the antenna port selection problem to an emerging area of "cloud" radio access networks. In particular, we consider a DAS in which UTs are served by arbitrary ports, not necessarily those of their original BSs. Such a broader configuration enables cell-edge UTs to be served by neighbouring BSs, thereby creating UT-centric virtual cells with boundaries that flex freely to accommodate mobility and time-varying demand. The creation of such virtual cells enriches the design with valuable degrees of freedom and offers the potential of achieving a significantly better performance. To realize this potential, we develop an optimization-based framework that uses the semidefinite relaxation (SDR) and Gaussian randomization technique [9]. This technique was originally devised in [10] to provide efficiently computable solutions for a class of NP-hard problems, including the max-cut and the satisfiability problems. It was shown in [10] that the solution yielded by this approach is at least 87.5% of the optimal solution, but in practice, this algorithm is known to yield solutions that are typically closer to the optimal solution [9]. Hence, it can be seen that SDR with Gaussian approximation offers performance guarantees that are usually not available to other polynomial-complexity algorithms. Simulation results demonstrate that although the proposed technique does not necessarily yield the optimal solution, it captures the flexibility offered by virtual cells for and yields superior performance for both homogeneous and heterogeneous traffic models [11].

The main contributions of this work are as follows:

1) We propose a DAS cloud configuration in which ports can transmit to any UT using binary or ternary states.
2) We apply the SDR technique to DAS clouds with homogeneous and heterogeneous UT distributions.

II. System Model

We consider a DAS cloud with L ports and K UTs. Transmissions in this cloud are coordinated by a central entity, which can be an elect BS with computational capabilities sufficient to coordinate transmissions from ports to UTs. To perform this task, the central entity is assumed to know the channel gains between the ports and the UTs. Each UT can be served by any port in the cloud. However, a port can transmit to at most one UT at any time instant.

Let $\mathbf{\Gamma} \in \{0, 1\}^{L\times K}$ be a matrix whose ℓk-th entry, $\gamma_{\ell k} = 1$ if the ℓ-th port is used to serve the k-th UT and $\gamma_{\ell k} = 0$ otherwise. Restricting the ℓ-th port to transmit to at most one UT yields $\sum_{k=1}^{K}[\mathbf{\Gamma}]_{\ell,k} \le 1$, $\ell = 1,\ldots,L$. Let P_ℓ be the transmit power of this port. Then the $M_{R_k}\times 1$ received signal of the k-th UT, $k = 1,\ldots,K$, is

$$\boldsymbol{y}_k = \sum_{\ell=1}^{L}\gamma_{\ell k}\sqrt{P_\ell}\boldsymbol{H}_{\ell k}\boldsymbol{x}_k + \sum_{i=1,i\neq k}^{K}\sum_{\ell=1}^{L}\gamma_{\ell i}\sqrt{P_\ell}\boldsymbol{H}_{\ell k}\boldsymbol{x}_i + \boldsymbol{\eta}_k,$$

where, $\boldsymbol{H}_{\ell k} \in \mathbb{C}^{M_{R_k}\times M_{T_\ell}}$ is the channel matrix between the ℓ-th port and the k-th UT, M_{T_ℓ} is the number of transmit antennas of the ℓ-th port, M_{R_k} is the number of receive antennas of the k-th UT, $\boldsymbol{x}_k$ is the normalized data vector and $\boldsymbol{\eta}_k \sim \mathcal{CN}(0, \sigma^2\boldsymbol{I}_{M_{R_k}})$ is the additive noise.

