Energy-Efficient Multi-Mode Transmission in Uplink Virtual MIMO Systems

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***Abstract*—In this paper, we tackle the energy efficiency (EE) issue in uplink virtual MIMO systems, which requires the optimization of two interlaced parameters: the number of constituent mobile users in the virtual MIMO and their corresponding power allocation. By exploiting the fact that increasing the number of active users can increase the number of contributors to the total EE on one hand but reducing the diversity order for each single user on the other, we can show the existence of an optimal transmission mode and find a simple way for its search. Through in-depth analysis, we show the existence of a unique globally optimal power allocator for the case without power constraints, and further reveal the impact of power constraints upon power allocation, as compared to its global counterpart, aiming to provide a powerful means for power-constrained EE optimization. Finally, we establish theories, for homogeneous networks, to narrow down the search range for possible transmission modes, leading to a significant reduction of computational complexity in optimization. Simulation results are presented to substantiate the proposed schemes and the corresponding theories.**

I. Introduction

Multiple-input multiple-output (MIMO) technology has attracted great attention due to its high spectral efficiency (SE). However, the application of MIMO uplink is often limited by the difficulty in practical implementation of multiple power amplifiers at users, especially in small hand-sets. To solve this problem, virtual MIMO (V-MIMO) transmission is proposed for the uplink [1], which allows several users, each of a single transmit antenna, to share the same time-frequency resource blocks. On the other hand, energy efficiency (EE) becomes increasingly important for mobile communications to prolong the life cycle of batteries [2]. Physically, EE represents the exhange rate between energy and data speed, measured by the number of information bits that can be reliably conveyed over the channel per-unit energy consumption [3].

In contrast to its high spectral efficiency, a MIMO system can have lower energy efficiency than a single-input and single output (SISO) system [4]. A key technology to improve the EE of MIMO systems is the use of adaptive techniques. By integrating adaptive modulation and adaptively choosing spatial transmission modes for MIMO systems, the EE can be significantly improved, achieving up to 30% improvement over its non-adaptive counterpart [5].

However, the operation of adaptive schemes relies on the instantaneous channel state information (CSI), and thus requires a base station (BS) to schedule huge *instantaneous CSI feedback* from multiple users, leading to a large overhead and a significant drop in system efficiency. In our previous work [6], a joint single-user/multi-user (SU/MU) mode switching with power loading algorithm was proposed for maximizing system energy efficiency based on statistical channel information. The mode switching and power optimization is based on average SNR or pathloss, which are easily available at the BS. But it only switches between SU mode and the full MU mode that serves the maximum number of users that can be supported, i.e., it is dual-mode switching strategy.

In this paper, we tackle the optimization issue of energy efficient uplink V-MIMO transmission based on the *statistical channel state information* (SCSI) and multi-mode switching strategy. The optimization includes two interlaced aspects, determining the optimal number of constituent (i.e., active) users in the V-MIMO and its corresponding optimal power allocation. The former parameter is a *structural* one of the V-MIMO while the latter is a usual system vector parameter but can be optimized only after the former is determined. The optimal number of constituent users is influenced by the channel SCSI. and signal-to-noise ratio (SNR) and thus varies with the channel operating conditions and the particulars of the constituent users. In this paper, we first establish the existence of global solution, and then derive efficient optimization techniques for V-MIMO systems with and without a power constraint. To reduce complexity in transmission mode adaptation, we further derive an efficient suboptimal strategy and theory for mode selection, in the context of homogeneous networks.

II. System Model

Consider the uplink transmission in which U mobile users within a cell communicate with the Node-B in a quasi-static Rayleigh flat-fading environment. Each user is assumed to employ only one transmit antenna, i.e., $N_t = 1$, while the Node-B is equipped with r receive antennas. The scheduler in the Node-B randomly selects $u \leq U$ users, from the total of U, to share the same time-frequency resource, forming a V-MIMO system characterized by an $r \times u$ channel matrix $\mathbf{H}$. After appropriately power loaded with a loading matrix $\mathbf{P}_u^{1/2} = \text{diag}\{\sqrt{P_1}, \cdots, \sqrt{P_u}\}$, the symbol vector $\mathbf{s} \in \mathcal{C}^{\mathbf{u}\times\mathbf{1}}$ from the u selected users is transmitted over the channel,

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producing an r-by-1 received vector $\mathbf{y}$ at the Node-B:

$$\mathbf{y} = \mathbf{H}\mathbf{G}_u\mathbf{P}_u^{1/2}\mathbf{s} + \mathbf{n}, \tag{1}$$

where $\mathbf{E}[\mathbf{s}\mathbf{s}^\dagger] = \mathbf{I}_u$, and $\mathbf{G}_u = \mathrm{diag}\{G_1, G_2, \cdots, G_u\}$ denotes the path-loss matrix. The entries of the random matrix $\mathbf{H}$ are independent and identically distributed (i.i.d.) complex Gaussian distributed with zero mean and unit variance. The vector $\mathbf{n}$ is modeled as zero-mean additive white Gaussian noise (AWGN) with covariance matrix $\mathbf{E}[\mathbf{n}\mathbf{n}^\dagger] = \sigma_n^2\mathbf{I}_r$.

The power P_i allocated to user i is expected to convert into a certain data rate (more accurately a spectral efficiency), usually measured in terms of $\log_2(1+\gamma_i)$ with γ_i denoting the instantaneous signal-to-noise ratio (SNR) at the Node-B receiver for user i. We are interested in the energy-conversion efficiency, as defined by

$$EE_i = \frac{\log_2(1+\gamma_i)}{P_i + P_c} \text{ bps/Hz/Joule}. \tag{2}$$

The circuit power P_c is also included in the denominator for calculation; it represents the average energy consumed in the relevant electronic devices. Clearly, EE_i is a random variable, depending on the channel matrix $\mathbf{H}$. It is therefore more practical to consider its statistical average:

$$\eta_i(P_i) = \mathbf{E_H}[EE_i] = \frac{E_{\mathbf{H}}[\log_2(1+\gamma_i)]}{P_i + P_c}, \tag{3}$$

which is sometimes called the achievable energy efficiency for i-th user, representing the ratio of the ergodic rate to the power consumption. For practical applications, the sum energy efficiency of all active users is more appealing, which is defined by

$$\eta(u, \mathbf{P}_u) = \sum_{i=1}^{u} \eta_i = \sum_{i=1}^{u} \frac{E_{\mathbf{H}}[\log_2(1+\gamma_i)]}{P_i + P_c}. \tag{4}$$

Choosing an appropriate number of active users, i.e., $1 \leq u \leq r$, can be considered as choosing a *transmission mode* in the uplink V-MIMO system.

The value γ_i depends not only on the channel, but also on the post-processing technique to be used. In this paper, it is assumed that perfect CSI is available at the Node-B and the zero-forcing (ZF) detection method is employed at the receiver [7], leading to the decision variables

$$\mathbf{H}^{\#}\mathbf{y} = \mathrm{diag}(P_1G_1, \cdots, P_uG_u)\mathbf{s} + \mathbf{H}^{\#}\mathbf{n}, \tag{5}$$

where $\mathbf{H}^{\#} = (\mathbf{H}^\dagger\mathbf{H})^{-1}\mathbf{H}^\dagger$ denotes the pseudo-inverse of $\mathbf{H}$. From (5), it follows that the output SNR for user i is given by

$$\gamma_i = \underbrace{(P_iG_i/\sigma_n^2)}_{\rho_i} \underbrace{\frac{1}{[(\mathbf{H}^\dagger\mathbf{H})^{-1})]_{ii}}}_{\xi_i}, \tag{6}$$

with $[\mathbf{A}]_{ii}$ signifying the i-th diagonal element of the matrix $\mathbf{A}$. For i.i.d. Rayleigh fading channels, $\mathbf{H}^\dagger\mathbf{H}$ follows the complex Wishart distribution as shown by $\mathbf{H}^\dagger\mathbf{H} \sim CW_u(r, \mathbf{I})$. Thus, the use of Theorem 3.2.11 of Muirhead [8] enables the assertion that ξ_i defined above is a chi-square variable with $2(r-u+1)$ degrees of freedom; i.e.,

$$\xi_i \sim \frac{1}{2}\chi^2(2(r-u+1)). \tag{7}$$

As such, we can represent the achievable energy efficiency for the i-th user as [9]

$$\eta_i(P_i) = \frac{E_{\xi_i}[\log_2(1+\rho_i\xi_i)]}{P_i + P_c}, \tag{8}$$

where $\rho_i = \frac{P_iG_i}{\sigma_n^2}$ is the equivalent transmit SNR for user i. With the above notation, the sum energy efficiency of all active users in (4) can be rewritten as

$$\eta(u, \mathbf{P}_u) = \sum_{i=1}^{u} \frac{\mathbf{E}_{\xi_i}[\log_2(1+\rho_i\xi_i)]}{P_i + P_c}. \tag{9}$$