Letting $\boldsymbol{\gamma} = \mathrm{vec}(\mathbf{\Gamma})$, the SINR of the k-th UT is

$$\begin{aligned}\mathsf{SINR}_k(\boldsymbol{\gamma}) &= \frac{\beta_k\left\|\sum_{\ell=1}^{L}\gamma_{\ell k}\sqrt{P_\ell}\boldsymbol{H}_{\ell k}\right\|^2}{\sum_{i=1,i\neq k}^{K}\left\|\sum_{\ell=1}^{L}\gamma_{\ell i}\sqrt{P_\ell}\boldsymbol{H}_{\ell k}\right\|^2 + \sigma^2 M_{R_k}},\\ &= \frac{\beta_k\boldsymbol{\gamma}^T\boldsymbol{A}_k\boldsymbol{\gamma}}{\boldsymbol{\gamma}^T\boldsymbol{B}_k\boldsymbol{\gamma} + \sigma^2 M_{R_k}}, \qquad (1)\end{aligned}$$

where $\beta_k > 0$ is a weight used to prioritize the SINR of the k-th UT [8], $\boldsymbol{A}_k \in \mathbb{R}^{LK\times LK}$ and $\boldsymbol{B}_k \in \mathbb{R}^{LK\times LK}$ are

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block-diagonal symmetric matrices defined as

$$\begin{aligned} \boldsymbol{A}_k &= \oplus_{i=1}^{k-1} \boldsymbol{0}_L \oplus \boldsymbol{D}_k \oplus_{i=k+1}^{K} \boldsymbol{0}_L, \\ \text{and} \quad \boldsymbol{B}_k &= \oplus_{i=1}^{k-1} \boldsymbol{D}_i \oplus \boldsymbol{0}_L \oplus_{i=k+1}^{K} \boldsymbol{D}_i, \end{aligned} \tag{2}$$

where $\oplus$ denotes the direct sum operation, $\boldsymbol{0}_L$ is an $L \times L$ all-zero matrix, and the mn-th entry of the matrix $\boldsymbol{D}_k \in \mathbb{R}^{L\times L}$ is given by $[\boldsymbol{D}_k]_{m,n} = \sqrt{P_m P_n}\ \mathrm{Re}\{\mathrm{Tr}(\boldsymbol{H}_{mk}\boldsymbol{H}_{nk}^H)\}$.

III. Coordinated Port Selection

Our objective is to obtain the ports associated with each UT such that the minimum SINR of all UTs is maximized. Such an objective introduces fairness by collectively improving the performance of all UTs. The optimal association solves

$$\max_{\boldsymbol{\gamma}\in\{0,1\}^{LK}} \quad \min_k \frac{\beta_k \boldsymbol{\gamma}^T \boldsymbol{A}_k \boldsymbol{\gamma}}{\boldsymbol{\gamma}^T \boldsymbol{B}_k \boldsymbol{\gamma} + \sigma^2}, \tag{3a}$$

$$\text{subject to} \quad \sum_{k=1}^{K} [\boldsymbol{\gamma}]_{\ell+(k-1)L} \leq 1, \quad \ell = 1, \ldots, L. \tag{3b}$$

The objective in (3a) represents the minimum weighted SINR, (3b) ensures that each port transmits to at most one UT, and the binary constraint in (3a) ensures that each port can be either on or off. This problem is NP-hard [12]. Hence, we invoke SDR to find a close-to-optimal solution [9]. A related formulation was considered in [7] but without the constraints in (3b) and without considering weighting and multiple antenna possibilities. Despite being linear, the interaction of these constraints with the binary constraint complicates the problem structure and must be properly handled when applying SDR.

To use SDR, let $\boldsymbol{\psi} = 2\boldsymbol{\gamma} - 1$, which implies that $\boldsymbol{\gamma} = (\boldsymbol{\psi} + 1)/2$ and yields $\boldsymbol{\psi} \in \{-1, 1\}^{LK}$. Using this transformation in (3), the port selection problem can cast as follows:

$$\max_{\boldsymbol{\psi}\in\{-1,1\}^{LK}} \quad \min_k \frac{\beta_k(\boldsymbol{\psi}^T \boldsymbol{A}_k \boldsymbol{\psi} + 2\boldsymbol{\psi}^T \boldsymbol{A}_k \boldsymbol{1} + \boldsymbol{1}^T \boldsymbol{A}_k \boldsymbol{1})}{\boldsymbol{\psi}^T \boldsymbol{B}_k \boldsymbol{\psi} + 2\boldsymbol{\psi}^T \boldsymbol{B}_k \boldsymbol{1} + \boldsymbol{1}^T \boldsymbol{B}_k \boldsymbol{1} + 4\sigma^2},$$

$$\text{subject to} \quad -K \leq \sum_{k=1}^{K} [\boldsymbol{\psi}]_{\ell+(k-1)L} \leq 2 - K, \ \forall \ell.$$

Define $\boldsymbol{1}_r \in \mathbb{R}^r$ to be the all-one vector, and $\boldsymbol{\Phi} \triangleq \boldsymbol{\psi}\boldsymbol{\psi}^T$,

$$\boldsymbol{\Xi} = \begin{bmatrix} \boldsymbol{\Phi} & \boldsymbol{\psi} \\ \boldsymbol{\psi}^T & 1 \end{bmatrix}, \ \boldsymbol{E}_k = \begin{bmatrix} \boldsymbol{A}_k & \boldsymbol{A}_k \boldsymbol{1}_{LK} \\ \boldsymbol{1}_{LK}^T \boldsymbol{A}_k & \boldsymbol{1}_{LK}^T \boldsymbol{A}_k \boldsymbol{1}_{LK} \end{bmatrix}, \ \text{and}$$
$$\boldsymbol{F}_k = \begin{bmatrix} \boldsymbol{B}_k & \boldsymbol{B}_k \boldsymbol{1}_{LK} \\ \boldsymbol{1}_{LK}^T \boldsymbol{B}_k & \boldsymbol{1}_{LK}^T \boldsymbol{B}_k \boldsymbol{1}_{LK} + 4\sigma^2 \end{bmatrix}.$$

The optimization problem can now be rewritten as

$$\max_{\boldsymbol{\Phi},\boldsymbol{\psi}} \quad \min_k \frac{\beta_k \mathrm{Tr}(\boldsymbol{E}_k \boldsymbol{\Xi})}{\mathrm{Tr}(\boldsymbol{F}_k \boldsymbol{\Xi})}, \tag{4a}$$

$$\text{subject to} \quad \boldsymbol{\Phi} - \boldsymbol{\psi}\boldsymbol{\psi}^T = \boldsymbol{0}, \tag{4b}$$

$$\mathrm{diag}\,(\boldsymbol{\Phi}) = \boldsymbol{1}, \tag{4c}$$

$$0 \leq K + \sum_{k=1}^{K} [\boldsymbol{\psi}]_{\ell+(k-1)L} \leq 2, \quad \forall \ell, \tag{4d}$$

$$2 \leq K + \sum_{k=1}^{K} [\boldsymbol{\Phi}]_{n,\ell+(k-1)L} \leq 2(K-1), \forall \ell, n. \tag{4e}$$

In this formulation, (4b) and (4c) replace the binary constraint, and (4d) and (4e) replace the linear constraints. Although (4e) is redundant when (4b) is enforced, it will help us to generate good solutions of (4) later when the equality in (4b) is relaxed.

The rank-1 constraint in (4b) cannot be cast in a convex form and results in the NP-hardness of (4). To obtain a close-to-optimal solution, we consider a relaxed version of (4) wherein the equality in (4b) is replaced with

$$\boldsymbol{X} - \boldsymbol{x}\boldsymbol{x}^T \succeq \boldsymbol{0}, \tag{5}$$