The maximization of the sum efficiency η in (9) requires efforts in two aspects. First, select an appropriate number of users, u, for transmission which corresponds to the selection of a transmission mode. Second, given a transmission mode, find an optimal power allocation strategy $\mathbf{P}_u$. Thus, the optimization at hand is to find u^* and $\mathbf{P}_u^*$ such that

$$\{u^*, \mathbf{P}_{u^*}^*\} = \arg\max_{u, \mathbf{P}_u} \eta(u, \mathbf{P}_u). \tag{10}$$

Clearly, this is a joint optimization problem.

III. Power Optimization for Energy Efficiency

In the joint optimization defined in (10), the parameters to be optimized are interrelated. To optimize $\mathbf{P}_u$, we need to figure out u first; the same is true for optimizing the transmission mode u. To get rid of such an entanglement, we define a conditional objective function $\eta(\mathbf{P}_u|u)$ for a given number of active users u, and break the optimization problem (10) into two steps. In the first step, we find the conditional optimizers:

$$\mathbf{P}_u^* = \arg\max_{\mathbf{P}_u} \eta(\mathbf{P}_u|u), \tag{11}$$

for all $u = 1, 2 \ldots, r$. Then in the second step, the final solution is determined as

$$u^* = \arg\max_{v}\{\eta(P_v^*|v),\ v = 1, \ldots, r\}, \tag{12}$$

which defines the optimal power allocator $\mathbf{P}_{u^*}^*$. Clearly, (11) is the key step to our optimization problem. In what follows, we will address it under two possible operational conditions, i.e., without and with power constraint on transmission.

As indicated in (4), the ZF receiver decouples the interference among different users. Thus, without a power constraint, the maximization of the sum energy efficiency is equivalent to maximizing the energy efficiency of each active user as if it were operating in an interference-free environment. Nevertheless, the objective function η_i is highly nonlinear in P_i thereby raising a question as regard to the existence of the optimal solution and its uniqueness. The following assertions address this concern.

Proposition 1: There exists one and only one point $P_i^* \in (0, \infty)$ that maximizes $\eta_i(P_i)$. The function $\eta_i(P_i)$ is monotonic increasing over the interval $P_i \in (0, P_i^*]$ while monotonic decreasing over the interval $P_i \in (P_i^*, +\infty)$. However, regardless of its concavity over $P_i \in (0, P_i^*)$, $\eta_i(P_i)$ is neither concave nor convex over $P_i \in (P_i^*, \infty)$.

The proof can be found in the journal version [10].

Given the existence of the optimal power, it remains to determine it. To this end, we denote

$$f(\rho_i) = \mathbf{E}_{\xi_i}[\log_2(1 + \rho_i \xi_i)], \; i = 1, \ldots, u, \tag{13}$$

so that the energy efficiency can be written as $\eta_i = f(\rho_i)/(P_i + P_c)$ where $\rho_i = P_i G_i / \sigma_n^2$. For a given number of active users, the optimal power P_i^* should satisfy the condition of $\frac{d\eta_i}{d P_i^*} = 0$, which, when simplified, reduces to

$$\alpha(P_i^*) \triangleq (G_i/\sigma_n^2)(P_i^* + P_c) f'(\rho_i^*) - f(\rho_i^*) = 0, \tag{14}$$

where $\rho_i^* = P_i^* G_i / \sigma_n^2$ and the derivative of $f(\rho_i)$ with respect to ρ_i can be explicitly expressed by

$$f'(\rho_i) = \mathbf{E}_{\xi_i}\left[\frac{\xi_i}{(1 + \rho_i \xi_i)\ln 2}\right]. \tag{15}$$

The optimal power is a root of the nonlinear function $\alpha(P_i)$ defined above, to which a closed-form solution is clearly impossible. A numerical solution can be obtained by resorting to the Newton-Raphson iteration method.

While considering power constraint, we can decouple this optimization problem into three cases based on the optimal power of unconstraint condition and power region. Since the analyzed method is the same as our previous work [6], the detailed process will be omitted here.

Then, the optimizers so obtained clearly depend on the channel conditions including SNR, average channel propagation loss, and the power constraint setting $P_{\min}$ and $P_{\max}$. Thus, as the channel conditions change, the transmission mode needs to adapt itself to the changing operational environment. This can be done by the global method of exhausted enumeration. To further reduce the computational complexity, a suboptimal solution for mode selection will be described in the next section.

IV. Mode Pre-selection for Complexity Reduction

In the preceding section, the optimization of the energy efficiency was done by comparing the conditional power optimizers exhaustedly for all the possible transmission modes $1 \leq u \leq r$. This type of exhausted enumeration is time consuming.

The computational complexity will be considerably reduced if we can narrow down the range for u, from some theoretical perspective, before power optimization. Though suboptimal in nature, the result so obtained is very close to the global optimal solution, as will be demonstrated in Section V.

Since we want to determine the most likely transmission modes without performing power allocation, it is reasonable to assume that each user transmits its signal with the maximal power. In this paper, we assume all users have the same maximal power, denoted as P. With these conditions, (9) can be rewritten as:

$$\eta(u) = \sum_{i=1}^{u} \frac{\mathbf{E}_{\xi_i}[\log_2(1 + \rho_i \xi_i)]}{P + P_c} \tag{16}$$

where $\rho_i = G_i P / \sigma_n^2$. Note that the denominator is now of irrelevance to the transmission mode. Thus, by denoting

$$\mathcal{R}(u) = \sum_{i=1}^{u} \underbrace{\mathbf{E}_{\xi_i}[\log_2(1 + \rho_i \xi_i)]}_{R_i(k)} \tag{17}$$

where $k = r - u + 1$ signifies the diversity order by each user. The maximization of η reduces to the maximization of $\mathcal{R}$, namely, to find the optimal transmission mode u^* for which,

$$u^* = \arg \max_{1 \leq u \leq r} \mathcal{R}(u). \tag{18}$$

Physically, $\mathcal{R}(u)$ is the sum ergodic rate of all u users and correspondingly, $R_i(u)$ is the ergodic rate of the i-th user in (17). Recall that transmission rate, up to a normalization factor, represents the spectral efficiency. The expression (18) suggests that the selection of optimal transmission mode can be done on the basis of spectral efficiency maximization, at least at the level of a suboptimal solution.

First, we investigate the behavior of each component in $\mathcal{R}$, ending up with results described below.

Proposition 2: Denote the ergodic rate of one user with channel gain G as $R(k) = \mathbf{E}_\xi[\log_2(1 + \rho\xi)]$ where $\xi \sim \chi^2(2k)$, $k = r - u + 1$, and $\rho = \frac{PG}{\sigma^2}$. Then $R(k)$ increases monotonically with k, and is concave with k, i.e.,

$$\Delta_R^1(k) = R(k+1) - R(k) > 0, \tag{19}$$

$$\Delta_R^2(k) = \Delta_R^1(k+1) - \Delta_R^1(k) < 0. \tag{20}$$

Proof: To show the monotone increasing property, by definition we can write the first-order difference as

$$\begin{aligned} \Delta_R^1(k) &= R(k+1) - R(k) \\ &= \frac{\log_2(e)}{k!} \int_0^\infty \frac{\rho}{1 + \rho x} e^{-x} x^k dx > 0. \end{aligned} \tag{21}$$

By the same token, we proceed for the second-order difference yielding

$$\begin{aligned} \Delta_R^2(k) &= \Delta_R^1(k+1) - \Delta_R^1(k) \\ &= -\frac{\log_2(e)}{(k+1)!} \int_0^\infty \frac{\rho^2}{(1 + \rho x)^2} e^{-x} x^{k+1} dx < 0 \end{aligned} \tag{22}$$

which along with (21) completes the proof.