where $\boldsymbol{X}$ and $\boldsymbol{x}$ are the optimization variables corresponding to the vectors $\boldsymbol{\Phi}$ and $\boldsymbol{\psi}$ in (4), respectively. Neither the constraint in (5) nor the objective in (4a) is convex. To cast the relaxed problem in a more convenient form, we lower bound the objective with an auxiliary variable, t. The matrix $\boldsymbol{X} - \boldsymbol{x}\boldsymbol{x}^T$ is the Schur complement of $\boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{X} & \boldsymbol{x} \\ \boldsymbol{x}^T & 1 \end{bmatrix}$, which is positive semidefinite (PSD) if and only if $\boldsymbol{\Omega}$ is PSD. Hence, the relaxed problem can be formulated as

$$\max_{t,\boldsymbol{X},\boldsymbol{x}} \quad t, \tag{6a}$$

$$\text{subject to} \quad \mathrm{Tr}\left((t\boldsymbol{F}_k - \beta_k \boldsymbol{E}_k)\,\boldsymbol{\Omega}\right) \leq 0, \quad \forall k. \tag{6b}$$

$$\boldsymbol{\Omega} \succeq \boldsymbol{0}, \tag{6c}$$

$$\mathrm{diag}\,(\boldsymbol{X}) = \boldsymbol{1}, \tag{6d}$$

$$0 \leq K + \sum_{k=1}^{K} [\boldsymbol{x}]_{\ell+(k-1)L} \leq 2, \quad \forall \ell, \tag{6e}$$

$$2 \leq K + \sum_{k=1}^{K} [\boldsymbol{X}]_{n,\ell+(k-1)L} \leq 2(K-1), \ \forall \ell, n. \tag{6f}$$

Since (6b) involves products of the form $t\boldsymbol{x}$ and $t\boldsymbol{X}$, the problem in (6) is still non-convex. However, the constraints in (6b) are quasi-linear in $(t, \boldsymbol{x}, \boldsymbol{X})$. To find the optimal t, we note that the left hand side of (6b) is monotonically increasing in t for any $\boldsymbol{x}$ and $\boldsymbol{X}$ satisfying (6c), which follows from the fact that $\mathrm{Tr}\,(\boldsymbol{F}_k \boldsymbol{\Omega}) > 0$ because both $\boldsymbol{\Omega}$ and $\boldsymbol{F}_k$ are PSD, $\forall k$. Using this, the optimal t and the corresponding $\boldsymbol{x}$ and $\boldsymbol{X}$, denoted by $t^\star$, $\boldsymbol{x}^\star$ and $\boldsymbol{X}^\star$, respectively, can be obtained by solving a series of convex feasibility problems of the form

$$\text{find} \quad \boldsymbol{X}, \boldsymbol{x}, \tag{7a}$$

$$\text{subject to} \quad \mathrm{Tr}\left((t_0 \boldsymbol{F}_k - \beta_k \boldsymbol{E}_k)\,\boldsymbol{\Omega}\right) \leq 0, \quad \forall k, \tag{7b}$$

$$\text{(6c)–(6f)}. \tag{7c}$$

For each instance of (7), the value of t_0 is fixed. To determine an interval within which it lies, we note that the optimal t_0 represents the minimum SINR observed by the UTs. This SINR is upper-bounded by $t_{\max} = \min_{m=1,\ldots,M} \tilde{\boldsymbol{x}}_m^T \boldsymbol{A}_m \tilde{\boldsymbol{x}}_m / \sigma^2$, where $\tilde{\boldsymbol{x}}_k = [-\boldsymbol{1}_{(k-1)L}^T, \boldsymbol{1}_L^T, -\boldsymbol{1}_{(K-k)L}^T]^T$. Hence, the optimal t_0 must lie in $[0, t_{\max}]$. If (7) is feasible for some t_0, then $t_0 \leq t^*$. Conversely, if (7) is found to be infeasible for this value of t_0, then $t_0 > t^*$. Hence, t^* must lie on the boundary of the feasible set of (6), and can be found using a bisection search.

A. Randomization for Coordinated Port Selection

Since (6) is a relaxation of the original optimization, it does not necessarily yield the same solution. However, a close-to-optimal solution can be found by applying Gaussian randomization. Specifically, generating a set of J random vectors $\mathcal{V} = \{\boldsymbol{v}^{(j)}\}_{j=1}^{J}$, where $\boldsymbol{v}^{(j)} \in \mathbb{R}^{LK}\ \forall j$, from the Gaussian distribution $\mathcal{N}(\boldsymbol{x}^\star, \boldsymbol{X}^\star - \boldsymbol{x}^\star\boldsymbol{x}^{\star T})$ implies that, for large J, the entries of $\mathcal{V}$ provide approximate solutions to the following stochastic optimization problem [9]:

$$\max_{\boldsymbol{X}^\star=\mathrm{E}\{\boldsymbol{v}\boldsymbol{v}^T\}\ \boldsymbol{x}^\star=\mathrm{E}\{\boldsymbol{v}\}} \quad t,$$
$$\text{subject to} \quad \mathrm{E}\big\{[\boldsymbol{v}^T\ 1]\big(t\boldsymbol{F}_k - \beta_k\boldsymbol{E}_k\big)[\boldsymbol{v}^T\ 1]^T\big\} \le 0,\ \forall k,$$
$$\mathrm{E}\{[\boldsymbol{v}]_n^2\} = 1, \quad n = 1, \ldots, LK.$$

Using (5), we see that this problem yields candidate solutions of (6), but without (6e) and (6f). The latter constraints arise due to the removal of cell boundaries considered herein and to satisfy them, we find the largest association between each port and the UTs. In particular, let

$$b_\ell^{(j)} = \max_{k=1,\ldots,K} [\boldsymbol{v}^{(j)}]_{\ell+(k-1)L}, \qquad \ell = 1, \ldots, L. \tag{8}$$

Next, we truncate the associations of the other ports with each UT, such that only the port with the largest association with this UT is allowed to transmit to it. Specifically, $\forall \ell, k$,

$$[\boldsymbol{u}^{(j)}]_{\ell+(k-1)L} = \begin{cases} b_\ell^{(j)}, & \text{if } [\boldsymbol{v}^{(j)}]_{\ell+(k-1)L} = a_\ell^{(j)} \\ -1, & \text{otherwise} \end{cases}, \tag{9}$$

Doing so ensures that (6e) and (6f) are satisfied. Now, to extract candidate binary solutions to the original optimization problem, we use $\boldsymbol{\psi}^{(j)} = \mathrm{sgn}(\boldsymbol{u}^{(j)})$, where $\mathrm{sgn}(\cdot)$ is the element-wise signum function. Finally, using $\boldsymbol{\gamma} = (\boldsymbol{\psi} + 1)/2$, the corresponding candidate solutions of (3) are obtained and the one yielding the largest objective is chosen, i.e.,

$$\boldsymbol{\gamma}^\star = \arg\max_j \min_k \mathsf{SINR}_\mathsf{k}(\boldsymbol{\gamma}^{(\mathrm{j})}). \tag{10}$$

B. Ternary Port State Vectors

In the previous section, port states were obtained by element-wise binary quantization of $\boldsymbol{u}$. Herein, we extend the solution space to include ternary states, which we denote by

$$\boldsymbol{\psi}'^{(j)} = \begin{cases} 1, & \boldsymbol{u}^{(j)} > c \\ g, & -c \le \boldsymbol{u}^{(j)} \le c \\ -1, & \boldsymbol{u}^{(j)} < -c \end{cases}, \qquad j = 1, \ldots, J. \tag{11}$$

To determine c and g, we revisit the binary case, in which $\mathrm{sgn}(\cdot)$ divided the area under the Gaussian probability distribution function (PDF) into two equal halves, each corresponding to a probability of $1/2$. To determine c for the ternary case, we divide the area under the Gaussian PDF into three equal parts. Using the symmetry of the PDF, the boundaries of these areas can be seen to be given by $\pm c$, where $c = Q^{-1}(1/3) \simeq 0.433$. To determine g, we note that the actual port states $\boldsymbol{\gamma}' = (\boldsymbol{\psi}' + 1)/2$ are power coefficients. Hence, for a port to transmit at half its maximum power, the square of the corresponding entry of $\boldsymbol{\gamma}'$ must be $1/2$. In other words, g must satisfy $(g+1)^2/4 = 1/2$, which yields $g = \sqrt{2}-1$. Using these values of c and g, in Section IV, we will show that ternary port states enable significant performance gains without invoking a substantial increase in design and implementation complexity.