The use of Proposition 2 to (17), alongside the fact that $k = r - u + 1$, enables us to assert that each R_i decreases with the number of active users u. Clearly, as the summation of u terms, $\mathcal{R}$ increases with u on one hand whereas each summand decreases with u on the other. As such, there must be an optimal transmission mode u^* that maximizes the sum energy efficiency.

Note that R_i depends on the channel gain G_i through $\rho_i = \frac{PG_i}{\sigma^2}$. Thus, how to select u^* active users among all U users is a key issue for the optimization problem (17). There is a tradeoff between the performance and the fair issue. In this paper, we aim to guarantee fair transmission and select users randomly.

We next consider an important special case of homogeneous networks, for which (17) can be simplified. The term homogeneous network implies identical propagation loss for all users, i.e., $G_i = G$ (for $1 \leq i \leq U$) which, in turn, implies equal SNR ρ_i and equal rate $R_i(k)$ for all the users, i.e., $\rho_i = \rho = \frac{PG}{\sigma^2}$ and $R_i(k) = R(k)$. Thus, we can rewrite (17) as

$$\mathcal{R}(u) = uR_i(r - u + 1) \tag{23}$$

which, by changing the variable $u = r - k + 1$, is alternatively expressible as

$$\mathcal{R}(k) = (r - k + 1)R(k) \tag{24}$$

with $R(k)$ defined in Proposition 2.

Lemma 1: The sum rate $\mathcal{R}(k)$ is a concave function of the diversity order k for each user.

Proof: By direct calculation, it is easy to obtain

$$\begin{aligned} \Delta^1_{\mathcal{R}}(k) &= \mathcal{R}(k+1) - \mathcal{R}(k) \\ &= (r - k + 1)\Delta^1_R(k) - R(k+1) \end{aligned} \tag{25}$$

whereby the second-order difference can be determined as

$$\begin{aligned} \Delta^2_{\mathcal{R}}(k) &= \Delta^1_{\mathcal{R}}(k+1) - \Delta^1_{\mathcal{R}}(k) \\ &= (r - k + 1)\Delta^2_R(k) - 2\Delta^1_R(k+1). \end{aligned} \tag{26}$$

Now, from Proposition 2, we know that $\Delta^2_R(k) < 0$ and $\Delta^1_R(k+1) > 0$. We can thus assert $\Delta^2_{\mathcal{R}}(k) < 0$ which completes the proof.

By virtue of Lemma 1, we are in position to present a main result for homogeneous networks.

Proposition 3: Asymptotically, the optimal transmission mode for homogeneous networks is given by

$$u^* = \begin{cases} [\frac{r}{2} + 1] & \rho \to 0 \\ r & \rho \to \infty. \end{cases} \tag{27}$$

where $[x]$ denotes the integer part of x.

Proof: In (25), using the rule of integration by part, and by passing $\rho \to 0$, yields

$$\Delta^1_{\mathcal{R}}(k) \approx \frac{\log_2(e)}{k!}\rho(r - 2k)\int_0^\infty e^{-x}x^k dx. \tag{28}$$

Form (28), it follows that $\Delta^1_{\mathcal{R}}([\frac{r}{2}]) \geq 0$ and $\Delta^1_{\mathcal{R}}([\frac{r}{2}+1]) < 0$. Hence, we have $k^* = [\frac{r}{2}]$ leading to $u^* = r - k^* + 1 = [\frac{r}{2}+1]$.

Next, letting $\rho \to \infty$, we obtain

$$\begin{aligned} &\Delta^1_{\mathcal{R}}(1) = r\Delta^1_R(1) - R(2) \\ &= \log_2(e)\int_0^\infty [\frac{r\rho}{1+\rho x} - \ln(1+\rho x)]xe^{-x}dx < 0 \\ &\quad (\text{Since } \frac{r\rho}{1+\rho x} - \ln(1+\rho x) < 0 \text{ when } \rho \to \infty). \end{aligned} \tag{29}$$

It follows that $k^* = 1$, which leads to $u^* = r$.

Another main result for homogeneous networks is summarized as follows.