C. Computational Complexity Analysis

Using interior point methods to solve (6), the computational complexity of the proposed technique can be obtained using the approach in [9]. This complexity is upper-bounded by $O\big((LK)^{4.5}\log(1/\epsilon)\log(t_{\max}/\epsilon) + (LK)^2 J\big)$, where $\epsilon > 0$ is the solution accuracy.

In contrast with the proposed technique, which offers polynomial complexity for finding close-to-optimal port state vectors, exhaustive search could be used to determine the optimal port state vector. However, the complexity of exhaustive search is exponential in total number of UTs and ports, i.e., $O\big(2^{LK}\big)$ for the binary case and $O\big(3^{LK}\big)$ for the ternary one. Such a complexity renders exhaustive search generally impractical.

IV. Performance Evaluation

We consider a system with a rectangular grid of L evenly-distributed ports. For ease of exposition, all ports are assumed to have a single antenna and identical transmit powers, i.e., $P_\ell = P, \forall \ell$. The SINRs are equally weighted, i.e., $\beta_k = 1, \forall k$, and the channel model is chosen to be the non-line-of-sight urban micro-cell one in the 3GPP specifications [13], [14]. The carrier frequency is 1.9 GHz. The noise power is -114 dBm. Port elevation is 12.5 m, and UT elevation is 1.5 m. The complex gains are $h_{\ell k} = \sqrt{\rho(d_{\ell k})s_{\ell k}}\, f_{\ell k}$, where $\rho(d_{\ell k}) = 10^{-34.53-38\log_{10}(d_{\ell k})}$ is the path loss, $d_{\ell k}$ is the distance between the ℓ-th port and the k-th UT, $s_{\ell k}$ is the log-normal shadowing with 0 dB mean and standard deviation $\sigma_s = 10$ dB, and $f_{\ell k}$ corresponds to Rayleigh fading.

For comparison, we will consider the two schemes presented in [4] as baseline schemes. The first scheme is a single transmit selection one in which the port with the smallest propagation pathloss to a particular UT is selected to transmit to it. The second scheme is a blanket transmission one in which the N available ports are used to transmit to a partiuclar UT. For our framework these schemes are applied in a round-robin fashion.

In all examples, the SINRs are averaged over 2000 channel realizations and the number of Gaussian samples, J, is chosen to be 500 for each iteration. To evaluate the proposed technique in realistic scenarios, we consider two user distributions:

- Homogeneous: UTs are distributed uniformly.
- Heterogeneous: UTs are distributed within the cloud according to the Matern cluster process [15]. The UTs in each drop are uniformly-distributed within a circle of a random uniformly-distributed centre and radius r. The value of r controls heterogeneity; a small r yields a hotspot scenario. Herein, we choose r to be 50 meters.

For ease of evaluation, β_k is chosen to be 1 for all UTs, and the number of antennas is set to one for all ports and UTs.

Example 1: We consider a 6-port cloud with 2 rows and 3 columns serving 2 homogeneously-distributed UTs with binary port states. Adjacent ports are spaced 200 meters apart.