Proposition 4: For a general SNR ρ, the optimal transmission mode of homogeneous networks can be narrowed down, ranging between $[\frac{r}{2} + 1]$ and r; namely,

$$[\frac{r}{2} + 1] \leq u^* \leq r. \tag{30}$$

Proof: When $k = [\frac{r}{2}]$, we have

$$\begin{aligned} \Delta^1_{\mathcal{R}}(k) &= r\Delta^1_R(k) - R(k+1) \\ &< 0 \; (\text{Since } \frac{\rho x}{1+\rho x} - \ln(1+\rho x) < 0). \end{aligned} \tag{31}$$

Thus $k^* \leq [\frac{r}{2}]$ and $u^* \geq [\frac{r}{2} + 1]$ which, when combined, allow us to write $[\frac{r}{2} + 1] \leq u^* \leq r$.

Based on the theory derived in this section, a low complexity pre-selection technique for transmission mode has been developed, which is summarized in Algorithm 1 for ease of use.

Algorithm 1 Low-Complexity Pre-Selection Algorithm

Initialize:
  Denote $u^* = 0$ as optimal transmission mode.
  Denote $\eta^* = 0$ as maximal energy efficiency.
for $[\frac{r}{2} + 1] \leq u \leq r$ **do**
  Doing optimal power allocation and obtain the maximal EE $\eta(u)$ according to (11) in Sec-III.
  if $\eta(u) > \eta^*$ **then**
    $\eta^* = \eta(u)$.
    $u^* = u$.
  end if
end for

V. Simulation Results

In this section, we examine the energy efficiency of the proposed mode-switching scheme with optimal power allocation for uplink V-MIMO systems. For simplicity, we assume a single cell scenario in which each user is assigned with all resource blocks, and the Node-B employs a ZF receiver with perfect CSI and perfect synchronization.

We first investigate the behavior of the energy efficiency (i.e., the objective) function defined in (9) by setting $r = 4$ and $P_i = P/u$ for all $i = 1, 2, \cdots, u$ with SNR$= \frac{P}{\sigma_n^2}$ in Fig. 1. Note that u is the number of paired users. It is observed that an optimal transmission mode (i.e., the optimal number of active users) does exist over a certain range of SNRs. For example, $u = 1$ outperforms other modes over SNR$\in (-20, -10)$dB, and so does u over SNR$\in (-10, -2)$dB. If we plot the curves in the linear scale as shown in the small window for $u = 1$, it is also observed that there exists a unique peak in the energy efficiency curve. The objective function is concave before the peak value and becomes neither concave nor convex, as asserted in Proposition 1. The curves based on simulations are also included for comparison.

For a homogeneous network with a total power constraint between $P_{\min}$ and $P_{\max}$, each transmission mode is optimal over a certain operational region defined by $P_{\min}$, $P_{\max}$ and $\delta_p = P_{\max} - P_{\min}$. The relationship is intuitively shown in Fig. 2(a). The influence of δ_p on the achievable energy efficiency is shown in Fig. 2(b). When δ_p is small, single user (SU) mode $u = 1$ is first activated, and then switch to other modes as the operating conditions change. Increasing δ_p from 1 dB to 5dB broadens the range of attaining the highest achievable EE.

Next consider the application of the low-complexity transmission mode pre-selection (LCPS) technique to homogeneous networks, with results graphed in Fig. 3. The results obtained by the global optimization algorithm (GO) is also included as a bench mark for comparison. For most power constraint situations, the LCPS performs equally well as the GO. The gap appears in the low $P_{\min}$ region; the reason is that the transmission modes with larger u are not feasible. However, the gap will be reduced as δ_p increases, as shown in this figure. Therefore in overall, the LCPS algorithm is an effective technique.

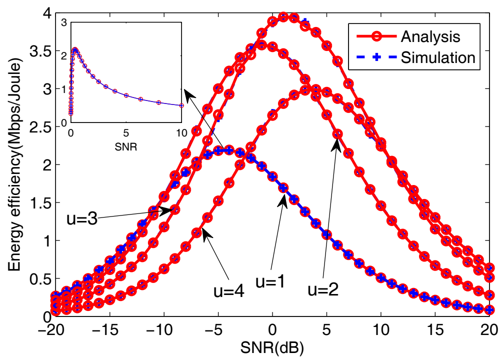
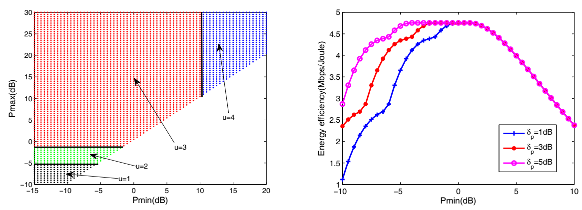


Fig. 1. Behaviors of energy efficiency as a function of SNR and user number u with $r = 4$.



(a) Operating regions.

(b) Variation of energy efficiency with different $\delta_p = P_{\max} - P_{\min}$.

Fig. 2. Operating regions and energy efficiency in the homogeneous network with $r = 4$.

VI. Conclusion

In this paper, we propose a multi-mode transmission strategy to maximize the sum energy efficiency among all active users in uplink V-MIMO systems. To reduce the computation complexity, a suboptimal algorithm in term of mode pre-selection is further proposed. Finally, the simulation results substantiate the effectiveness of our proposed joint mode switching and power loading scheme.

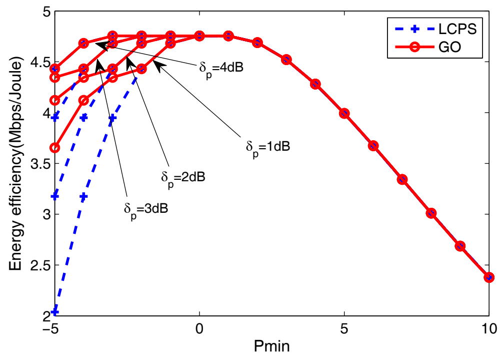


Fig. 3. Energy efficiency comparison between GO and LCPS algorithms with different $\delta_p = P_{\max} - P_{\min}$.

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References

[1] 3GPP TR 25.814(V7.1.0), "Physical layer aspects for evolved universal terrestrial tadio access (UTRA)," Sept. 2006.

[2] Y. Chen, S. Zhang, S. Xu, and G. Y. Li, "Fundamental trade-offs on green wireless networks," *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 30-37, Jun. 2011.

[3] K. Lahiri, A. Raghunathan, S. Dey, and D. Panigrahi, "Battery-driven system design: a new frontier in low power design," in *Proc. Intl. Conf. VLSI Design*, Bangalore, India, Jan. 2002, pp. 261-267.

[4] S. Cui, A. J. Goldsmith, and A. Bahai, "Energy-efficiency of MIMO and cooperative MIMO techniques in sensor networks," *IEEE J. on Sel. Areas in Comm.*, vol. 22, no. 6, pp. 1089-1098, Aug. 2004.

[5] B. Bougard, G. Lenoir, A. Dejonghe, L. van der Perre, F. Catthor, and W. Dehaene, "Smart MIMO: an energy-aware adaptive MIMO-OFDM radio link control for next-generation wireless local area networks," *Eurasip J. on Wireless Commun. and Networking*, vol. 2007, no. 3, pp. 1-12, Jul. 2007.

[6] Y. Rui, Q. T. Zhang, M. Q. Li, L. Deng and P. Cheng, "Energy Efficiency Optimization in Uplink Virtual MIMO Systems," *IEEE ICC'12*, Ottawa, Canada, June 10-15, 2012. .

[7] P. Wolniansky, G. Foschini, G. Golden, and R. Valenzuela, "V-BLAST: an architecture for realizing very high data rates over the rich-scattering wireless channel," in *Proc. Intl. Symp. on Sign., Sys., and Electr.*, Sept. 1998, pp. 295-300.

[8] R. J. Muirhead, *Aspects of multivariate statistical theory*, New York: Wiely, 1982, p. 95.

[9] Y. Rui, H. Hu, H. Yi, and H.-H. Chen, "A robust user pairing algorithm under channel estimation errors for uplink virtual MIMO systems," *IET Commun.*, vol. 6, no. 3, pp. 318-323, Feb. 2012.

[10] Y. Rui, Q. T. Zhang, L. Deng, P. Cheng, M. Li. "Mode Selection and Power Optimization for Energy Efficiency in Uplink Virtual MIMO Systems," *IEEE Journal on Selected Areas in Communications*, Accepted, Feb. 2013.