In Fig. 1, the largest minimum SINR achieved by the proposed technique is compared with that of the optimal solution obtained using exhaustive search over all $2^{LK} = 4096$ port state vectors, and with those of the baseline schemes. It can be seen that its performance approaches that of exhaustive search. The proposed technique also outperforms the baseline schemes, e.g., at $P = 5$ dBm, the minimum SINR achieved

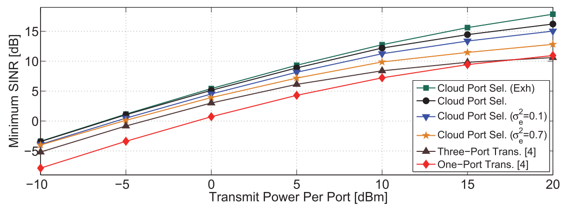

Fig. 1. Proposed vs. baseline schemes.

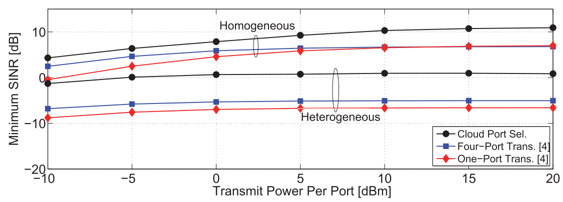

Fig. 2. Homogeneous vs heterogeneous distributions.

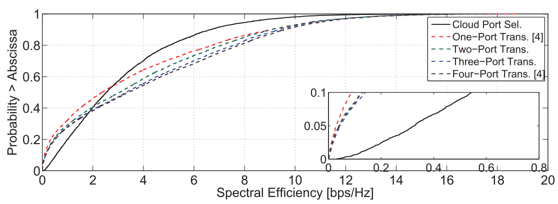

Fig. 3. CDF comparison of spectral efficiencies of all UTs.

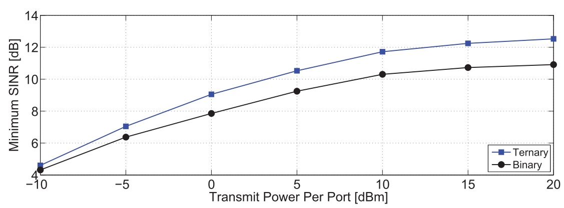

Fig. 4. Performance comparison: binary and ternary states.

by this technique is 3 and 5 dB higher than three-port and one-port transmission, respectively.

Here we also investigate the effect of imperfect CSI on the performance of the proposed technique by introducing channel estimation error with variance σ_e^2. In Fig. 1, this performance impact is shown for two error variances, $\sigma_e^2 = 0.1$ and $\sigma_e^2 = 0.7$ [16]. It can be seen that while its performance degrades as the CSI imperfection increases, the proposed technique continues to outperform the baseline schemes, even though those solutions are generated with perfect CSI.

Example 2: Now we consider a 12-port cloud with 3 rows and 4 columns serving 3 UTs. The distance between adjacent ports is 100 meters. Exhaustive search is computationally prohibitive here because there are 2^{36} port state vectors.

In Fig. 2, the performance of the proposed technique with binary port state vectors is compared with that of the one-port and three-port schemes for homogeneous and heterogeneous user distributions. It can be seen that the proposed technique outperforms the baseline schemes for both user distributions.

Fig. 3 shows the cumulative distribution functions (CDFs) of the spectral efficiency achieved by the proposed and baseline techniques for all UTs with heterogeneous distribution and $P = 5$ dBm. It can be concluded that although the proposed technique maximizes the minimum SINR of the UTs, it maintains superior performance for *all* the other UTs. This element of fairness is a product of the chosen design objective.

Fig. 4 compares the minimum SINRs achieved by binary and ternary port states. Ternary states outperform binary ones, suggesting that additional power levels improve performance.

V. Conclusion

We considered the downlink of a DAS cloud, wherein any port can transmit to any UT. A coordinated port selection technique based on SDR and Gaussian randomization was proposed to maximize the minimum SINR of the UTs. Binary and ternary port states were considered and although the proposed technique does not necessarily yield the optimal solution, its performance approaches that of exhaustive search, but with much less computational complexity.

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